

Optimal reservoir management for maximizing production in deep-offshore fields

Diego F.B. Oliveira

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Applied Optimal Reservoir Management

- 1- Context
- 2- Field Description
- 3- Optimization Workflow and Results
- 4- Field Experience: Pilot Implementation
- 5- Final Remarks

Applied Optimal Reservoir Management in Context



Motivation



Mature Field Operation

Excessive water production bottlenecks offshore vessels:

- Constrains oil production;
- Increases operational costs.

Proactive Reservoir Management

Planning is always better than React!

- Robust techniques are already available;
- Why is not widely applied?





Applied Optimal Reservoir Management in Context

Motivation	Efficient Ensemb	ble-Based C	losed-loop	rs & Fluids 46 (2011) 40−51 sts available at ScienceDirect	3
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Applied Optimal Reservoir Management in Context

Objective



Field implementation is key!

• Overcoming operational barriers;

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- Spreading new technical culture;
- Assessing optimization gains!



Field Description

Offshore • Brazil • Campos Basin

Late 90's Jequitinhonha 1000 2000 3000 4000 5000 6000 700 S. Francisco Cumuruxatiba Mucuri Espírito Santo Campos 1 Santos





Field Injection Optimization under Uncertainty - Results (1/2)



Cumulative Oil Production - 4.2% increase on average total oil production; Cumulative Water Production - 5.9% reduction on average total water production; Cumulative Water Injection - 6.0% reduction on average total water injection; Cumulative Gas Production - 10.5% increase on average total gas production;

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Field Injection Optimization under Uncertainty - Results (2/2)





Optimal Strategy

Few Highlights:

- Life-cycle considered: 20 years;
- Temporal correlation is imposed;
- Optimal Solution ensures smoothness (easier to operational implementation);



Operational Pilot: Main targets







Pilot Site

- Hydraulically Isolated;
- Good Sensors (PDGs);
- Moderate Water-cut level.

Pilot Optimization





Operational Capability

TARGET	TASKS				
Guarantee operational success	RESERVOIR ENGINEERING	PLATFORM	SURVEILLANCE		
	 Perform OPTIMIZATION; Submit rates to PLATFORM Feedback data to models (VALIDATION) 	 PURSUE optimal rates; PRIORITIZE optimal rates in operational failures; Report RE of any ISSUE. 	 Production Tests more often; ALERT: excessive Water or Gas production; ALERT: injection BHP. 		
-					





Modelling Consistency







Modelling Consistency





Modelling Consistency







Final Remarks

- State-of-art optimization applied in a field offshore Brazil, with robust gains;
- Difficult task: Field Implementation! But a Field Pilot was successfully performed;
- We guaranteed operational feasibility, which is critical for future endeavors, and testified the model consistency;
- We believe the **implementation**, **monitoring and analysis** of this field pilot is the main contribution of our work;
- To the best of our knowledge, it is the first time that an offshore field is actually operated based on a set of optimal controls;
- Clearly, this result indicates broader perspectives in terms of full-field applications, which we are currently pursuing.
- Ref: Oliveira, D. F. B. de, Pereira, D. F. A., Silveira, G. E., & Melo, P. A. L. S. de. (2019). Pioneer Field Pilot of Optimal Reservoir Management in Campos Basin. SPE Reservoir Evaluation & Engineering. doi:10.2118/199355-PA



Thank You!

Questions, suggestions, general comments?

Diego F. B. Oliveira diego.oliveira@petrobras.com.br





Backup Slides

Diego F. B. Oliveira diego.oliveira@petrobras.com.br





Ensemble-based History Matching

- We have applied ES-MDA (Emerick & Reynolds, 2012) to history-match production data from Petrobras field;
- Ten iteration were assigned for ES-MDA with decreasing inflation factors (not adaptive) in an ensemble of **300 models**;
- Historical data are composed of:
 - **Producers:** oil and water rates, GOR and bottom-hole pressure (flowing and build-up periods);
 - Injectors: water rates and bottom-hole pressure (flowing and fall-off periods);
 - Data available every 60 days along 10 years, but during shut-in periods the frequency of 1 to 5 days is considered for BHP;
- Model **parameters** are horizontal permeability, porosity, vertical transmissibility, relative permeability, anisotropy ratio and fault transmissibilities;
- Model contains four facies handled with a truncated Gaussian transformation.



6000

7000

Optimal Reservoir Management Workflow

Ensemble-based History Matching



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Model Selection

- We consider a model selection approach proposed by Heitsch and Römisch (2003), and modified by Armstrong et al. (2012);
- This approach is based on minimizing the weight of the discarded models, where weight is a distance-based function as discussed below;
- Given a set of $\ N_{\omega}$ chosen model properties (static/dynamic), for each reservoir model we have a vector

$$\omega_j^T = \begin{bmatrix} \omega_j^1 & \omega_j^2 & \cdots & \omega_j^w & \cdots & \omega_j^{N_\omega} \end{bmatrix}, \qquad j = 1, \dots, N_e$$

where ω_j is the vector of model properties of the jth ensemble member and N_e is the ensemble size. Each vector ω_j is normalized to avoid scaling problems.



Model Selection

• Let $d_{i,j}$ be the distance between ensemble members i and j, such that

$$d_{i,j} = \sqrt{(\omega_i - \omega_j)^T (\omega_i - \omega_j)}$$

- Let \mathcal{M} be the set of all models that composes the ensemble from which we wish to extract a subset \mathcal{S} with N_s selected models, such that $\mathcal{M} \supset \mathcal{S}$. Also let \mathcal{D} be the subset of discarded models, such that $\mathcal{M} = \mathcal{S} \cup \mathcal{D}$.
- We define the distance-based selection function as

$$C(\mathcal{S}) = \sum_{j \in \mathcal{D}} p_j \cdot \min_{i \in \mathcal{S}} d_{i,j}$$

where p_j is the probability or weight of the jth model. So, we find S^* by

$$\mathcal{S}^{\star} = \arg\min C(\mathcal{S})$$

for a fixed and preset value $\,N_{s}\,$.



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Field Injection Optimization under Uncertainty

- We have applied an **ensemble-based approximate gradient method** as optimization algorithm.
- Gradients are approximated using the so-called Stochastic Simplex Approximate Gradient (StoSAG) of Fonseca et al. (2017), where the search direction at point u is given by

$$\tilde{g}(u) = \frac{1}{N_s} \sum_{k=1}^{N_s} \left[\frac{1}{N_p} \sum_{j=1}^{N_p} \left[(\hat{u}_{k,j} - u) \left(J(m_k, \hat{u}_{k,j}) - J(m_k, u) \right)^T \right] \right],$$

where \mathbf{N}_s is the ensemble size, \mathbf{N}_p is the number of perturbed controls, and $\{\hat{u}_{k,j}\}$ are independent samples of |u| .

- We used seven (7) selected models as the ensemble and five (5) perturbed controls.
- A line-search procedure is performed based on $~~ ilde{g}(u)$,



Field Injection Optimization under Uncertainty

 Current application aims to maximize the discounted Np (cumulative oil production) given by

$$J(m_k, u) = \sum_{n=1}^{N_t} \left\{ \frac{1}{(1+b)^{\frac{t_n}{365}}} \cdot \Delta t_n \sum_{j=1}^{N_w} \overline{q_{o,j}^n} \right\}$$

- Considering the geological uncertainty, the average among the seven (7) selected models is set as objective function;
- Except for bound constraints, all other state constraints are imposed in the simulation deck, although we recognize that other better approaches may be applied.

Field Injection Optimization under Uncertainty



As demanded by the field operators, only Water Injection Rates are considered as control variables.

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- 20-year remaining production period;
- 5-year Correlation Length;
- 11 Water Injecting wells;
- Non-uniform Control Steps;
- Optimization starts from current injection rates after historical period
 - Different initial value and bounds for each well.
- Logarithm transformation of Gao and Reynolds (2006) is applied to enforce bound constraints.