Advances in Particle Swarm Optimization and application to history Matching: Stanford VI

Juan Luis Fernández Martínez  
Stanford University.  
UC Berkeley-Lawrence Berkeley Lab.  
Oviedo University Spain.

In collaboration with  
Tapan Mukerji, Amit Suman  
and Esperanza García-Gonzalo (Oviedo University, Spain).
INDEX

• Advances in PSO design
• Application of PSO to the History Matching Problem (Uncertainty analysis)
• (TIP) Preliminary results on Differential Evolution
I. Advances in PSO design

Work done in collaboration with Esperanza García-Gonzalo (University of Oviedo)
The spring-mass analogy

\[ x_i''(t) + (1 - w) \cdot x_i'(t) + (\phi_1 + \phi_2) \cdot x_i(t) = \phi_1 \cdot l_i(t) + \phi_2 \cdot g(t). \]

(Fernández Martínez et al, 2008)

\[ v_i(k + 1) = (1 - (1 - w)\Delta t)v_i(k) + \phi_1\Delta t(x_i(k) - g(k)) + \phi_2\Delta t(x_i(k) - l_i(k)), \]
\[ x_i(k + 1) = x_i(k) + v_i(k + 1)\Delta t. \]

(GPSO)

(Fernández Martínez and García Gonzalo, 2008)
PSO Analysis & Design

Based on this mechanical analogy we have

1. Shown that **PSO BELONGS TO A FAMILY:**
   - Design and stochastic stability analysis of a whole family of PSO optimizers: **PSO, CC-PSO, CP-PSO** (Fernández Martínez and García Gonzalo, Swarm Int., 2009), **PP-PSO, RR-PSO** (García Gonzalo and Fernández Martínez, 2010).

2. Shown that **PSO IS NOT HEURISTIC:**
   - Full stochastic stability of the PSO family (Fernández Martínez and García Gonzalo, 2010).

3. Designed a **PSO Cloud Algorithm with variable time step (cooling and exploration)** (Fernández Martínez et al, 2009, 2010).
   - Avoids tuning of the PSO parameters (automatic)
Parameter tuning: the cloud of particles
RR-PSO is very different

(a) RR-PSO second order spectral radius

(b) RR-PSO second order trajectory frequency
The $\Delta t$ parameter

$$v(k + 1) = (1 - (1 - w)\Delta t)v(k) + \phi_1 \Delta t(x(k) - g(k)) + \phi_2 \Delta t(x(k) - l(k)),$$

$$x(k + 1) = x(k) + v(k + 1)\Delta t.$$

$\Delta t \geq 1$  INITIAL BIG EXPLORATION

Stability region shrinks.

$\Delta t < 1$  FINAL TUNING

Stability region expands.
II. HISTORY MATCHING, TIME LAPSE SEISMICS AND UNCERTAINTY ANALYSIS

With the collaboration of Tapan Mukerji and Amit Suman

Acknowledgments: David Echeverría, Eduardo Santos and Grégoire Mariethoz
Optimization Workflow
(Echeverría and Mukerji, 2009)

Few PCA parameters ➔ PCA ➔ rock properties ➔ \( O_p(m) \) ➔ PSO
many parameters ➔ \( m \) ➔ \( O_s(m) \) ➔ DE

facies ➔ \( \xi \) ➔ \( m^* \) ➔ to optimizer

(SCRF 2010)
WHY UNCERTAINTY ANALYSIS IS NEEDED IN THE HISTORY MATCHING PROBLEM?

1. MINIMA ARE LOCATED ALONG FLAT ELONGATED VALLEYS.

2. NOISE IN DATA INTRODUCES LOCAL MINIMA.

3. NOISE HAS ALSO A REGULARIZATION EFFECT (MAKES THE SAMPLING EASIER).

4. THE MODEL REDUCTION INTRODUCES SINGULARITIES IN THE COST FUNCTION TOPOGRAPHY (potential danger for local methods).
PSO Results: Swarm size 20

Similar results are obtained for swarm sizes of 50 and 100 particles.
PSO as a posterior sampler
(In collaboration with Gregoire Mariethoz, Stanford University)
Computing uncertainty from samples

Convergence rate

Swarm dispersion

Median sample
Median layer 1  |  True layer 1  |  IQR layer 1  
Median layer 2  |  True layer 2  |  IQR layer 2  
Median layer 3  |  True layer 3  |  IQR layer 3  
Median layer 4  |  True layer 4  |  IQR layer 4  
Median layer 5  |  True layer 5  |  IQR layer 5  

**Gaussian Error**  10%
Data Match: Production

Cumulated oil

Injected water

INITIAL SWARM

Misfit region <0.015

Cumulated Oil

Injected water

Time (days)

SCRF 2010
Data Match: Tomograms

Section 1

(A) Tomographic section 1

Reference

Median for the Initial swarm

(C) Median tomo. for initial swarm

Section 2

(B) Tomographic section 2

Median of low misfit samples

(D) Median tomo. for initial swarm

(E) Median tomo (0.015 misfit region)

(F) Median (0.015 misfit region)
III. DIFFERENTIAL EVOLUTION

With the collaboration of Esperanza García-Gonzalo
(University of Oviedo)
Differential Evolution
(Storn and Price, 1997)

PSO like-mechanism

1. MUTATION
\[ v_i(k+1) = F_1 (x_i(k) - x_n(k)) + F_2 (x_r(k) - x_s(k)), \]
\[ m_i(k+1) = x_j(k) + v_i(k+1), \]

Rand-1, Best-1, Target-to-best, Rand-2, Best-2

GA like-mechanisms

2. CROSSOVER \[ C_r : \text{Crossover probability} \]
3. SELECTION

3 parameters to tune: \( F_1, F_2, C_r \)
DE Performance

Convergence rate

![Convergence rate graph]

Exploration capabilities

![Exploration capabilities graph]
CONCLUSIONS

- **PSO**
  - All the PSO family members are able to provide facies models from the low misfit region, and can be used with small number of particles.
  - Sequential inversion allows to increase dynamically the number of PCA parameters as needed.
  - The topography of the cost function corresponds to flat valleys. The seismic data helps to partially constraint the space of possible solutions.
  - PSO samples can be used to provide an approximate measure of model uncertainty.

  A paper has been submitted to Computational Geosciences.

- **DE**
  - Very promising results: good balance between exploration and exploitation.
Acknowledgments

• Smart Fields and SCRF Consortia.
• Schlumberger-EMI.
• University of California-Berkeley and Lawrence Berkeley Lab.

• University of Oviedo and Spanish Ministry of Innovation.

• Eduardo Santos (formerly Stanford University) and David Echeverría for providing the forward programs to model the HM problem (Stanford VI), and Grégoire Mariethoz for collaboration in the posterior sampling in hydrogeology.
ARE THERE ANY QUESTIONS?

THANK YOU FOR YOUR ATTENTION

When you see the face of the anger, look behind it, and it will suddenly change to the face of the pride.

Jalaluddin Rumi (1207-1273)