SELF-LEARNING RESERVOIR MANAGEMENT
SPE 84064

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Agenda

• Motivation: The reservoir management challenge
  – What is the Problem?,
  – What have been done?
  – What are the challenges?
• Problem Formulation
• The specific objectives and scope of this research
• Reservoir modeling and identification
• Model Predictive Control
• Self Learning Reservoir Management
• Conclusions
• The Way Forward
Objective of this presentation

- To review current petroleum production issues regarding real time decision making and,
- To present the results of a continuous self-learning optimization strategy to optimize field-wide productivity while satisfying reservoir physics, production and business constraints.
Reservoir Management is about a careful orchestration of technology, people & resources

The Reservoir Management Challenge

Exploitation Plan
- Well location & number
- Recovery mechanism
- Surface facilities
- Well intervention

Drill, build & Operate

Monitor

Control

Establish or revise Optimum Plan

Subsurface Characterization

Update Model

Drainage Area

Production Well & Facilities

Compression & Treatment Plants

Injection Facilities

4
**Motivation**

<table>
<thead>
<tr>
<th>Traditional Problems</th>
<th>Current Approach</th>
<th>Challenges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complex &amp; risky operations (Drilling, Workover, Prod.)</td>
<td>More front-end engineering and knowledge sharing</td>
<td>More data for analysis and integration limitations.</td>
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<tr>
<td>Poor reservoir prediction &amp; production forecasting</td>
<td>Integrated Characterization &amp; Modern visualization tools</td>
<td>Long-term studies, Ill-posed tools, simple or incomplete.</td>
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<tr>
<td>Limited resources: injection volumes, facilities, people.</td>
<td>Multivariable optimization, reengineering.</td>
<td>Models are not linked among different layers</td>
</tr>
<tr>
<td>Unpredictability of events: gas or water, well damage.</td>
<td>Monitoring &amp; control devices, Beyond well measurements</td>
<td>Poor Justification, real time analysis in early stage.</td>
</tr>
<tr>
<td>Poor decision making ability to tune systems, thus, not optimized operations</td>
<td>Isolated optimization trials with limited success.</td>
<td>Decisions made only on few pieces. Lack of Integration between subsurface-surface</td>
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To develop a field-wide continuous self-learning optimization decision engine

Research Specific Objectives

- **Model based control system** used to continuously optimize three-phase fluid migration in a multi-layered reservoir.

- A **data-driven model** that is continuously updated with collected production data.

- A self-learning and self-adaptive engine **predicts the best operating points** of a hydrocarbon-producing field, while integrating subsurface elements surface facilities and constraints (business, safety, quality, operability).
### Research Framework

<table>
<thead>
<tr>
<th>Data Handling</th>
<th>Model Building</th>
<th>System Identification</th>
<th>Reservoir Performance</th>
<th>Bi-layer Optimization</th>
<th>Close-loop Control</th>
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</table>

- **Data handling**
  - Data acquisition, filtering, de-trending, outliers detection
- **Model building and identification**
  - Gray box modeling: empirical reservoir modeling
  - Partial least square impulse response, neural network and sub-space
- **Reservoir performance prediction**
  - Real time Inflow performance and well restrictions
  - Havlena-Odeh Material Balance
- **Bi-layer optimization of operating parameters**
  - Reservoir best operating point based on the net present value optimization
  - Regulatory downhole sleeves and wellhead choke controls
- **Closed-loop control with history-matched numerical reservoir model**
  - Study of the system behavior in closed-loop
Attempt to solve two significant reservoir management challenges

Problem Definition

**Injector - Producer Profile Mngt.**
- Control undesired fluid production
- Exploit efficiently multilayer horizons
- Characterize inter-well relationship
- Maximize reserves and production
- Control from surface measurement

**Field-Wide Management**
- Optimization fluid production (< bottle-necks)
- Commingle multilayer reservoirs
- Minimize production costs
- Maximize reserves and production
- Control from surface measurement
By collecting data, a digital image is used to make decisions

Traditional (Ideal) Integrated Management Approach

1. Data Collection
2. Database Parameters Check Condition Applications
3. Reservoir Model
4. Well Model
5. Surface Model
6. Business Constraints
7. Optimization
8. Decision Making
9. Implementation

Exploitation Options

Parameters Check Condition Applications
Spatial distribution of pressure as a time function of saturation

Reservoir Modeling: Fluid Transport in Porous media

Multiphase Darcy's Law

\[ \mathbf{v}_p = -\frac{k_{rp} K}{\mu_p} \left( \nabla p_p - \rho_p \frac{g}{g_c} \nabla Z \right) \]

Continuity Equation

\[ \frac{\partial c}{\partial t} + \nabla \cdot (cv) = 0 \]

Molar density in terms of Porous Volumes

\[ c = \frac{M_W}{V_M} = \frac{A \Delta x \phi S_p}{\beta_p} = \phi S_p \frac{\Delta x}{\beta_p} \]

Pressure Laplacian as a function of the saturation change

\[ \frac{k_{rp} K}{\mu_p} \nabla \cdot \left[ c \left( \nabla p_p - \rho_p \frac{g}{g_c} \nabla Z \right) \right] = \frac{\partial}{\partial t} \left( \frac{\phi S_p}{\beta_p} \right) \]

This realization is not used in this research, since it requires the knowledge of parameters that cannot be directly measured.
Reservoir Modeling: Flow through Wellbore

Radial Diffusivity Equation

\[
\frac{K}{\phi \mu (c_f + c)} \left( \frac{\partial^2 p}{\partial r^2} + \frac{1}{r} \frac{\partial p}{\partial r} \right) = \frac{\partial p}{\partial t}
\]

General Solution given by Exponential Integral

\[
p(r, t) = p_i - \frac{q \mu}{4\pi kh} E_i \left( \frac{\phi \mu c_i r^2}{4kt} \right)
\]

Wellbore flow given by logarithmic approximation

\[
p_{wf} = p_i - \frac{q \mu}{4\pi kh} \ln \left( \frac{4kt}{\gamma \phi \mu c_i r_w^2} \right)
\]

Steady-state Equation for the Undersaturated Oil-Flow

\[
q_{o,b} = \frac{kk_{ro} h (p_e - p_{wf})_o}{141.2 B_o \mu_o \left[ \ln \left( \frac{r_e}{r_w} \right) + s \right]}
\]

Inflow Performance (IPR) for Saturated reservoirs

\[
q_o = q_{o,b} + \frac{p_b \cdot J^*}{1.8} \left[ 1 - 0.2 \left( \frac{p_{wf}}{p_b} \right) - 0.8 \left( \frac{p_{wf}}{p_b} \right)^2 \right]
\]

\[
q^k_o = a_0 + a_1 \cdot p^k_e + a_2 \cdot p^k_{wf} + a_3 \cdot (p^k_{wf})^2
\]

\[
q^k_w = b_0 + b_1 \cdot p^k_e + b_2 \cdot p^k_{wf} + b_3 \cdot (p^k_{wf})^2
\]

\[
q^k_g = c_0 + c_1 \cdot p^k_e + c_2 \cdot p^k_{wf} + c_3 \cdot (p^k_{wf})^2
\]
Reservoir Modeling: Average Pressure Modeling

Material Balance Equation

\[ f[p(t)] = g(N_p, G_p, W_p, W_e) \]

\[ \Rightarrow p = a_0 + a_1 \int q_o + a_2 \int q_w + a_3 \int q_g + a_4 \int q_{wi} \]

\[ \Rightarrow \frac{dp}{dt} = b_1 q_o + b_2 q_w + b_3 q_g + b_4 q_{wi} \]

\[ \Rightarrow \frac{1}{\Delta t} \left( p^k - p^{k-1} \right) \approx c_0 + c_1 \cdot p^k + c_2 \cdot p_{wf1}^k + c_3 \cdot \left( p_{wf1}^k \right)^2 + c_4 \cdot p_{wf2}^k + c_5 \cdot \left( p_{wf2}^k \right)^2 \]

Proposed Pressure Modeling for continuous monitoring

\[ \left( \overline{p} \right)^k = \left( \overline{p} \right)^{k-1} + c_1 + c_2 \cdot p_{wf1}^k + c_3 \cdot \left( p_{wf1}^k \right)^2 + c_4 \cdot p_{wf2}^k + c_5 \cdot \left( p_{wf2}^k \right)^2 \]
Reservoir Modeling: Flow Through Pipes

**Mechanical Energy Equation**

\[
\frac{dp}{\rho} + \frac{u d u}{g_c} + \frac{g}{g_c} \frac{d z}{g_c D} + \frac{2 f_j u^2 d L}{g_c D} + d W_s = 0
\]

**Single-Phase Solution, Incompressible**

\[
\Delta p = p_1 - p_2 = \frac{g}{g_c} \rho \Delta z + \frac{\rho}{2 g_c} \Delta u^2 + \frac{2 f_j u^2 d L}{g_c D}
\]

**Two-Phase Solution, Hagerdorn & Brown (1965)**

\[
144 \frac{dp}{dz} = -\frac{f m^2}{\rho \left(7.413 \times 10^{10} D^5\right)} + \frac{\Delta \left(u_m^2 / 2 g_c\right)}{\Delta z}
\]

**Proposed Pressure Drop Modeling for Continuous Monitoring**

\[
\left( p_{wf}^k - p_{th}^k \right)^k = b_1 q_o^k + b_2 q_w^k + b_3 q_g^k + b_4 \left( q_o^k \right)^2 + b_5 \left( q_w^k \right)^2 + b_6 \left( q_g^k \right)^2
\]
Well operating point given by the intersection of reservoir and tubing performance

Reservoir Modeling: Well Deliverability

Well operating point given by the intersection of reservoir and tubing performance
Knowing input-output relationships, reservoir could be seen as a process plant.

Reservoir as a Process Control System Structure

- **Measured Disturbances**
  - Well flowing Pressure: $p_{wf}$
  - Reservoir Pressure: $p_{res}$
  - Reservoir Saturations: $S_o$, $S_w$
  - Flow Impairment: $S$, $K_r$'s
  - Zone Multiphase Flow: $q_o$, $q_w$, $g_q$
  - Drainage Area: $A$

- **Unmeasured Disturbances**
  - Reservoir Rock Heterogeneity
  - Reservoir Fluid Distribution Scheduling

- **Manipulated Inputs**
  - Controller: Flow Choke, Zone Control, ESP Speed, Gas Lift, Solvent Injection, Water Injection, Heat Injection, Gas Injection

- **Feed forward path**
  - Backpressure
  - Ambient Temperature
  - Flow Restrictions
  - Injection Fluid Restriction

- **Feed back path**
  - Reservoir Rock Heterogeneity
  - Reservoir Fluid Distribution Scheduling

**Measured Outputs**
- Tubing Head Pressure: $p_{THP}$
- Tubing Head Temperature: $T_{THT}$
- Multiphase Flow: $q_o$, $q_w$, $g_q$
- Solid Production, Water Analysis
Reservoir Model Identification

Recursive self-adaptive identification

Reservoir Simulator

Control Implementation

Physical System

Model Identification

Reservoir Value Optimization

\[ q_o^k = a_0 + a_1 \cdot p_e^k + a_2 \cdot p_{wf}^k + a_3 \cdot (p_{wf}^k)^2 \]
\[ q_w^k = b_0 + b_1 \cdot p_e^k + b_2 \cdot p_{wf}^k + b_3 \cdot (p_{wf}^k)^2 \]
\[ q_g^k = c_0 + c_1 \cdot p_e^k + c_2 \cdot p_{wf}^k + c_3 \cdot (p_{wf}^k)^2 \]

\[
\begin{bmatrix}
q_o^k \\
q_w^k \\
q_g^k
\end{bmatrix} =
\begin{bmatrix}
a_0 & a_1 & a_2 & a_3 \\
b_0 & b_1 & b_2 & b_3 \\
c_0 & c_1 & c_2 & c_3
\end{bmatrix}
\begin{bmatrix}
p_e^k \\
p_{wf}^k
\end{bmatrix}
\]

\[
\hat{y}_{k+n+jk} = \sum_{i=n+1}^{n+N} h_i u_{k+n+j-i} + \hat{a}_{kk}
\]

LS Optimization Loop
\[ \hat{Y} = X\hat{\theta} + e \]
\[ \min_{\hat{a},\hat{b}} \left\{ \sum_{i=1}^{N} e_i^2 \right\} \Rightarrow (X^T X)^{-1} X^T Y \]
\[ \begin{cases}
q_{o,g,w} = f_1(p^k, p^{k-1}, \ldots, q_{T}, q_{T-1}, \ldots) \\
p_{res} = f_n(p^k, p^{k-1}, \ldots, q_{T}, q_{T-1}, \ldots)
\end{cases} \]
Example for Model Identification and Block Diagram

**Inputs (U)**
- Producer Flowing Pressure, \( p_{wf1} \)
- Injector Flowing Pressure, \( p_{wf2} \)

**Empirical model whose structure is determined by first principles**

**Identification**

**Empirical Model**

**Reservoir (Simulator)**

**Outputs (Y)**
- Reservoir Pressure: \( P \)
- Oil Rate: \( q_o \)
- Water Rate: \( q_w \)
- Water Fraction: \( f_w \)
- Gas Rate: \( q_g \)
- Water Injection Rate: \( q_{wi} \)
Model Identification Experimental Set-up

Windows and Eclipse Environment

- Generate Data File
- Run Eclipse
- Reservoir Numerical Model
- Run Summary File
- Convert Eclipse To Excel
- Run Matlab

Matlab Environment Level

- Plot Rsc Calculated & Measured
- Subspace Identification
- Neural Network
- FIR PLS
- Least Squares Estimator
- x, y
- ς = 1
- ς = 0
- U, Y
- Select Input and Outputs
- A_c, A_d
- cumsum(A)
- diff(A)
- Auto Scale
- Split Data Test & Pred
- Rescale Parameters
- x

18
Predictions Using Empirical Structured models
Errors Using Empirical models
Coefficients Using Empirical models

- Coef. of reservoir pressure
- Coef. of Prod. Oil Rate
- Coef. of Prod. Water Rate
- Coef. of Prod. Gas Rate
At time $k$ future predictions of the output $y$ can be made as

$$\hat{y}_{k+n+j|k} = \sum_{i=n+1}^{n+N} h_i u_{k+n+j-i} + \hat{d}_{k|k}$$

where

$$\hat{d}_{k|k} = y_k - \sum_{i=n+1}^{n+N} h_i u_{k-i}$$

Minimization Problem to solve

$$\min \left\{ \sum_{j=1}^{p} \left( \hat{y}_{k+n+j|k} - y^{sp} \right)^2 + R \sum_{j=1}^{m} \Delta u^2_{k+j-1|k} \right\}$$

s.t.

$$y_{\min} \leq \hat{y}_{k+n+j|k} \leq y_{\max} \quad j = 1, \ldots, p$$
$$u_{\min} \leq u_{k+j-1|k} \leq u_{\max} \quad j = 1, \ldots, m$$
$$u_{k+i|k} = u_{k+m-1|k} \quad i = m, \ldots, p - 1$$

- Controls operation while optimizing performance
- Done over a receding or moving horizon
- Requires a setpoint from an upper level

Set Point Tracking Example
All Variables normalized so that They have zero mean and Std. Dev = 1
Example for Control and Block Diagram

**Inputs (U)**
- Producer Flowing Pressure, $p_{wf1}$
- Producer Flowing Pressure, $p_{wf2}$
- Injection Flowing Rate, $q_{winj}$

**Outputs (Y)**
- Reservoir Pressure: $P$
- Oil Rate Layer 1: $q_{o1}$
- Oil Rate Layer 2: $q_{o2}$
- Water Rate Layer 1: $q_{w1}$
- Water Rate Layer 2: $q_{w2}$
- Water Injection Rate: $q_{wi}$

Diagram:
- $q_{o,sp}$
- $q_{w,sp}$
- $q_{g,sp}$
- $\Delta q_o$
- $u_1$
- $u_2$
- $u_3$
- $d$
- $p_{wf}$
- $q_{oT}$
- $q_{o}$
- $q_{w}$
- $q_{g}$
- PLS Impulse Identification
- Empirical Model
- MPC Controller
- Reservoir (Simulator)
MPC minimizes future prediction error by satisfying input constraints

Model Predictive Control Response
New Self-learning Reservoir Management Technique

Continuous self-learning optimization decision engine

Reservoir Simulator

Model Identification

Reservoir Value Optimization

Control Implementation

LP Optimization Loop

\[
\max \left\{ \text{NPV} = \sum_{i=1}^{N} f(q_o, q_w, q_g, S, \Delta T) \right\}
\]

s.t.

\[
\begin{align*}
0 & \leq p_{min} \leq p_{k+p, k} \leq p_{max} \\
0 & \leq q_{min} \leq q_{k+p} \leq q_{max}
\end{align*}
\]

\[
\Leftrightarrow \begin{cases} 
\hat{q}_{o, opt}, \hat{q}_{g, opt}, \hat{q}_{w, opt}
\end{cases}
\]
Upper optimization layer passes the best operating point to lower layer

Multilayer Reservoir Control Model

Linear Programming Optimizer

Net Present Value Function

Reservoir Forecasts

Optimization Layer

MPC Controller

Reservoir (Simulator)

PLS Impulse Identification

Empirical Model

Net Present Value Function Reservoir Forecasts

Information

$q_{o,sp}$

$q_{w,sp}$

$q_{g,sp}$

$\Delta q_o$

$p_{wf}$

$d$

$q_o$

$q_w$

$q_g$
Best operating point (LP) problem subject to well constraints

Linear Optimization Problem

$$\max \left\{ \text{NPV} = \sum_{i=1}^{N} f \left( q_o, q_w, q_g, S, \Delta T \right) \right\}$$

$$\text{NPV} = \sum_{k=1}^{N} \left[ \left( q_o^k P_o + q_g^k P_g - q_{wp}^k C_{wp} - q_{wi}^k C_{wi} \right) \Delta T_k - I_T^k - C_F^k \right] \left( 1 - r^k \right)$$

$$\left( 1 + i \right)^{\frac{k \cdot \Delta T_k}{365}}$$

Reservoir Performance

Down hole Flowing Pressure, psia

Total Liquid Rate, BPD

VLP 1: $q_w, \text{min} + p_{\text{THP, min}}$

VLP 2: $q_w, \text{min} + p_{\text{THP, max}}$

VLP 3: $q_w, \text{max} + p_{\text{THP, max}}$

VLP 4: $q_w, \text{max} + p_{\text{THP, min}}$
The self-learning cased permitted less water and more oil produced

Injector-producer Management Problem Results

Experimental Base: History-matched Model from El Furrial, HPHT, deep onshore, light oil

**Base Case No control**
- Early water irruption reduced
- High water cut reduced well’s vertical lift
- Further recovery possible at a greater cost

**Self Learning Case**
- Water irruption detected and controlled
- Zone shut off permitted better well’s vertical lift
- Recovery accelerated at a minimum cost
Clear benefits from extra little oil but with a lot less effort.

Field-wide life cycle comparison Results

- **Oil rate**
  - Non-Controlled
  - Self-Learning
  - $\Delta N_p = 500$ Mbbls
  - $\Delta Rev = $5 Million

- **Water rate**
  - Non-Controlled
  - Self-Learning
  - $\Delta W_p = -18$ MMbbls
  - $\Delta W_i = -19$ MMbbls
  - $\Delta Rev = -$92.5 Million
New Self-learning Reservoir Management Technique

Continuous self-learning optimization decision engine

QP Optimization Loop
\[
\min_{\Delta u} \left\{ \sum_{j=1}^{p} (\hat{y}_{k+j} - y^{SP})^2 + R \sum_{j=1}^{m} \Delta u_{k+j}^2 \right\} \\
\text{s.t.} \\
y_{\text{min}} \leq \hat{y}_{k+j|k} \leq y_{\text{max}}; j = [1, p] \\
u_{\text{min}} \leq u_{k+j|k} \leq u_{\text{max}}; j = [1, m] \\
u_{k+j|k} = u_{k+m-l_k|k}; i = [m, p]
\]

LP Optimization Loop
\[
\max \left\{ \text{NPV} = \sum_{i=1}^{N} f \left( q_o, q_w, q_g, S, \Delta T \right) \right\} \\
\text{s.t.} \\
p_{\text{min}} \leq p_{k+p,k} \leq p_{\text{max}} \\
q_{\text{min}} \leq q_{k+p} \leq q_{\text{max}} \\
\Leftrightarrow \{ \hat{q}_{o,\text{opt}}, \hat{q}_{g,\text{opt}}, \hat{q}_{w,\text{opt}} \}
\]

LS Optimization Loop
\[
\hat{Y} = X\hat{\theta} + \epsilon \\
\min_{a,b} \left\{ \sum_{i=1}^{n} e_i^2 \right\} \Rightarrow (X^TX)^{-1} XY \\
\Leftrightarrow \left\{ q_{o,g,w} = f_1(p^i, p^{i-1} \ldots q_T^k, q_T^{k-1} \ldots) \\
p_{\text{res}} = f_2(p^i, p^{i-1} \ldots q_T^k, q_T^{k-1} \ldots) \right\}
\]
Summary & Conclusions

• Novel multilevel self adaptive reservoir performance optimization architecture
  – Upper level calculates the optimum operating point
  – Based on NPV
  – Optimum set point passed to underlying level

• Feasibility of the method demonstrated through a case study
  – Reservoir performance continuously optimized by an adaptive self-learning decision engine
  – Method capitalizes on available remotely actuated devices

• Algorithm feasible for downhole implementation
  – Impart intelligent to downhole and surface actuation devices
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