High-Resolution Subsurface Imaging Under Geologic Uncertainty with Emerging Signal Processing Techniques

Behnam Jafarpour, USC

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION

JOIN THE CONVERSATION
@SPE_EVENTS
#SPEWEBEVENTS

June 26, 2013

Related R&D Grand Challenge

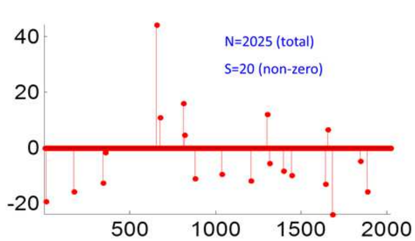
Research Objective:
Exploiting emerging sparse signal processing techniques for high resolution reservoir imaging

Related R&D Grand Challenge:
Transparent Earth: High Resolution Subsurface Imaging

Sparsity

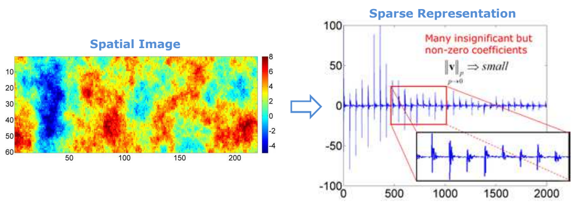
$$\|\mathbf{v}\|_0 = \#\{i, v_i \neq 0\} \qquad \|\mathbf{v}\|_0 << \dim(\mathbf{v})$$

Sparsity



Sparsity and Subsurface Images

Sparsity of spatially distributed reservoir properties



Overview

Reservoir History Matching (Inverse Modeling)

Parameterization of Reservoir Properties

Sparsity-Promoting History Matching

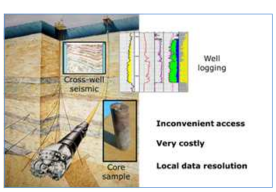
Sparse Geologic Dictionaries

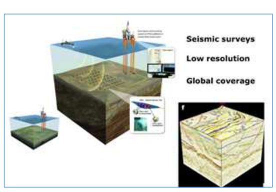
Geologic Uncertainty

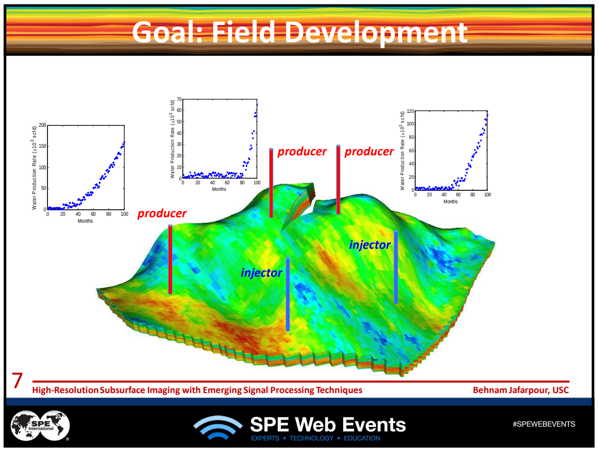
Field Application

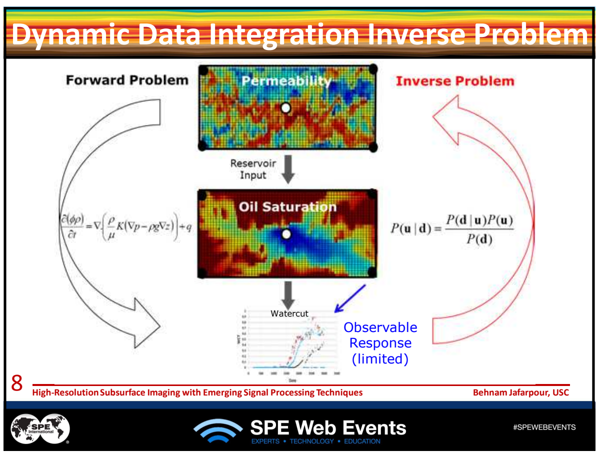
Predictive Model Construction

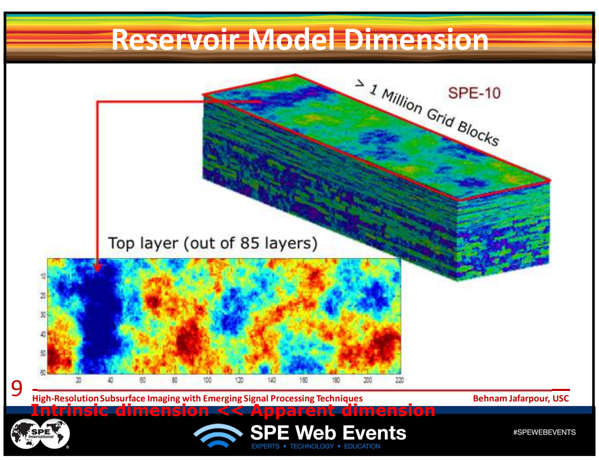
Descriptive static model(s) → Predict dynamic behavior/response → Integrate dynamic data (calibration)



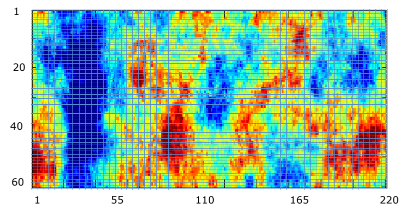



Goal: Field Development
producer
producer
producer
injector
injector
Months
7
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS


Dynamic Data Integration Inverse Problem
Forward Problem
Permeability
Inverse Problem
Reservoir Input
Oil Saturation
$\frac{\partial(\phi\rho)}{\partial t} = \nabla\left(\frac{\rho}{\mu}K(\nabla p - \rho g \nabla z)\right) + q$
$P(\mathbf{u} \mid \mathbf{d}) = \frac{P(\mathbf{d} \mid \mathbf{u})P(\mathbf{u})}{P(\mathbf{d})}$
Watercut
Observable
Response
(limited)
8
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS


Reservoir Model Dimension
> 1 Million Grid Blocks
SPE-10
Top layer (out of 85 layers)
9
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
Intrinsic dimension << Apparent dimension
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Need for Reduced Reservoir Descriptions



N=220x60=
13,200 cells

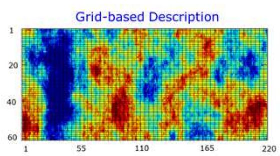
Grid-based description issues:

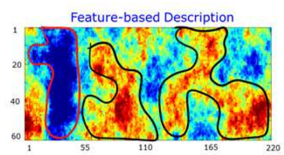
- Over-parameterization → Non-unique solutions
- Dimensionality → computational stability & complexity
- Preserving geologic continuity

Focusing on Reservoir Connectivity

Number of grid cells
N=220x60= 13,200 cells

Focus on important
features (connectivity)



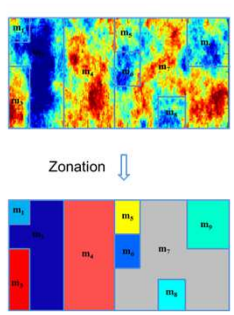


Spatial Parameterization (e.g., Zonation)

Zonation

Parameter size reduction through regionalized description

(Since 1965, Jacquard & Jain, Jahns,…)



Main Issues:

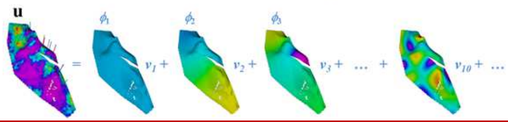
Identifying regions/zones

Sharp boundaries →
geologically unrealistic

Transform-Domain Parameterization

Compact representations in compressive bases

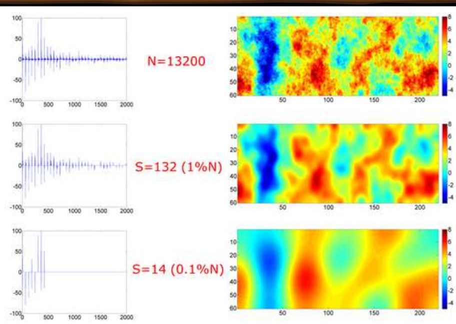
Full-Rank Representation		Low-Rank Approximation
$\mathbf{u} = \sum_{i=1}^{N} \phi_i v_i$	$\Rightarrow$	$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
N expansion terms		*S* (<<*N*) expansion terms



13 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events — EXPERTS • TECHNOLOGY • EDUCATION — #SPEWEBEVENTS

Large-Scale Connectivity Approximation

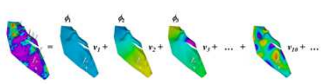


14 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events — EXPERTS • TECHNOLOGY • EDUCATION — #SPEWEBEVENTS

Transform-Domain Parameterization

Full-Rank Representation		Low-Rank Approximation
$\mathbf{u} = \sum_{i=1}^{N} \phi_i v_i$	$\Rightarrow$	$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
N expansion terms		*S* (<<*N*) expansion terms



Questions to Address:

1) What class of basis functions ϕ_i? (desirable properties)
2) $\boxed{\text{Which } (S) \text{ expansion terms to retain?}}$ **Novelty is in here!**
3) How to compute corresponding v_i's?
4) History matching implementation?

15 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

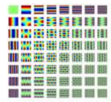
SPE Web Events — EXPERTS • TECHNOLOGY • EDUCATION — #SPEWEBEVENTS

Non-Geologic Compressive Basis Φ

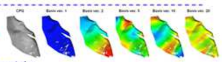
- Discrete Cosine Transform (DCT)

  Harmonics of cosine function (JPEG)

  Jafarpour and McLaughlin, 2009, SPEJ
  Bhark et al., 2010 JPSE



- Grid-Connectivity Transform



  Eigen-vectors of grid-adjacency matrix

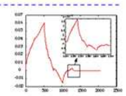
  Bhark et al., 2010 WRR
  Bhark et al., 2011 SPEJ

  Generalized DCT for irregular geometry & unstructured grid

- Discrete Wavelet Transform (DWT)

  Wavelets & filter banks (JPEG2000)

  Sahni and Horne, 2005, SPEREE
  Jafarpour, 2010, IEEE-TGRS



16 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

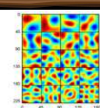
SPE Web Events — EXPERTS • TECHNOLOGY • EDUCATION — #SPEWEBEVENTS

Geologic Compressive Basis Φ

- Principle Component Analysis (PCA)

  Leading eigenvectors of the given property covariance matrix

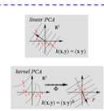
  Gavalas, 1976, SPEJ



- Kernel-Based PCA (K-PCA)

  PCA in nonlinear feature space

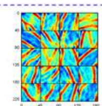
  Sarma et al., 2008, MATHGEO



- Sparse Geologic Dictionaries

  Learned sparse priors (K-SVD, MOD)

  Aharon, 2006 IEEE-TSP
  Khaninezhad et al., 2012 AWR



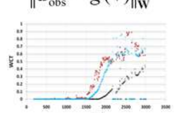
17 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events — EXPERTS • TECHNOLOGY • EDUCATION — #SPEWEBEVENTS

Inversion with Reduced Parameters

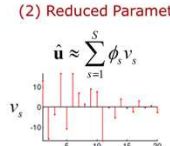
(1) Flow Response

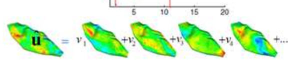
$$\|\mathbf{d}_{\text{obs}} - g(\mathbf{v})\|_{\mathbf{W}}^{2}$$



(2) Reduced Parameters

$$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$$



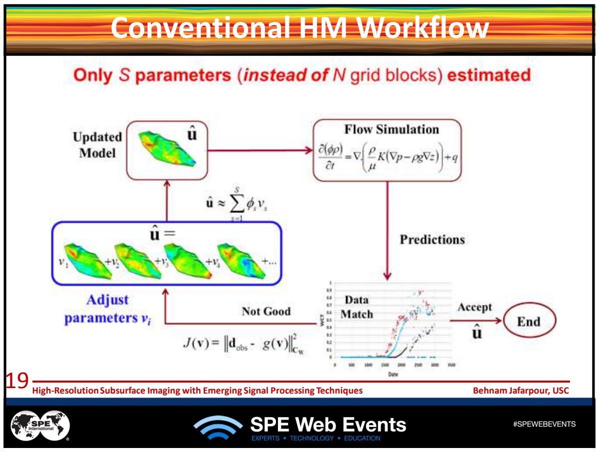


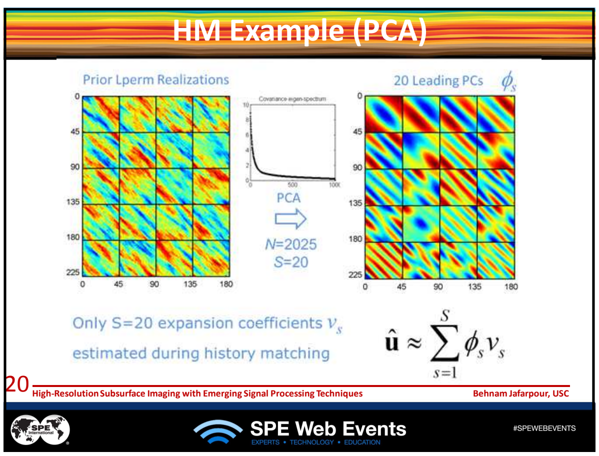
S-dimensional Minimization over $\mathbf{v}$

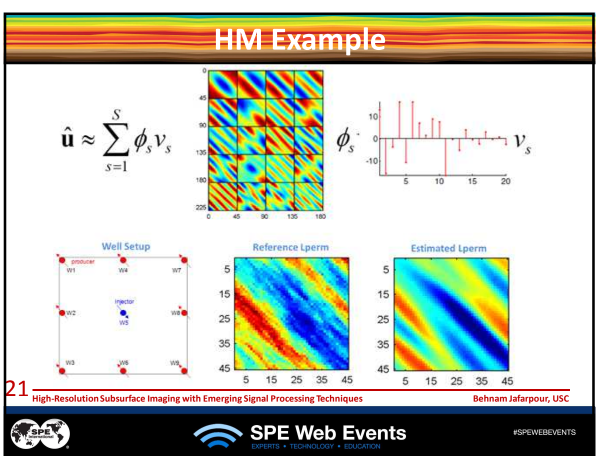
$$\hat{\mathbf{v}} = \underset{\mathbf{v}\in\Re^{N}}{\arg\min}\left\{\|\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{v})\|_{\mathbf{W}}^{2} + \ldots\right\}$$

18 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events — EXPERTS • TECHNOLOGY • EDUCATION — #SPEWEBEVENTS


Conventional HM Workflow
Only S parameters (instead of N grid blocks) estimated
Updated Model
Flow Simulation
Predictions
Adjust parameters v_i
Not Good
Data Match
Accept
End
$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
$J(\mathbf{v}) = \|\mathbf{d}_{obs} - g(\mathbf{v})\|^2_{C_W}$
19
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS


HM Example (PCA)
Prior Lperm Realizations
20 Leading PCs ϕ_s
PCA
N=2025
S=20
Only S=20 expansion coefficients v_s estimated during history matching
$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
20
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS


HM Example
$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
ϕ_s
v_s
Well Setup
Reference Lperm
Estimated Lperm
21
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS

Main Issues of Conventional Methods

1) Significant components are **pre-determined** (i.e., PCA)

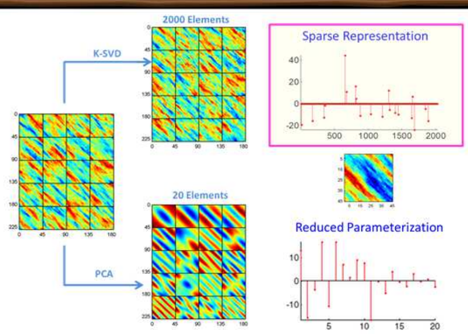
2) Solutions **too smooth**

3) Sensitive to **uncertainty in prior continuity** model

4) Parameter reduction and **prior diversity** tradeoff

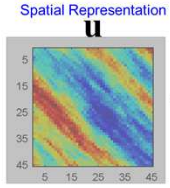
5) **Complex geology?** (meandering channels, etc.)

Sparse Reconstruction

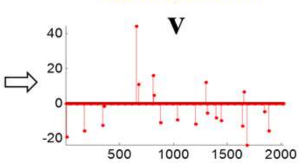


Solution Approach

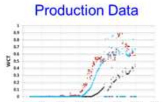
Spatial Representation



Sparse Representation



Production Data



1) Match Available Data

2) Minimize the number of non-zero elements in V

Solution Approach (Minimum Support)

(1) Sparsity of $\mathbf{v}$

$$\min_{\mathbf{v}\in R^N} \|\mathbf{v}\|_0$$ Minimize solution support

(2) Incomplete Measurements

$$\mathbf{u}_M = \mathbf{\Phi}_{M\times N}\,\mathbf{v}_N$$

$$(P_0)\quad \boxed{\min_{\mathbf{v}\in R^N} \|\mathbf{v}\|_0 \quad \text{s.t. } \mathbf{u}_M = \mathbf{\Phi}_{M\times N}\,\mathbf{v}_N}$$

L_0-norm is discontinuous and non-convex (indicator function)

Discrete (combinatorial) Optimization → NP-Hard

Heuristic approximate solutions have to be sought

25 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events EXPERTS • TECHNOLOGY • EDUCATION #SPEWEBEVENTS

Compressed Sensing Paradigm

Compressed Sensing Theory Donoho 2006 (and others)

Minimum l_1-norm reconstruction Donoho, Candes

$$\min_{\tilde{\mathbf{v}}\in R^N} \|\tilde{\mathbf{v}}\|_1 \text{ subject to } \mathbf{u}_M = \mathbf{\Phi}_{M\times N}\,\tilde{\mathbf{v}}_N$$

Efficient LP solution (effectively identifies sparsity)

Perfect reconstruction with very high probability if:

i) **v** is sufficiently sparse

ii) Φ is nearly orthonormal

$$(1-\delta_s)\|\mathbf{u}\|_2^2 \le \|\mathbf{\Phi}_s\mathbf{u}\|_2^2 \le (1+\delta_s)\|\mathbf{u}\|_2^2$$

Restricted Isometry Property (RIP)

iii) Sufficient measurements → $M > C\, S \log(N/S)$

26 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events EXPERTS • TECHNOLOGY • EDUCATION #SPEWEBEVENTS

Constructing Sparse Geologic Dictionaries

Aharon et al., 2006

Example: K-SVD Algorithm

Given a training data with L models $\mathbf{U}_{N\times L} = [\mathbf{u}_1 \;\ldots\; \mathbf{u}_i \;\ldots\; \mathbf{u}_L]$

Find a dictionary $\mathbf{\Phi}_{N\times K}$ of size K that provides *S*-**sparse** representation $\mathbf{V}_{K\times L} = [\mathbf{v}_1 \;\ldots\; \mathbf{v}_i \;\ldots\; \mathbf{v}_L]$ of $\mathbf{U}$.

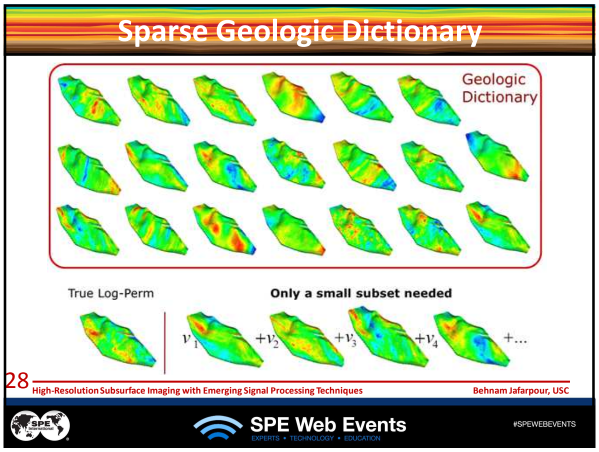
K-SVD Algorithm:

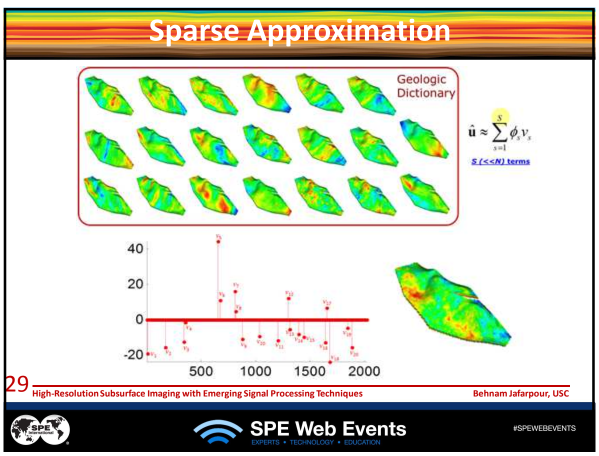
Greedy algorithm that solves the following optimization

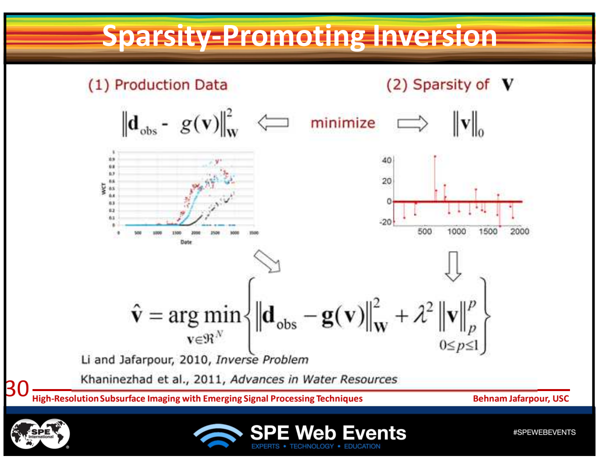
$$\{\hat{\mathbf{\Phi}}, \hat{\mathbf{V}}\} = \arg\min_{\mathbf{\Phi},\mathbf{V}} \|\mathbf{U}-\mathbf{\Phi}\mathbf{V}\|_F^2 \quad \text{s.t.} \quad \|\mathbf{v}_i\|_0 \le S, \quad i = 1,2,\ldots,L$$

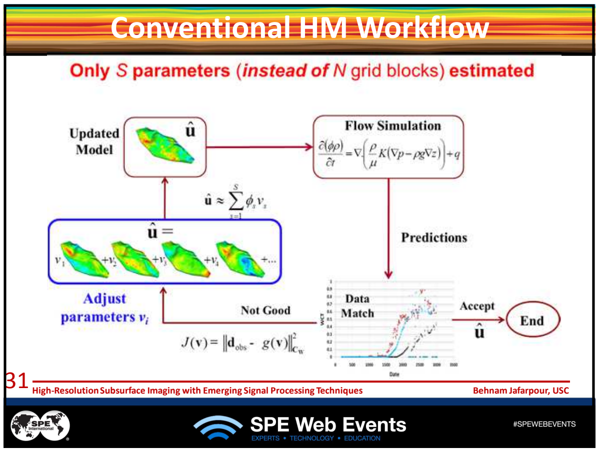
27 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

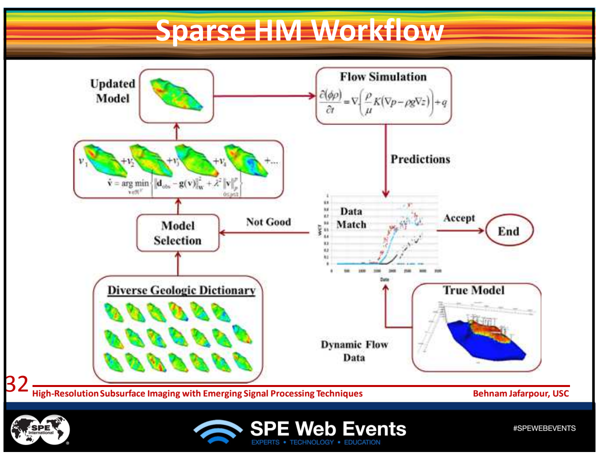
SPE Web Events EXPERTS • TECHNOLOGY • EDUCATION #SPEWEBEVENTS

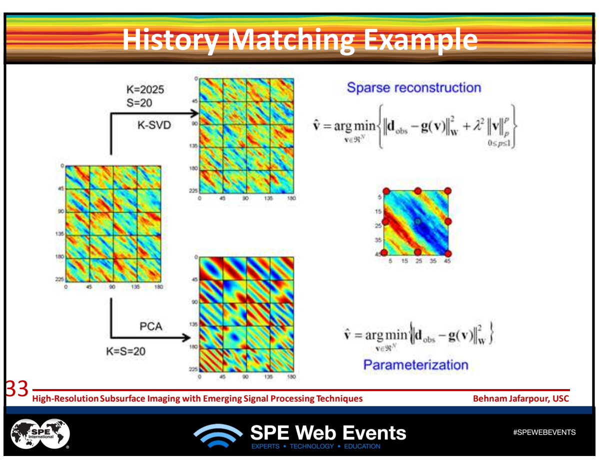

Sparse Geologic Dictionary
Geologic Dictionary
True Log-Perm
Only a small subset needed
v_1 $+v_2$ $+v_3$ $+v_4$ $+\ldots$
28
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS


Sparse Approximation
Geologic Dictionary
$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
S (<<N) terms
40
20
0
-20
500
1000
1500
2000
29
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS

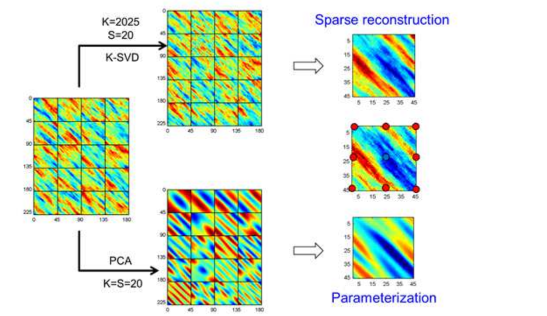

Sparsity-Promoting Inversion
(1) Production Data
(2) Sparsity of $\mathbf{v}$
$\|\mathbf{d}_{obs} - g(\mathbf{v})\|_{\mathbf{W}}^2$ ⇐ minimize ⇒ $\|\mathbf{v}\|_0$
40
20
0
-20
500
1000
1500
2000
$\hat{\mathbf{v}} = \arg\min_{\mathbf{v}\in\Re^N} \left\{ \|\mathbf{d}_{obs} - \mathbf{g}(\mathbf{v})\|_{\mathbf{W}}^2 + \lambda^2 \|\mathbf{v}\|_p^p \right\}_{0\le p\le 1}$
Li and Jafarpour, 2010, Inverse Problem
Khaninezhad et al., 2011, Advances in Water Resources
30
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS


Conventional HM Workflow
Only S parameters (instead of N grid blocks) estimated
Updated Model
Flow Simulation
$\frac{\partial(\phi\rho)}{\partial t} = \nabla\left(\frac{\rho}{\mu}K(\nabla p - \rho g \nabla z)\right) + q$
$\hat{\mathbf{u}} \approx \sum_{s=1}^{S} \phi_s v_s$
Predictions
Data Match
Accept
End
Adjust parameters v_i
Not Good
$J(\mathbf{v}) = \|\mathbf{d}_{obs} - g(\mathbf{v})\|^2_{C_W}$
31
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS

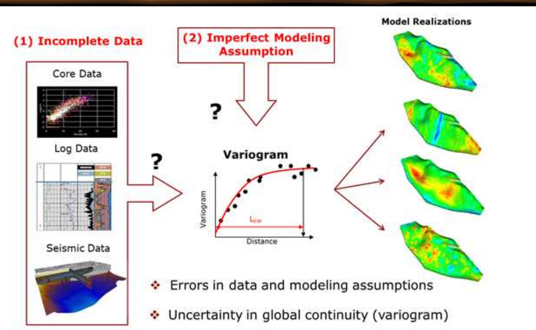

Sparse HM Workflow
Updated Model
Flow Simulation
Predictions
Data Match
Accept
End
Model Selection
Not Good
Diverse Geologic Dictionary
True Model
Dynamic Flow Data
32
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS


History Matching Example
K=2025
S=20
K-SVD
Sparse reconstruction
$\hat{\mathbf{v}} = \arg\min_{\mathbf{v}\in\Re^N} \left\{ \|\mathbf{d}_{obs} - \mathbf{g}(\mathbf{v})\|^2_{\mathbf{W}} + \lambda^2 \|\mathbf{v}\|^p_p \right\}_{0\le p\le 1}$
PCA
K=S=20
$\hat{\mathbf{v}} = \arg\min_{\mathbf{v}\in\Re^N} \left\{ \|\mathbf{d}_{obs} - \mathbf{g}(\mathbf{v})\|^2_{\mathbf{W}} \right\}$
Parameterization
33
High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques
Behnam Jafarpour, USC
SPE Web Events
#SPEWEBEVENTS

History Matching Example

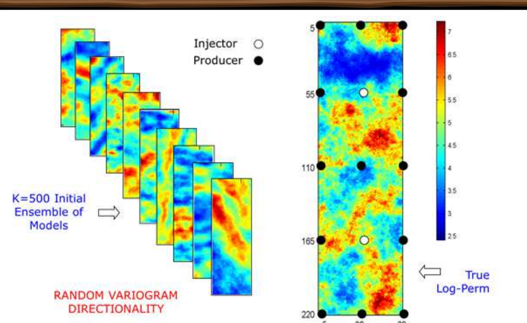


Uncertain Geologic Continuity



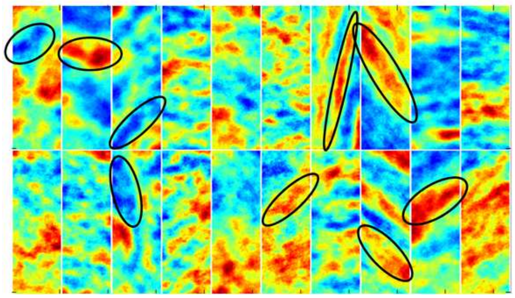
- Errors in data and modeling assumptions
- Uncertainty in global continuity (variogram)

Example : Highly Uncertain Prior

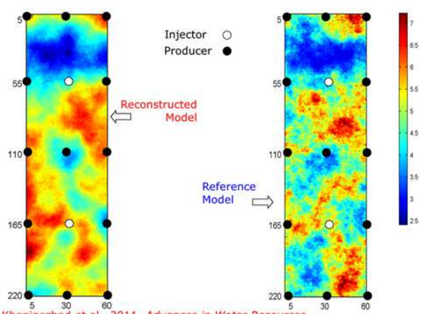


Sparse Geologic Dictionary

Sample K-SVD Dictionary Elements (RANDOM DIRECTIONALITY)



History Matching Results



Khaninezhad et al., 2011, *Advances in Water Resources*

Conclusions

- Reservoir properties are **amenable to sparse representations**
- Sparse representations are useful for **model calibration** with sparsity-promoting methods
- **Compressed sensing** paradigm provides useful guidelines for model calibration under sparse priors
- **Sparse geologic dictionaries** are robust for model calibration under geologic uncertainty
- **Sparsity promoting inversion** has the potential to improve ill-posed model calibration inverse problems

Ongoing and Planned Work

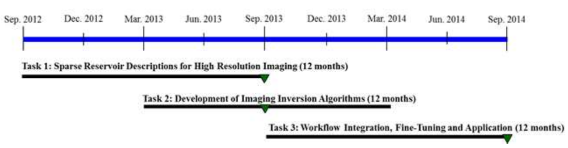
- Prior model (error) identification for history matching under geologic uncertainty
- Uncertainty quantification using Bayesian formulations
- Efficient algorithms for constructing geologic dictionaries
- Innovative applications of sparse HM: adaptive sparsity, joint data/model sparsity, …

Project Schedule

Graduate Student:

M. Reza M. Khaninezhad (Ph.D., EE)

Tentative Schedule:



Questions?

Characterization of Reservoir Fluids using an EOS

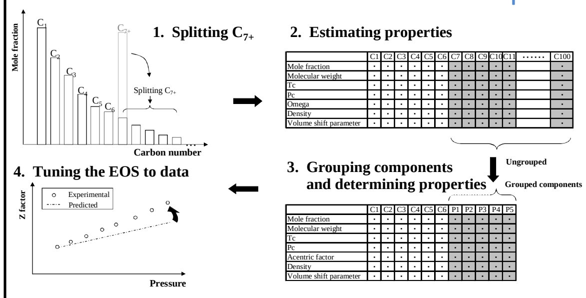
R. Okuno
School of Petroleum Engineering
University of Alberta

Outline

- Brief review of fluid characterization
  - Gibbs free energy and EOS parameters
  - Volume shift parameters
- Perturbation from n-alkanes (PnA)
- Case studies
- Conclusions

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Conventional Characterization Steps



SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Common Questions/Issues

- What should I do with so many adjustment parameters?
  - Implicit relationship between phase behavior predictions and adjustment parameters
- I matched some PVT data, but am not sure if this EOS model is reliable in gasflooding simulation.
  - Characterization under unavoidable uncertainties
- Why are different methods used for different fluids?

Objective

- Universal characterization method that works for heavy oils, volatile oils, gas condensates, and near-critical fluids.
  - Peng-Robinson EOS with van der Waals mixing rules
  - Multiphase behavior; oleic, gaseous, solvent-rich liquid, and aqueous phases
- The focus of the first year was on the normal oleic-gaseous phase behavior.

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Compositional Reservoir Simulation

- Mass conservation equations for components
  - Local equilibrium assumption
- Phase behavior solution
  - Gibbs free energy is minimized at T, P, and overall composition for each gridblock

Fluid characterization is to build a Gibbs free energy using an EOS.
Comp. res. simulator then minimizes the Gibbs free energy at T, P, and z on the fly.

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Gibbs Free Energy, Peng-Robinson EOS

$$\underline{G}_R = \sum_{i=1}^{N_C} z_i \ln\left(z_i \bar{\varphi}_i\right)$$

z_i : Overall concentration of component i
$\bar{\varphi}_i$: Fugacity coefficient of component i in a mixture
N_C : Number of components

$$P = \frac{RT}{\underline{V} - b} - \frac{a(T)}{\underline{V}(\underline{V}+b) + b(\underline{V}-b)}$$

$a = \Omega_a \frac{(RT_C)^2}{P_C}\alpha(T)$: Attraction parameter

$b = \Omega_b \frac{RT_C}{P_C}$: Covolume parameter

van der Waals mixing rules are used for mixtures.

Overview of Phase Behavior Modeling

Steps	Input	Output
1. a and b for components	$(T_C, P_C, \omega)_i$	a_i, b_i
2. a and b for mixtures	Binary interaction parameters van der Waals mixing rules	a_{mix}, b_{mix}
3. Gibbs free energy	Peng-Robinson EOS	Gibbs free energy
4. Compositional behavior (Flash calculation)	Temperature, Pressure, Composition	Phase compositions and amounts
5. Volumetric behavior	Volume-shift parameters	Volumetric phase properties

Match?

PVT data

Gibbs free energy depends on volume shift through Tc, Pc, ω, and BIPs.

Effect of Volume Shift on Gibbs Energy

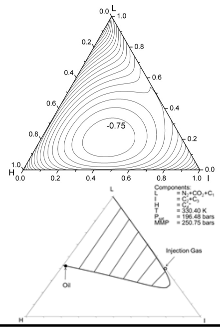
- An oil is characterized using three components with/without volume shift
- Two characterizations give the same predictions of
  - Saturation pressure 196.48 bars at 330.4 K
  - Oil densities at pressures between 7.1 bars and 276.3 bars at 330.4 K
- However, they have different properties for the H component

			PR EOS with volume shift				PR EOS without volume shift		
Comp.	Mole Fractions	MW (gm/mol)	T_C (K)	P_C (bars)	ω	C_{PEN} (cc/mol)	T_C (K)	P_C (bars)	ω
L	0.4219	16.10	190.86	46.07	0.0089	-5.19	190.86	46.07	0.0089
I	0.0176	31.66	315.59	47.83	0.1065	-5.85	315.59	47.83	0.1065
H	0.5605	291.30	**848.33**	**24.18**	**0.4373**	**-110.14**	**1022.44**	**19.48**	**0.5108**
Temperature (K)			330.40						
Saturation Pressure (bars)			196.48						

L= N_2+CO_2+C_1, I= C_2+C_3, H= C_4^+

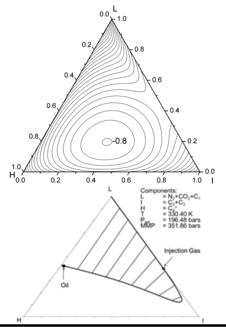
Gibbs Free Energy

With volume shift



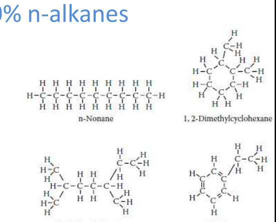
330.4 K
196.48 bars

Without volume shift



Perturbation from n-Alkane (PnA)

- Paraffin-naphthene-aromatic (P-N-A) distribution of a plus fraction is interpreted as a perturbation from 100% n-alkanes
- No volume shift
- No change in EOS and mixing rules



Pedersen and Christensen 2007

SPE Web Events

New Correlations for n-Alkanes for PR EOS

Kumar and Okuno (2012) Fluid Phase Equilibria

$$T_C = 1154.35 - 844.83\left(1.0 + 1.7557\times10^{-3}MW\right)^{-2.0}$$

$$P_C = 559.93(MW)^{-0.638} - 1.49$$

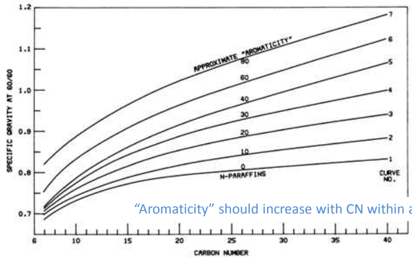
$$m = 0.4707 + 2.4831(MW)^{-\left(\frac{39.933}{MW}\right)}$$

$m = m(\omega)$ as defined by Peng and Robinson (1978)

$$MW \leftarrow f_T MW$$
$$MW \leftarrow MW / f_P$$
$$MW \leftarrow f_m MW$$

- They give 3.0% and 3.4% AADs in density and vapor pressure predictions, respectively, for n-alkanes from C_7 to C_{100}.
- Conventional correlations give AADs of 87% for density prediction and 61% for vapor pressure prediction for n-C_{100}.
- T_C and P_C of n-alkanes are lower that those of other hydrocarbons for a given carbon number. The trend is the other way around for ω.

Yarborough's Trend Curves (1979)



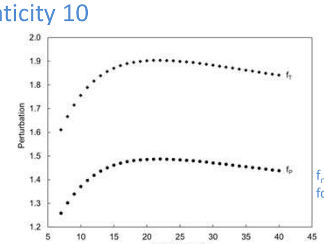
"Aromaticity" should increase with CN within a given fluid

Figure 19. Arbitrary curves relating specific gravity to carbon-number fraction which allow for different molecular types of hydrocarbons

Aromaticity (Yarborough 1979): Percentage of total carbon atoms in a molecule which are within the benzene ring.

Perturbation for Different Carbon Numbers

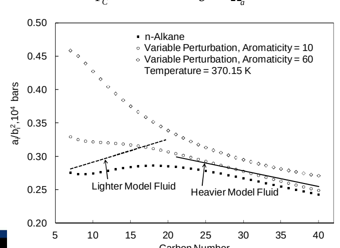
- Perturbations required to match the trend for aromaticity 10



f_m is converged to 0.6040 for each CN given above.

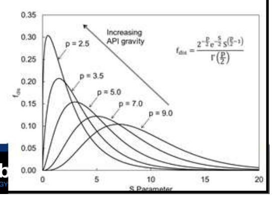
ψ (= a/b²) for Model Fluids

$$a = \Omega_a \frac{(RT_C)^2}{P_C}\alpha(T) \qquad b = \Omega_b \frac{RT_C}{P_C} \qquad \psi = \frac{a}{b^2} = \frac{\Omega_a}{\Omega_a^{\ 2}} P_C \alpha(T)$$



Characterization Steps

- Composition characterization
  - E.g., chi-squared distribution fitted to composition data
- Perturbation from n-alkanes
  - f_T, f_P, and f_m
  - One more parameter γ to control the trend of ψ



SPE Web Events

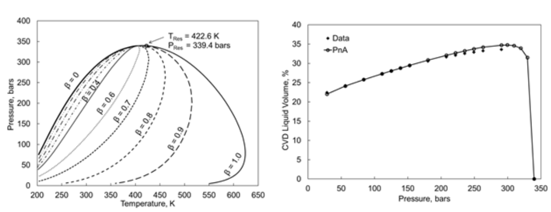
Case Studies

- 77 different reservoir fluids
  - Heavy oils, volatile oils, gas condensates, and near-critical fluids
- Saturation pressure and densities at T_{res}
- Other data are used to test the predictions
- Four pseudo components
- Four adjustment parameters
  - f_T, f_P, f_m, and γ

SPE Web Events #SPEWEBEVENTS

Gas Condensates

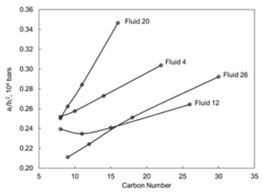
Liquid volume calculation for constant-volume depletion
Fluid 10 in Al-Meshari (2004), Near-critical gas condensate, 39.23 gm/mol



β: Mole fraction of vapor phase

SPE Web Events #SPEWEBEVENTS

Trends of ψ for Gas Condensates



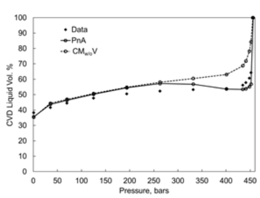
Lighter
Heavier

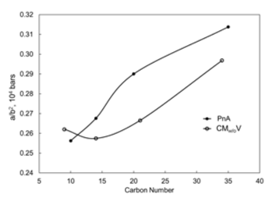
Fluid 20 from Hosein et al. (2013), 19.75 gm/mol, 367.59 K
Fluid 4 from Al-Meshari (2004), 36.62 gm/mol, 397.59 K
Fluid 12 from McVay (1994), 40.58 gm/mol, 387.59 K
Fluid 26 from Drohm et al. (1988), 54.92 gm/mol, 410.90 K

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Volatile Oil

Fluid 12 in Al-Meshari (2004), near-critical oil, 46.07 gm/mol, 50.3°API, 354.82 K

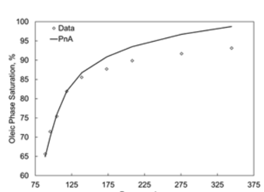


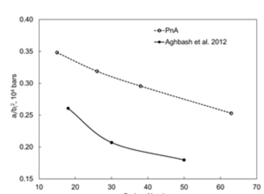


SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Heavy Oil

West Sak oil in Sharma (1990), 228.88 gm/mol, 18.68°API, 299.81 K





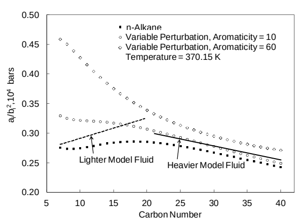
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Conclusions

- Volume-shift parameters affect compositional behavior predictions when used as regression parameters.
- The PnA method
  - f_P, f_T, f_m, and γ
  - No volume shift
  - PR EOS with van der Waals mixing rules

Conclusions

- Perturbation should consider the CN range.



Papers to be presented at ATCE 2013

- SPE 166135 “Universal Fluid Characterization using an EOS based on Perturbation from n-Alkanes”
- SPE 166345 “Mass Transfer on Multiphase Transitions in Low-Temperature CO_2 Floods”
- SPE 166371 “A New Method for Modeling Bypassed Oil Recovery in EOS Compositional Simulation”

Effect of Volume Shift

- Effect on Gibbs free energy

$$g^{nvs} = \left(\frac{\Delta_{mix}G}{RT}\right)^{nvs} = \sum_{i=1}^{N_c} z_i \ln\left[\frac{z_i\bar{\varphi}_i(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{z})^{nvs}}{\varphi_i(T_{Ci},P_{Ci},\omega_i,T,P)^{nvs}}\right]$$

$$g^{vs} = \left(\frac{\Delta_{mix}G}{RT}\right)^{vs} = \sum_{i=1}^{N_c} z_i \ln\left[\frac{z_i\bar{\varphi}_i(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{z})^{vs}\exp\left(\frac{c_iP}{RT}\right)}{\varphi_i(T_{Ci},P_{Ci},\omega_i,T,P)^{vs}\exp\left(\frac{c_iP}{RT}\right)}\right] = \sum_{i=1}^{N_c} z_i \ln\left[\frac{z_i\bar{\varphi}_i(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{z})^{vs}}{\varphi_i(T_{Ci},P_{Ci},\omega_i,T,P)^{vs}}\right]$$

- Effect on fugacity equations

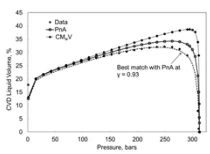
$$x_i^{nvs}\bar{\varphi}_i^{L}(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{x})^{nvs} = y_i^{nvs}\bar{\varphi}_i^{V}(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{y})^{nvs}$$

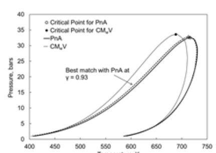
$$x_i^{vs}\bar{\varphi}_i^{L}(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{x})^{vs} = y_i^{vs}\bar{\varphi}_i^{V}(\underline{T_C},\underline{P_C},\underline{\omega},\underline{k},T,P,\underline{y})^{vs}$$

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Gas Condensates

Liquid volume calculation for constant-volume depletion
Fluid 11 in Al-Meshari (2004), Near-critical gas condensate, 41.71 gm/mol, 424.82 K





SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Questions?

69 High-Resolution Subsurface Imaging with Emerging Signal Processing Techniques — Behnam Jafarpour, USC

SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Full-Resolution Simulations of Multiscale Processes

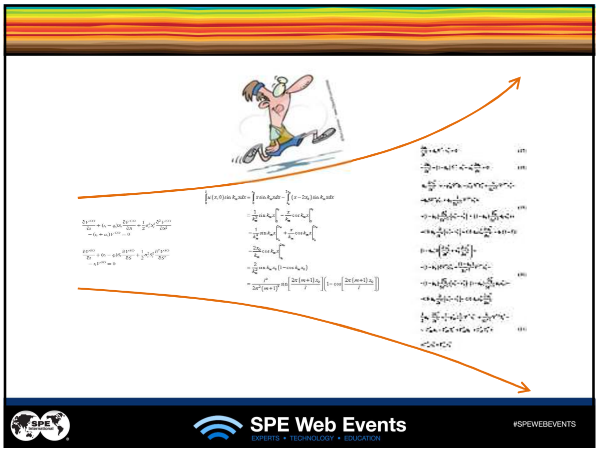
Rami M Younis
Assistant Professor
McDougall School of Petroleum Engineering
The University of Tulsa

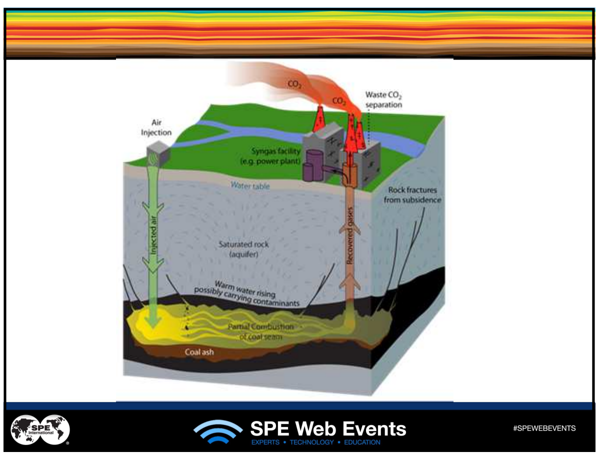
ADAPTIVE SOLVERS - NEW USAGE PARADIGMS - RESERVOIR SIMULATION SOFTWARE -
RESERVOIR SIMULATION SYSTEMS & TECHNOLOGY - FUTURE
THE UNIVERSITY of TULSA

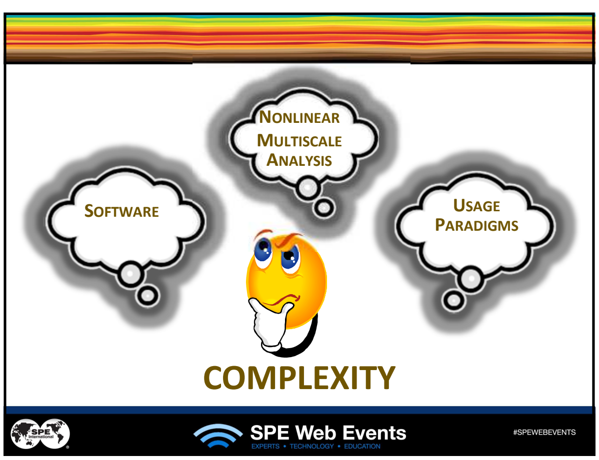
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Nonlinearity and Complexity

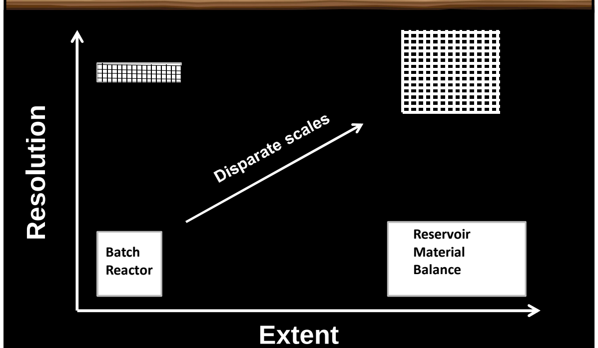
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS


SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS


CO_2
CO_2
Waste CO_2 separation
Air Injection
Syngas facility (e.g. power plant)
Water table
Rock fractures from subsidence
Saturated rock (aquifer)
Injected air
Recovered gases
Warm water rising possibly carrying contaminants
Partial Combustion of coal seam
Coal ash
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

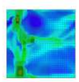

Nonlinear Multiscale Analysis
Software
Usage Paradigms
COMPLEXITY
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Nonlinearity + Multiscale
=
Unhappy Solver



ADAPTIVITY and LOCALITY

Two types of "adaptive strategy"



$$\frac{\partial a(p)}{\partial t} + \mathrm{F}(p, \nabla p, \Delta p) = 0$$

$\downarrow$

Type A: AMR, AIM, Fractional Stepping, Operator splitting

$$R\left(p^{n+k}, p^{n+k-1}, \cdots, p^{n}; \delta_t, \delta_x\right) = 0$$

$\downarrow$

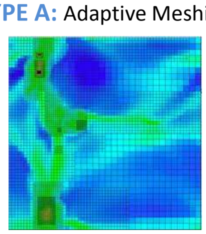
Type B: Nonlinear and linear preconditioners, localized solvers

$$p^{n}$$

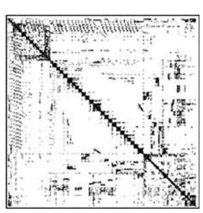
SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Examples

TYPE A: Adaptive Meshing



TYPE B: Localized solvers



SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Both strategies need to know:

Define $\delta(x,t) = |p(x,t) - p(x,t+\epsilon)|, \epsilon > 0.$

Need $\Omega = supp\ \ \delta(x,t)$

Or if, $\tilde{\delta}(x,t) \geq \delta(x,t) \geq 0,$

Can use $\tilde{\Omega} = supp\ \ \tilde{\delta}(x,t) \subseteq \Omega$

Recall, $supp\ f(x) = \{x: f(x) \neq 0\}$

SPE Web Events

EXPERTS • TECHNOLOGY • EDUCATION

#SPEWEBEVENTS

The precise spatiotemporal support of change in reservoirs

- The specific problem of interest
- Mathematical derivation
- Examples
- The future for multiscale models

SPE Web Events

EXPERTS • TECHNOLOGY • EDUCATION

#SPEWEBEVENTS

Canonical form of problem of interest:

Coupled flow and transport

$$\frac{\partial}{\partial t} a(p,Z) + \nabla[\boldsymbol{K}(p,Z)\nabla p] + w(p,Z) = 0$$

Flow state: $p(x,t)$

Transport states: $Z(x,t)$

SPE Web Events

EXPERTS • TECHNOLOGY • EDUCATION

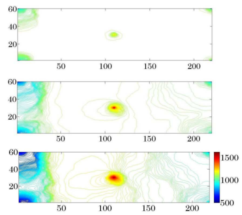
#SPEWEBEVENTS

1 FLOW

Pressure distribution | Infinite domain-of-dependence | Travelling (Very) Fast

Parabolic Character | Potential

$$\frac{\partial}{\partial t}a(p) + \nabla[\boldsymbol{K}(p).\nabla\psi(p)] + w(p) = 0$$

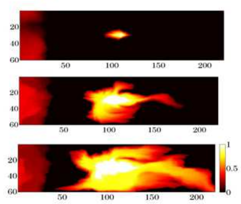


2 TRANSPORT

Travelling Waves | Finite domain-of-dependence

Hyperbolic Character | Entropy Solutions | Rankine-Hugoniot

$$\frac{\partial \boldsymbol{a}(\boldsymbol{Z})}{\partial \boldsymbol{t}} + \nabla \boldsymbol{f}(\boldsymbol{Z}) = \boldsymbol{q}(\boldsymbol{Z})$$



How to get $\tilde{\Omega} = supp\ \tilde{\delta}(x,t)$!

Using the fully-implicit semidiscrete form

Seek $p^n(x)$ and $Z^n(x)$ for $t^n = n\Delta t, n = 0,1,\cdots$

$$\begin{aligned} R(p^{n+1}, Z^{n+1}) \\ &= a(p^{n+1}, Z^{n+1}) + \Delta t \nabla[\boldsymbol{K}(p^{n+1}, Z^{n+1})\nabla p^{n+1}] \\ &+ w(p^{n+1}, Z^{n+1}) \end{aligned}$$

SPE Web Events

EXPERTS • TECHNOLOGY • EDUCATION

#SPEWEBEVENTS

Solve nonlinear PDE using Newton's Method!

Solve,

$$R(p^{n+1}(x)) = 0$$

First guess,

$$[p^{n+1}]^{\mu=0} = p^n$$

Then,

$$R'([p^{n+1}]^{\mu})\delta^{\mu} = -R([p^{n+1}]^{\mu})$$

and,

$$\delta^{\mu} = [p^{n+1}]^{\mu+1} - [p^{n+1}]^{\mu}$$

SPE Web Events

EXPERTS • TECHNOLOGY • EDUCATION

#SPEWEBEVENTS

There we have it…

Since,

$$\delta^{\mu} = [p^{n+1}]^{\mu+1} - [p^{n+1}]^{\mu},$$

and,

$$[p^{n+1}]^{\mu=0} = p^n,$$

We have,

$$\sum_{\mu=0}^{K} \delta^{\mu} = \delta(x, t^n)$$

SPE Web Events

EXPERTS • TECHNOLOGY • EDUCATION

#SPEWEBEVENTS

Flow with frozen transport

Solve

$$R(p^{n+1}) = a(p^{n+1}) + \Delta t \nabla[\boldsymbol{K}(p^{n+1})\nabla p^{n+1}] + w(p^{n+1})$$

For each μ solve $R'([p^{n+1}]^{\mu})\delta^{\mu} = -R([p^{n+1}]^{\mu})$

A conservative estimate $\tilde{\delta} \geq \delta^{\mu}$:

$$\Delta\tilde{\delta} - \lambda^2\tilde{\delta} = R(p^{\mu})$$

where

$$\lambda = inf\sqrt{\frac{a'(p^{\mu})}{\Delta t K(p^{\mu})}}$$

The screened Poisson equation,

$$\Delta\tilde{\delta} - \lambda^2\tilde{\delta} = R(p^{\mu})$$

has the Fundamental Solution,

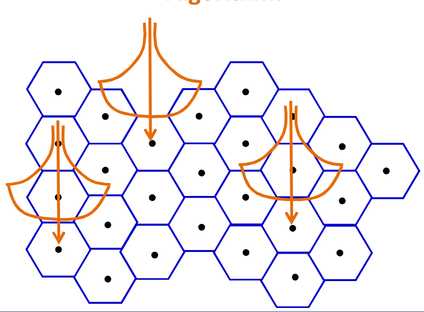
$$\Phi(x) = \begin{cases} -\frac{1}{2\lambda}\exp(-\lambda|x|) & x \in \mathbb{R}, \\ -\frac{1}{2\pi}K_o(\lambda|x|) & x \in \mathbb{R}^2, \\ -\frac{1}{4\pi}\frac{\exp(-\lambda|x|)}{|x|} & x \in \mathbb{R}^3 \end{cases}$$

So given a corrector function, h, the solution is

$$\tilde{\delta} = \int_D [\Phi(x-y) - h(y)]R\ dy$$

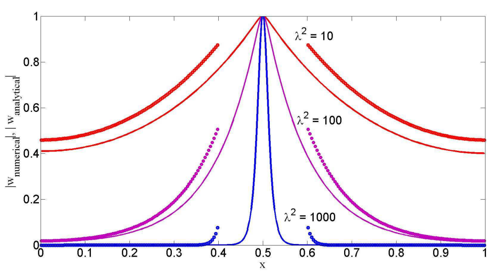
$$\leq supR\int_D [\Phi(x-y) - h(y)]\ dy$$

Algorithm:



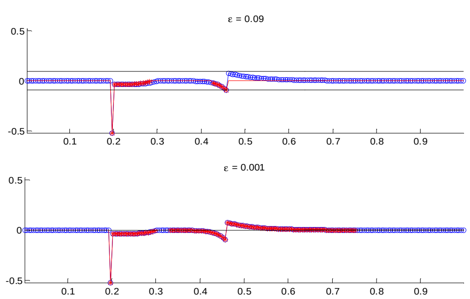
Computational Examples

Example 1: flow in 1-dimension



SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

Example 2: Transport and localized linear algebra



SPE Web Events
EXPERTS • TECHNOLOGY • EDUCATION
#SPEWEBEVENTS

A future for full-resolution multiscale

- Type A methods:
  - Exploit locality in finite volume multiscale methods
  - AMR that knows exactly where and when to adapt
- Type B methods
  - Full-resolution Cartesian grid with solver that knows about locality!

Thank You

Rami M Younis
ryounis@utulsa.edu