SELF-LEARNING RESERVOIR MANAGEMENT

SPE 84064

L. Saputelli[1,2,3], M. Nikolaou[2], and M. J. Economides[2,3]
[1]PDVSA, [2]University of Houston, [3]SPE member

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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

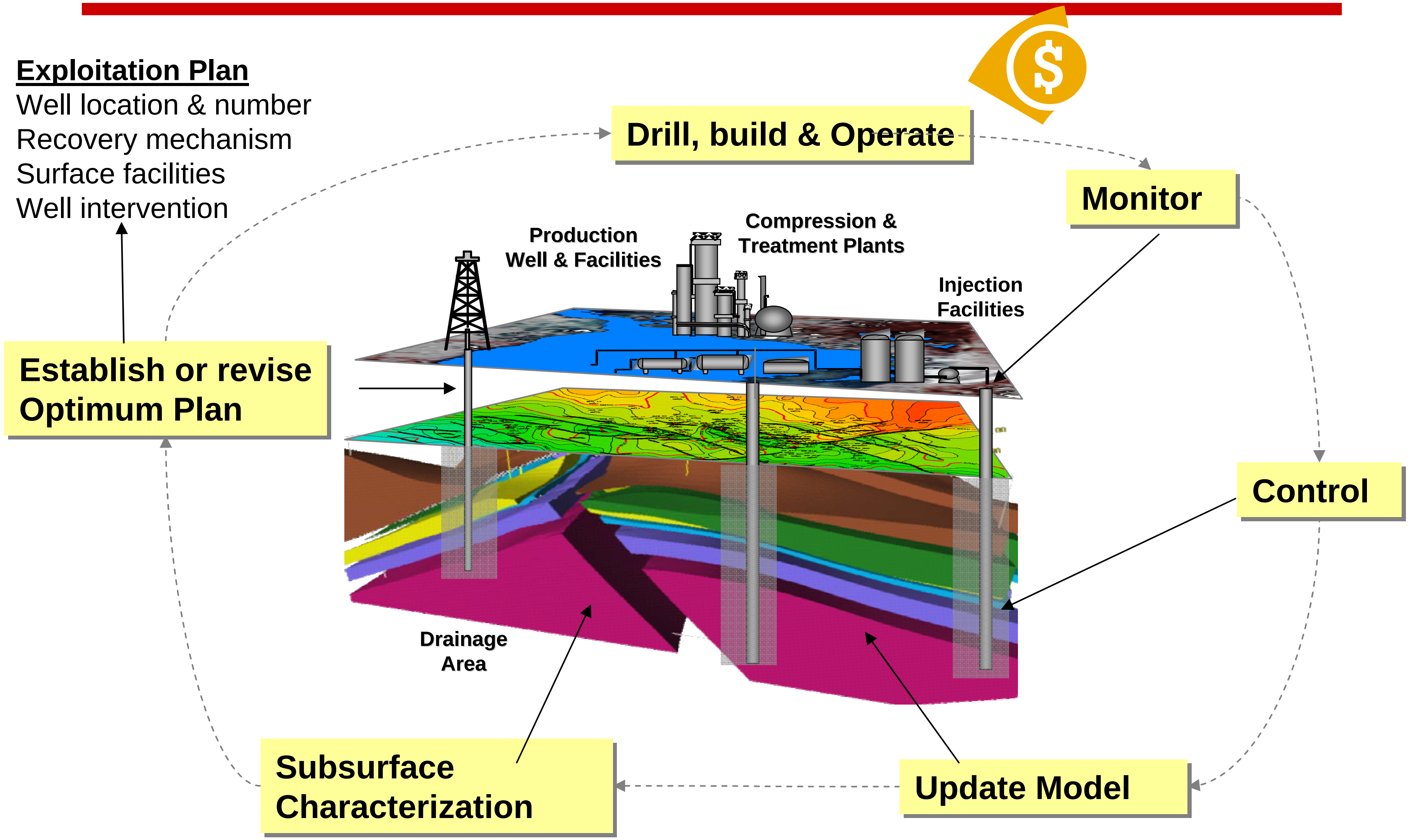
- To review current petroleum production issues regarding real time decision making and,
- To present the results of a continuous self-learning optimization strategy to optimize field-wide productivity while satisfying reservoir physics, production and business constraints.

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



Hydrocarbon production system suffering major technical problems

Motivation

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

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

Data Handling	Model Building	System Identification	Reservoir Performance	Bi-layer Optimization	Close-loop Control

- 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

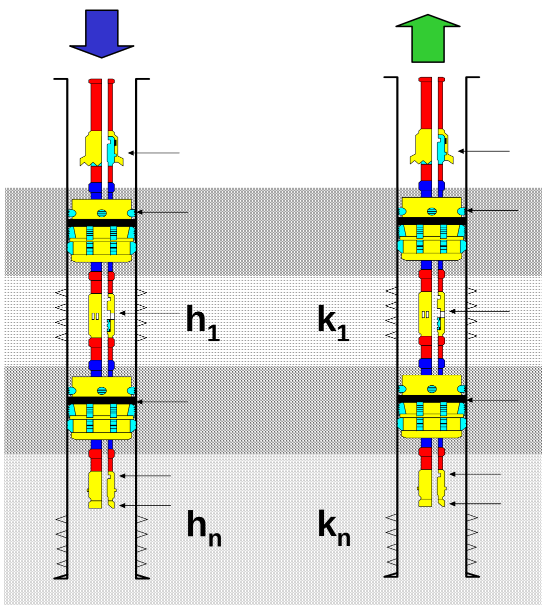
Problem Definition

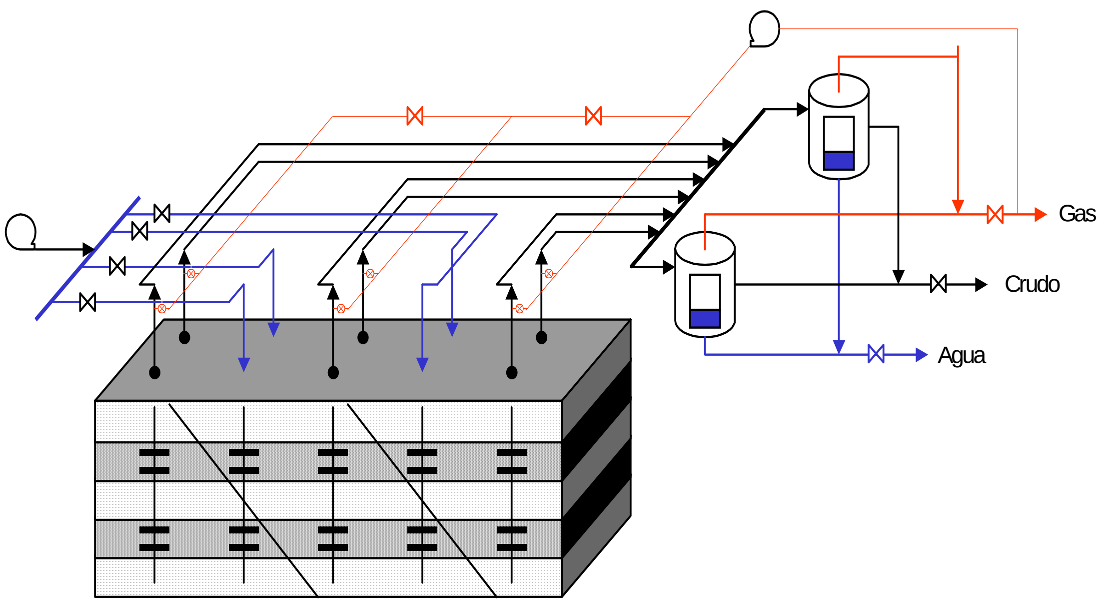
Injector - Producer Profile Mngt.

- Control undesired fluid production
- Exploit efficiently multilayer horizons
- Characterize inter-well relationship
- Maximize reserves and production
- Control from surface measurement

Field-Wide Management

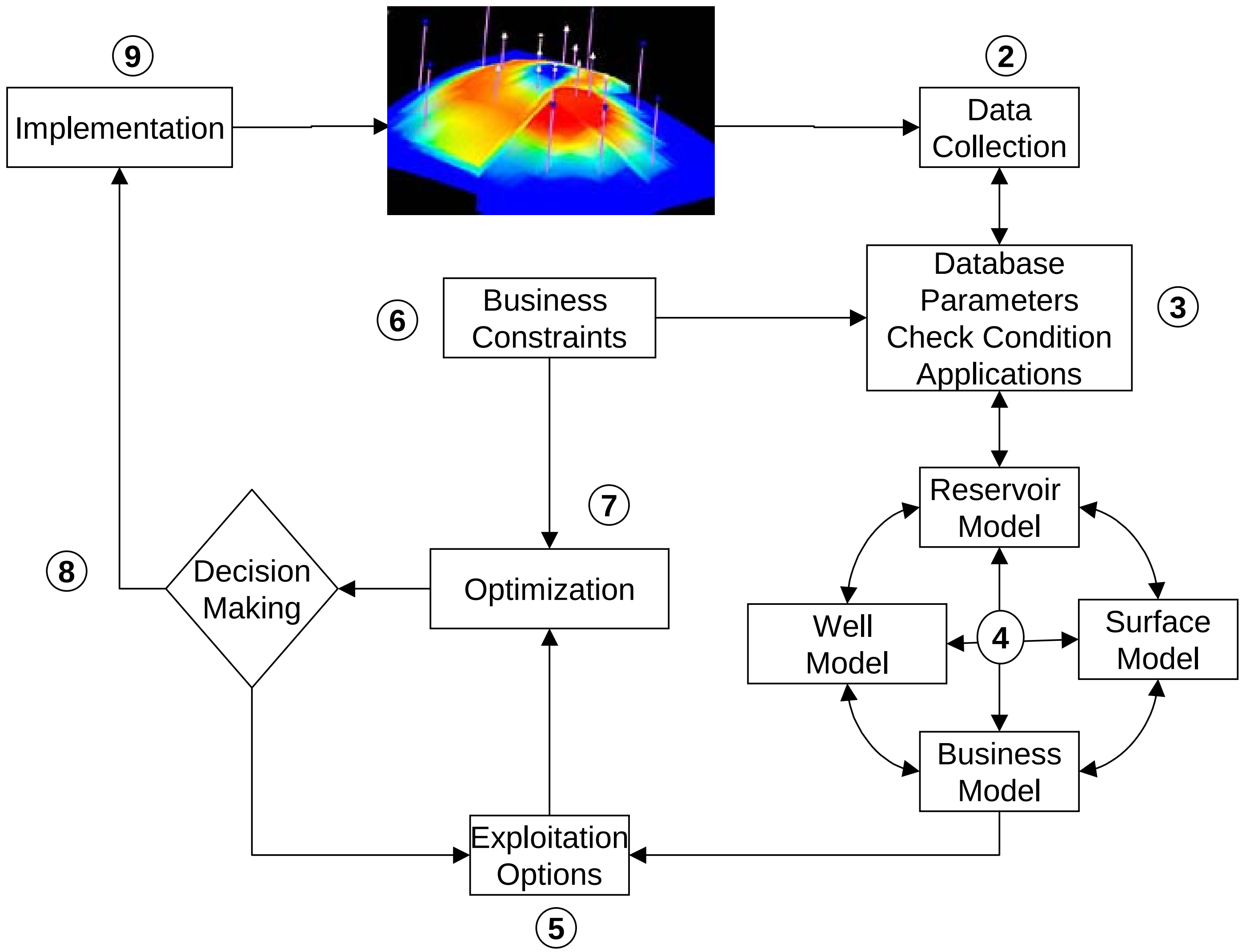
- Optimization fluid production (< bottle-necks)
- Commingle multilayer reservoirs
- Minimize production costs
- Maximize reserves and production
- Control from surface measurement





By collecting data, a digital image is used to make decisions

Traditional (*Ideal*) Integrated Management Approach



Reservoir Modeling: Fluid Transport in Porous media

Multiphase Darcy's Law

$$\mathbf{v_p} = -\frac{k_{rp}\mathbf{K}}{\mu_p}\left(\underline{\nabla} p_p - \rho_p \frac{\mathbf{g}}{g_c}\underline{\nabla} Z\right)$$

This realization is not used in this research, since it requires the knowledge of parameters that cannot be directly measured

Continuity Equation

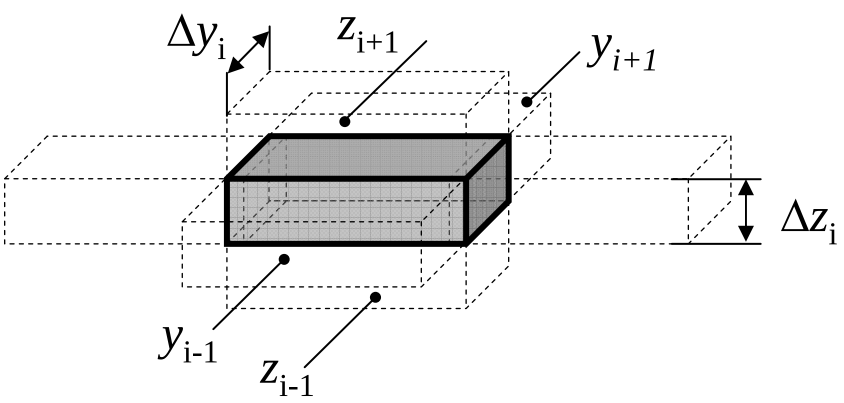
$$\frac{\partial c}{\partial t} + \underline{\nabla}\cdot\left(c\mathbf{v}\right) = 0$$

Pressure Laplacian as a function of the saturation change

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

$$c = \frac{M_W}{V_M} = \frac{A\Delta x \phi S_p / \beta_p}{A\Delta x} = \frac{\phi S_p}{\beta_p}$$

Molar density in terms of Porous Volumes



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

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

Wellbore flow given by logarithmic approximation

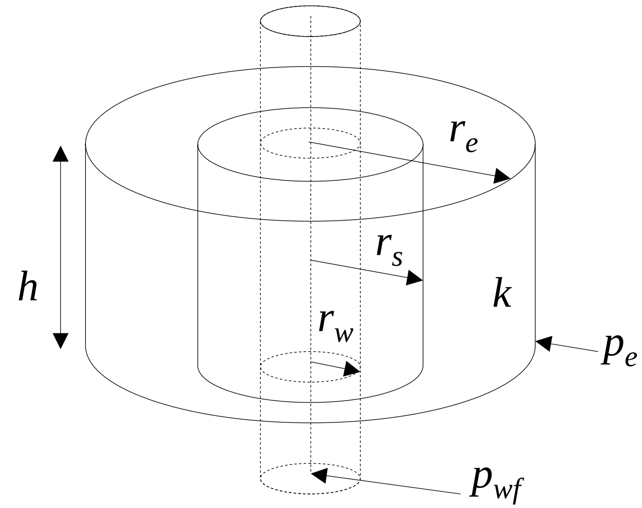
$$p_{wf} = p_i - \frac{q\mu}{4\pi kh}\ln\frac{4kt}{\gamma\phi\mu c_t r_w^2}$$

Steady-state Equation for the Undersaturated Oil-Flow

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

Inflow Performance (IPR) for Saturated reservoirs

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



Proposed IPR for continuous monitoring

$$q_o^k = a_0 + a_1 \cdot p_e^k + a_2 \cdot p_{wf}^k + a_3 \cdot \left(p_{wf}^k\right)^2$$

$$q_w^k = b_0 + b_1 \cdot p_e^k + b_2 \cdot p_{wf}^k + b_3 \cdot \left(p_{wf}^k\right)^2$$

$$q_g^k = c_0 + c_1 \cdot p_e^k + c_2 \cdot p_{wf}^k + c_3 \cdot \left(p_{wf}^k\right)^2$$

Average Reservoir Pressure is a function of net mass production

Reservoir Modeling: Average Pressure Modeling

Material Balance Equation

Net Underground = Withdrawal, F

Expansion of Oil and Original dissolved gas, E_o
+ Expansion of Gas Caps, E_g
+ Reduction of Hydrocarbon Pore Volume, E_{fw}
+ Natural Water Influx, W_e

Simplification

$$f\left[\overline{p}(t)\right] = g\left(N_p, G_p, W_p, W_e\right)$$

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

$$\Rightarrow \frac{d\overline{p}}{dt} = b_1 q_o + b_2 q_w + b_3 q_g + b_4 q_{wi}$$

$$\Rightarrow \frac{1}{\Delta t}\left(\overline{p}^k - \overline{p}^{k-1}\right) \approx c_0 + c_1\cdot\overline{p}^k + c_2\cdot p_{wf1}^k + c_3\cdot\left(p_{wf1}^k\right)^2 + c_5\cdot p_{wf2}^k + c_6\cdot\left(p_{wf2}^k\right)^2$$

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

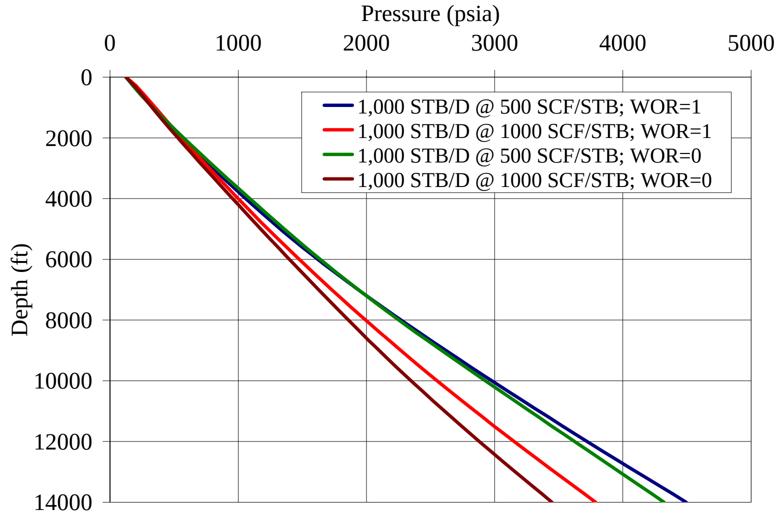
$$\frac{dp}{\rho}+\frac{udu}{g_c}+\frac{g}{g_c}dz+\frac{2f_f u^2 dL}{g_c D}+dW_s=0$$

Single-Phase Solution, Incompressible

$$\Delta p = p_1 - p_2 = \frac{g}{g_c}\rho\Delta z+\frac{\rho}{2g_c}\Delta u^2+\frac{2f_f u^2 dL}{g_c D}$$

Two-Phase Solution, Hagerdorn & Brown (1965)

$$144\frac{dp}{dz}=\bar{\rho}+\frac{f\dot{m}^2}{\left(7.413\times10^{10}D^5\right)\bar{\rho}}+\bar{\rho}\frac{\Delta\left(u_m^2/2g_c\right)}{\Delta z}$$

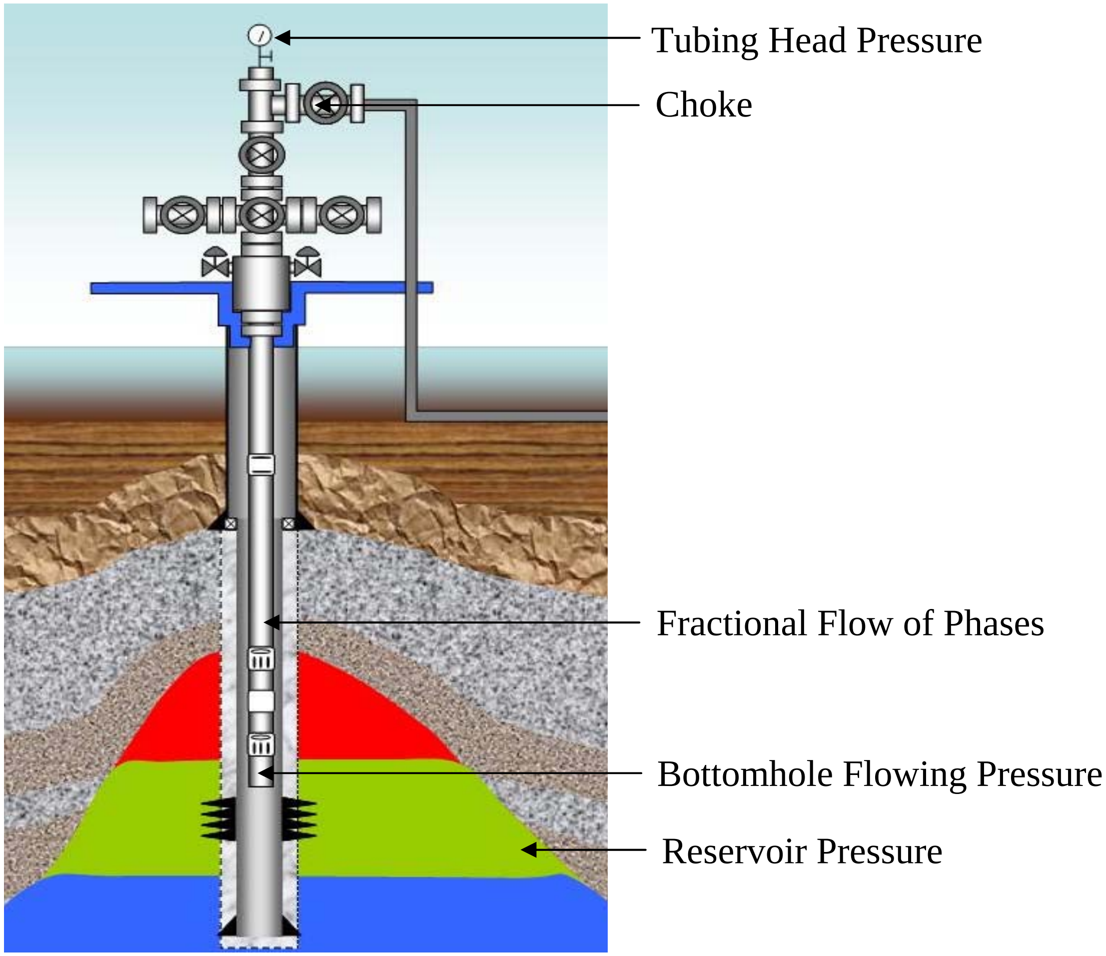


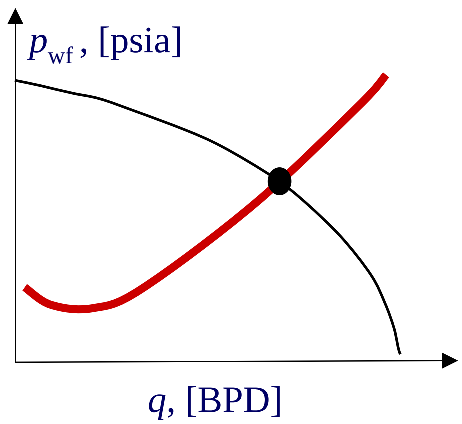
Proposed Pressure Drop Modeling for Continuous Monitoring

$$\left(p_{wf}{}^{k}-p_{th}\right)^{k}=b_1q_o^k+b_2q_w^k+b_3q_g^k+b_4\left(q_o^k\right)^2+b_5\left(q_w^k\right)^2+b_6\left(q_g^k\right)^2$$

Well operating point given by the intersection of reservoir and tubing performance

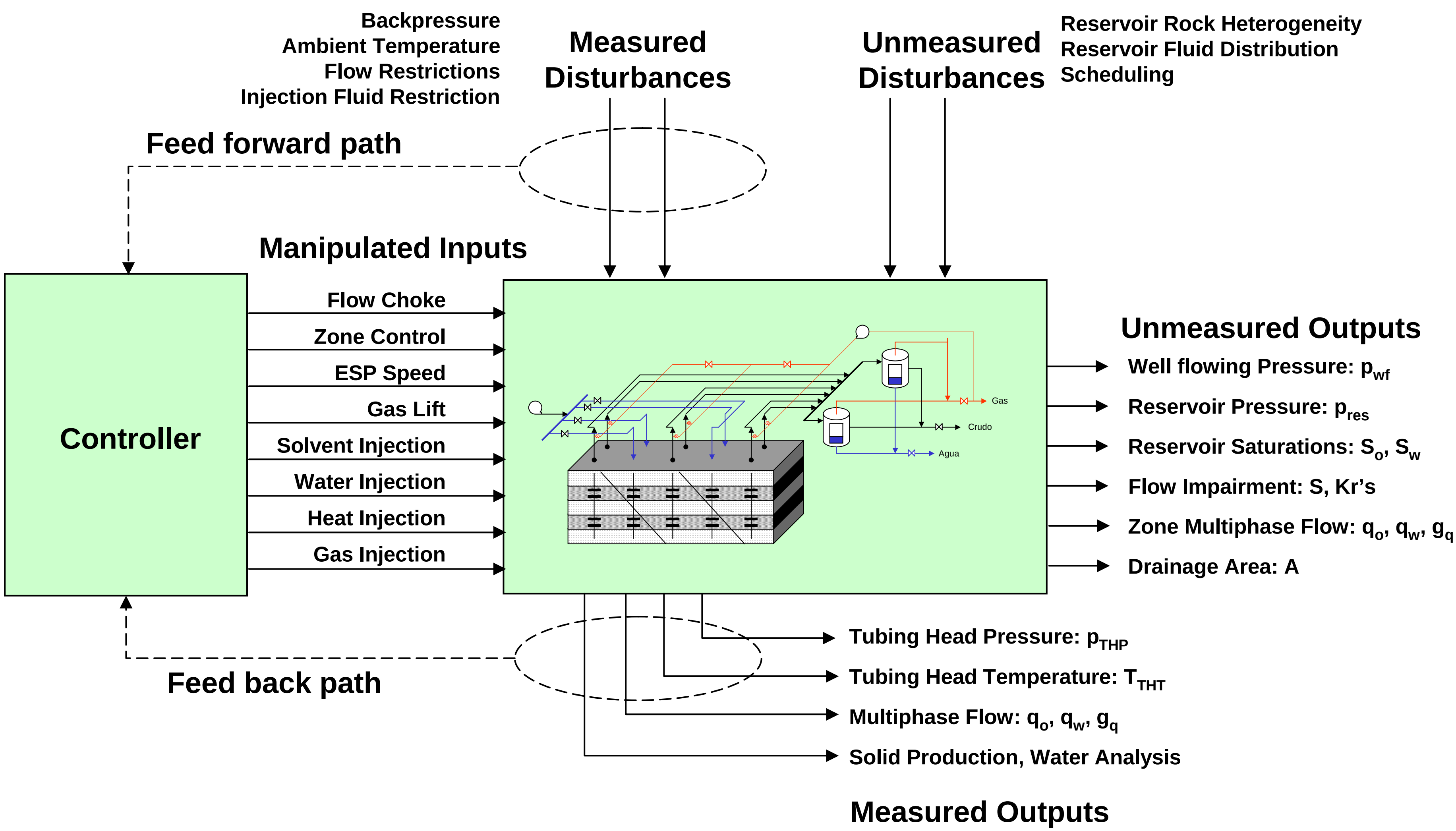
Reservoir Modeling: Well Deliverability



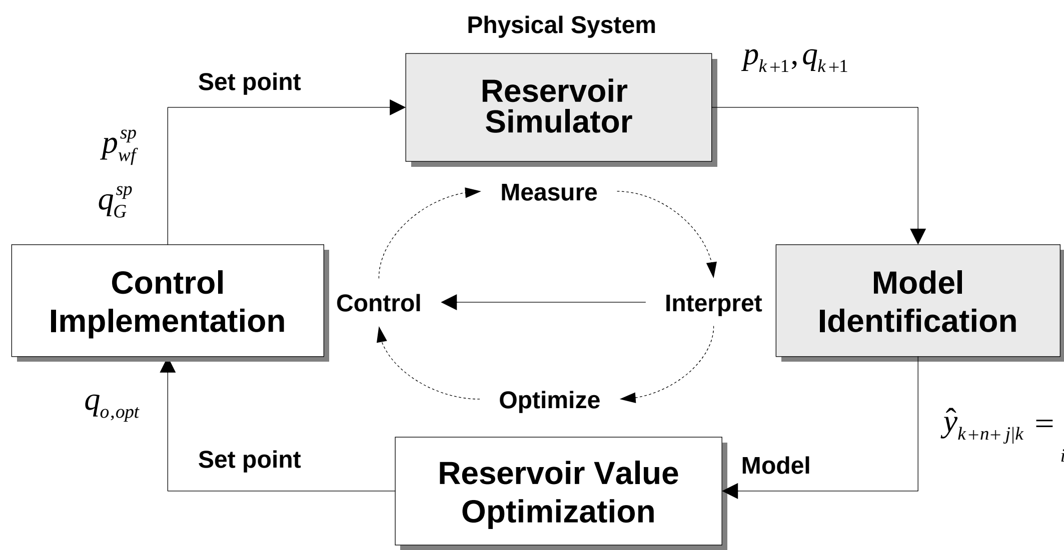


Knowing input-output relationships, reservoir could seen as a process plant

Reservoir as a Process Control System Structure



Reservoir Model Identification



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

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

$\Leftrightarrow$

$$\begin{bmatrix} q_o^k \\ q_w^k \\ q_g^k \end{bmatrix} = \begin{bmatrix} a_0 & a_1 & a_2 & a_3 \\ b_0 & b_1 & b_2 & b_3 \\ c_0 & c_1 & c_2 & c_3 \end{bmatrix} \begin{bmatrix} 1 \\ p_e^k \\ p_{wf}^k \\ \left(p_{wf}^k\right)^2 \end{bmatrix}$$

$\Leftrightarrow$

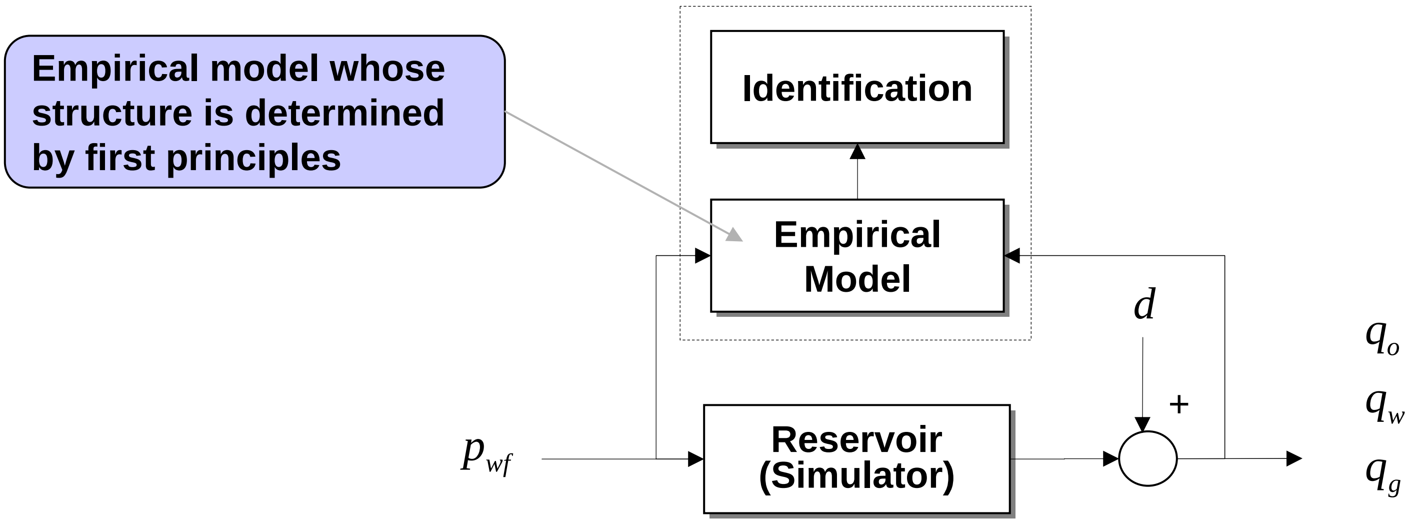
LS Optimization Loop

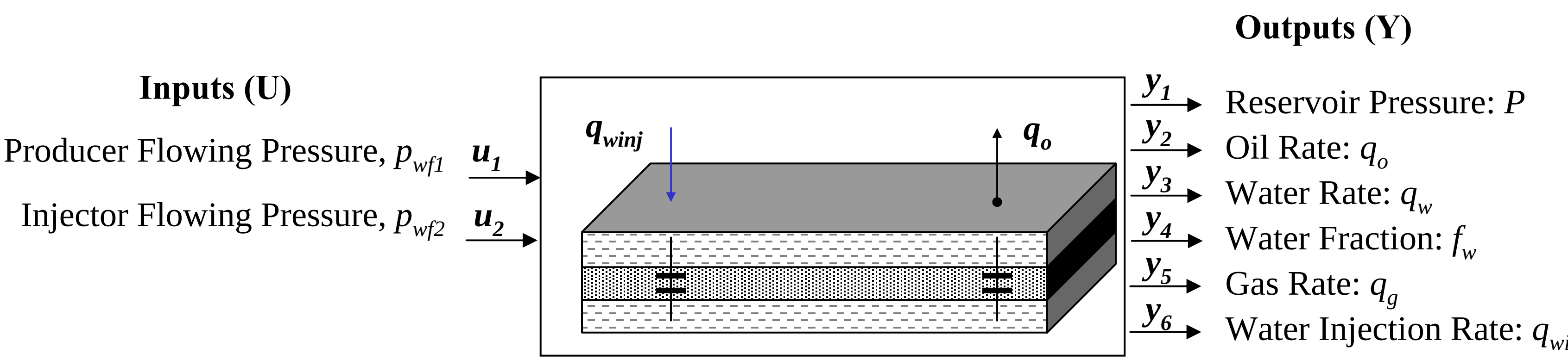
$$\hat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\theta}} + \mathbf{e}$$

$$\min_{a,b} \left\{ \sum_{i=1}^{N} \mathbf{e}_i^2 \right\} \Rightarrow \left(\mathbf{X}^{\mathrm{T}}\mathbf{X}\right)^{-1} \mathbf{X}^{\mathrm{T}}\mathbf{Y}$$

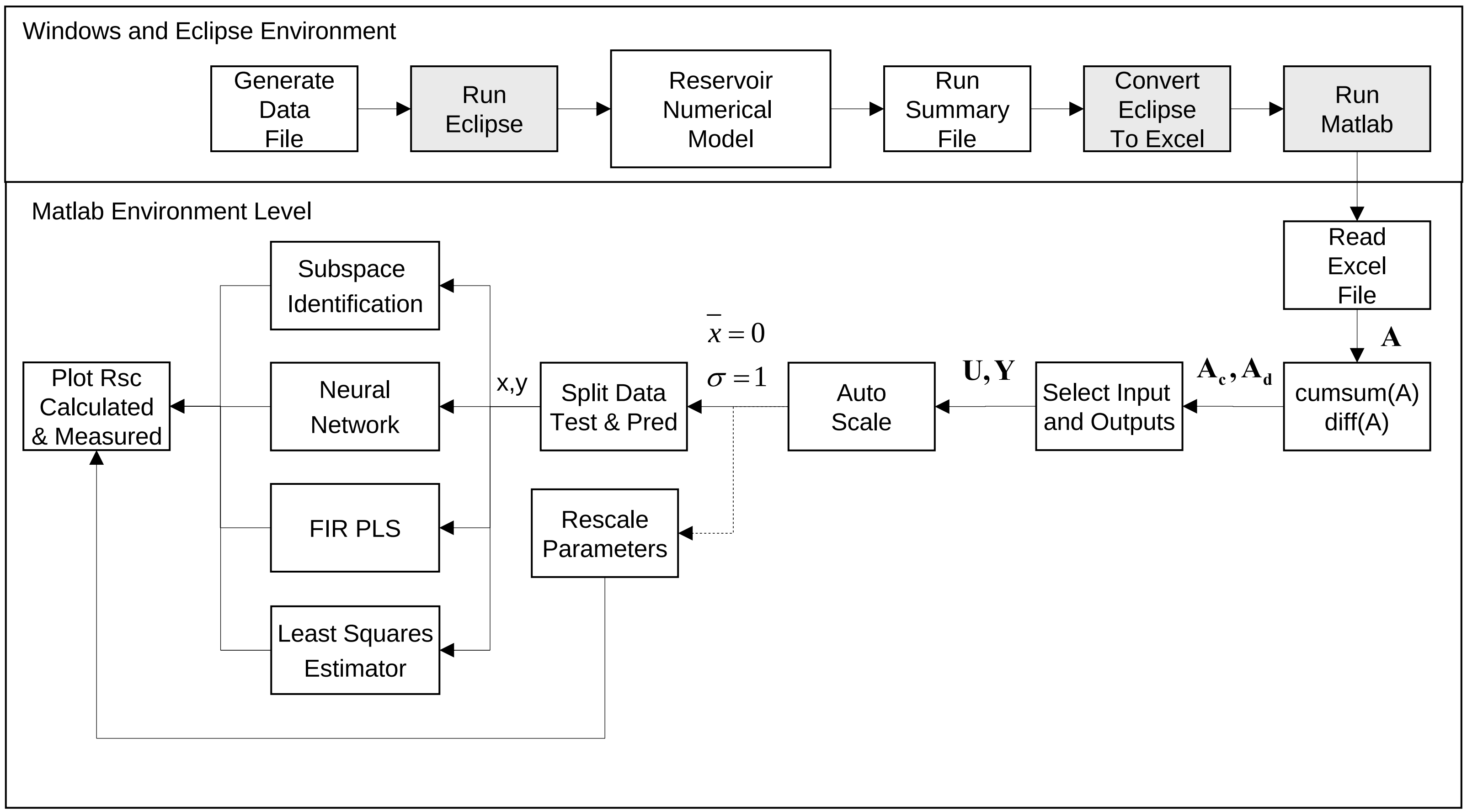
$$\Leftrightarrow \begin{cases} q_{o,g,w} = f_1\left(p^k, p^{k-1} \ldots \quad q_T^k, q_T^{k-1}, \ldots\right) \\ p_{res} = f_n\left(p^k, p^{k-1} \ldots \quad q_T^k, q_T^{k-1}, \ldots\right) \end{cases}$$

Example for Model Identification and Block Diagram

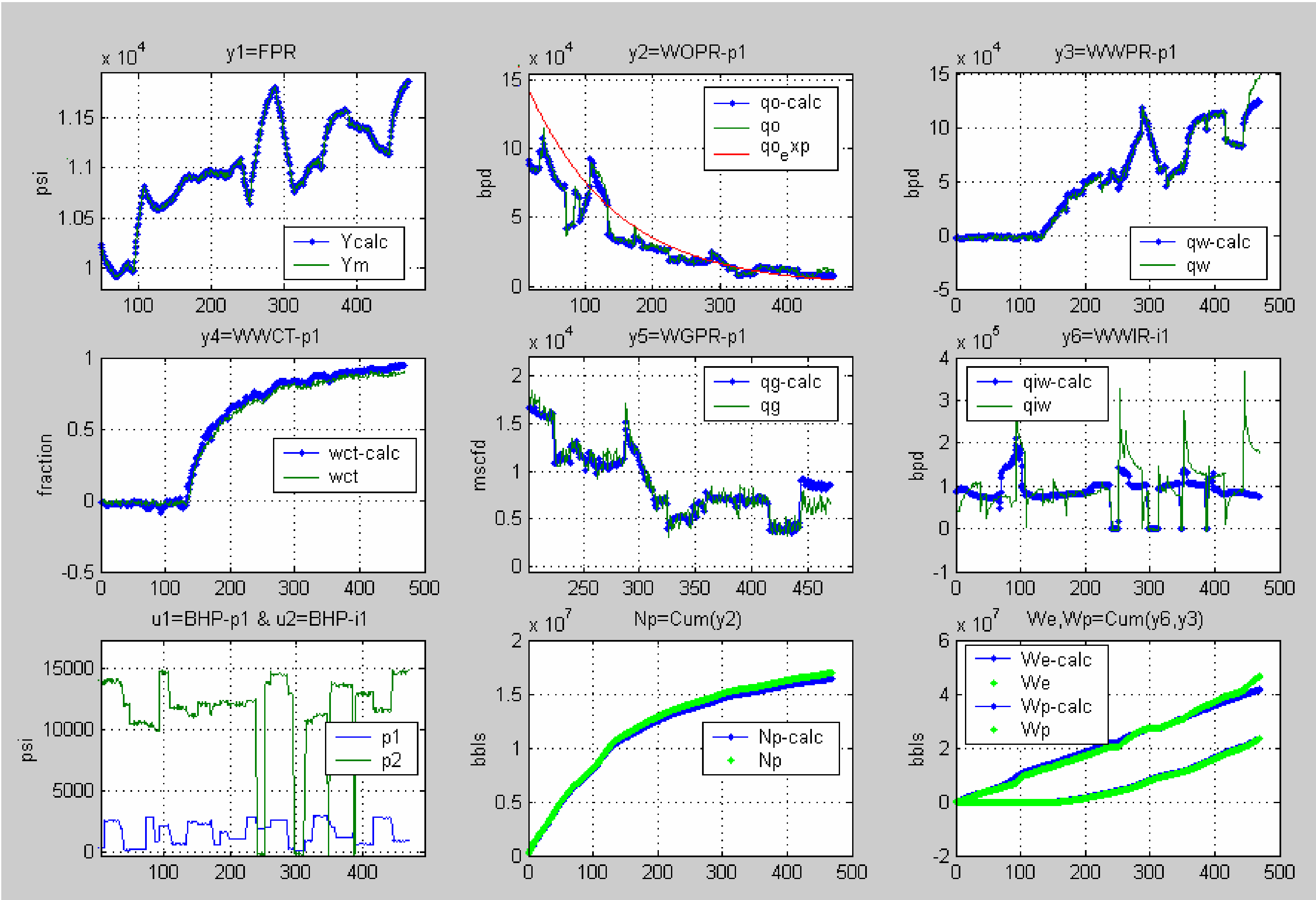




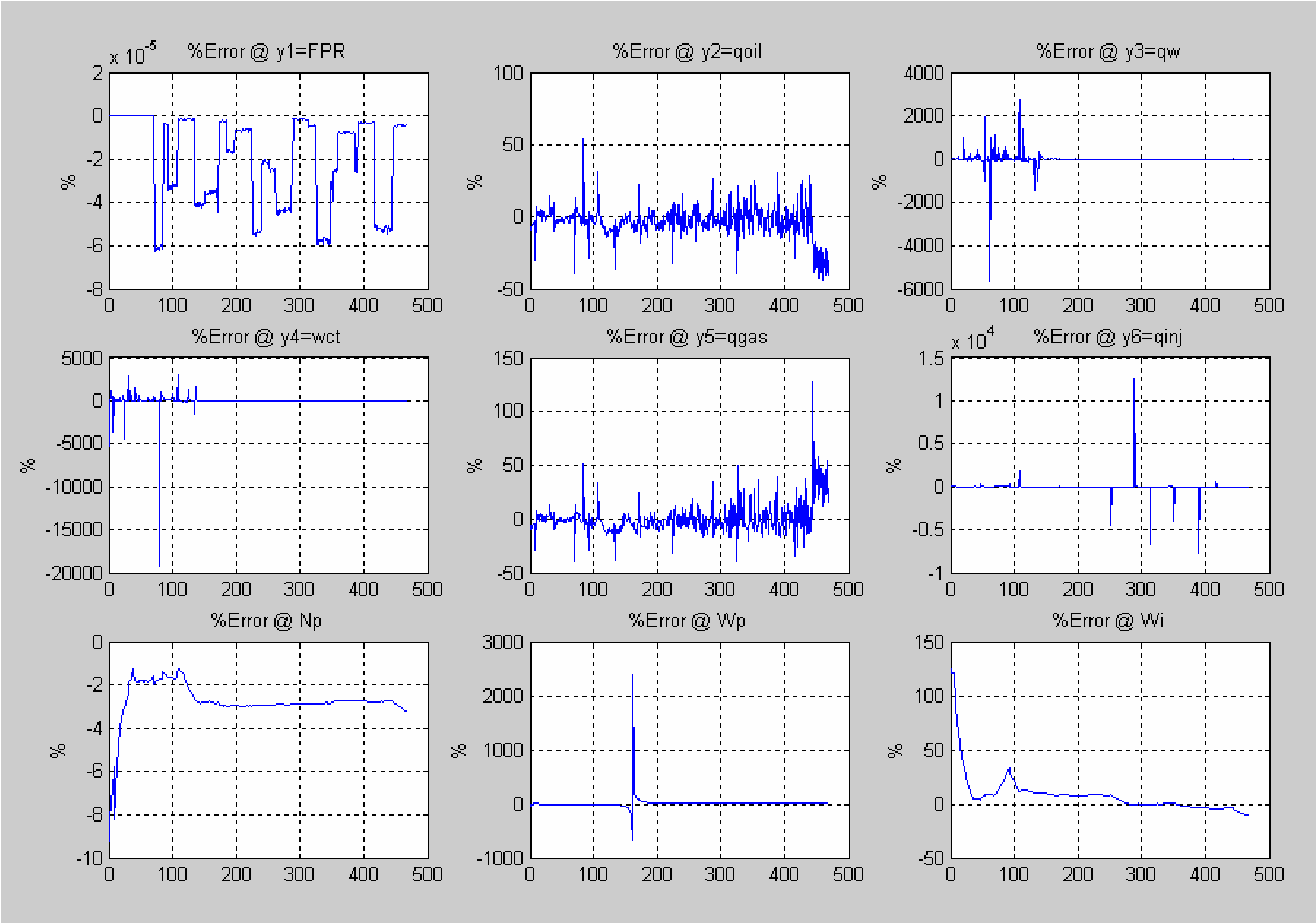
Model Identification Experimental Set-up



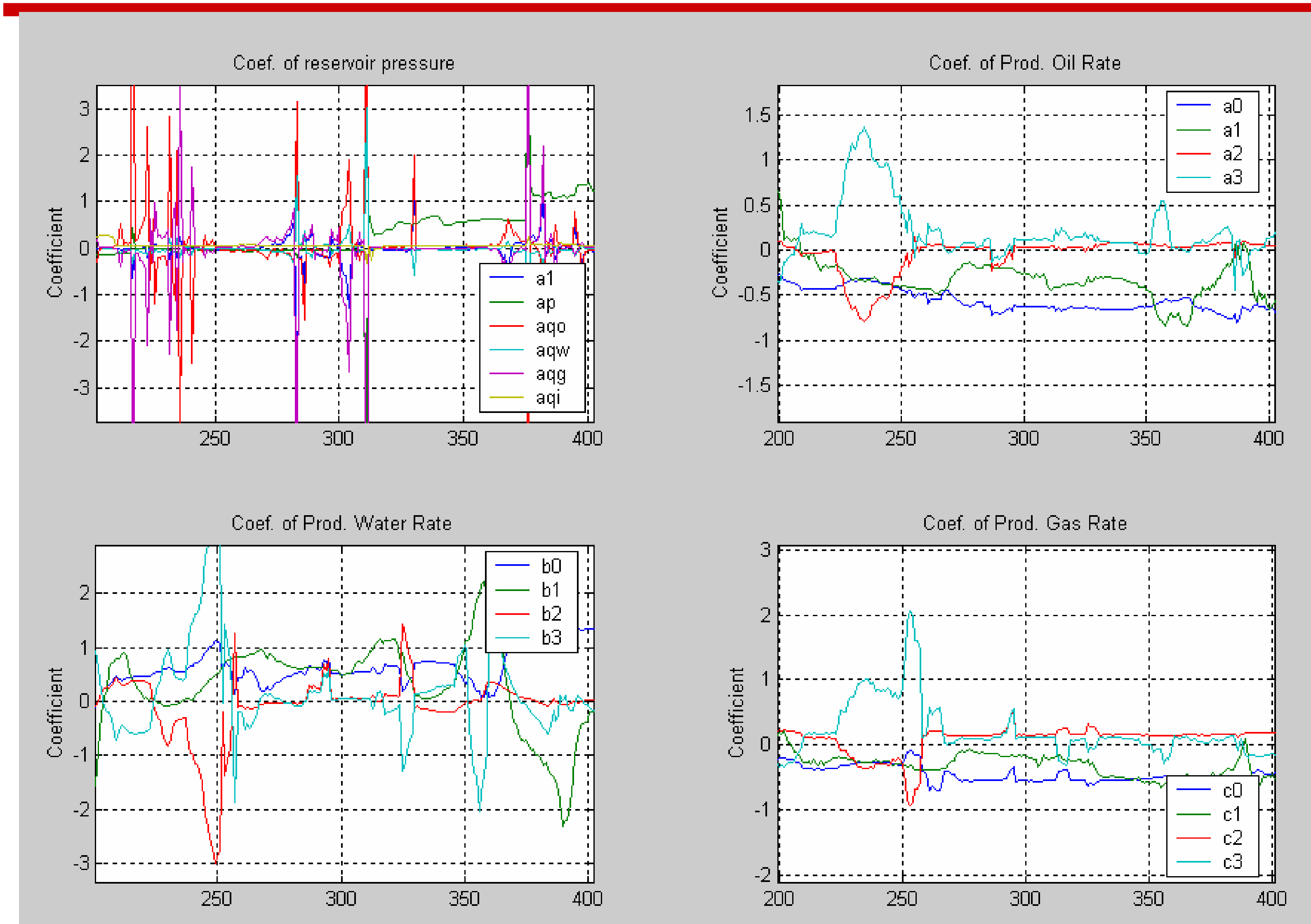
Predictions Using Empirical Structured models



Errors Using Empirical models



Coefficients Using Empirical models



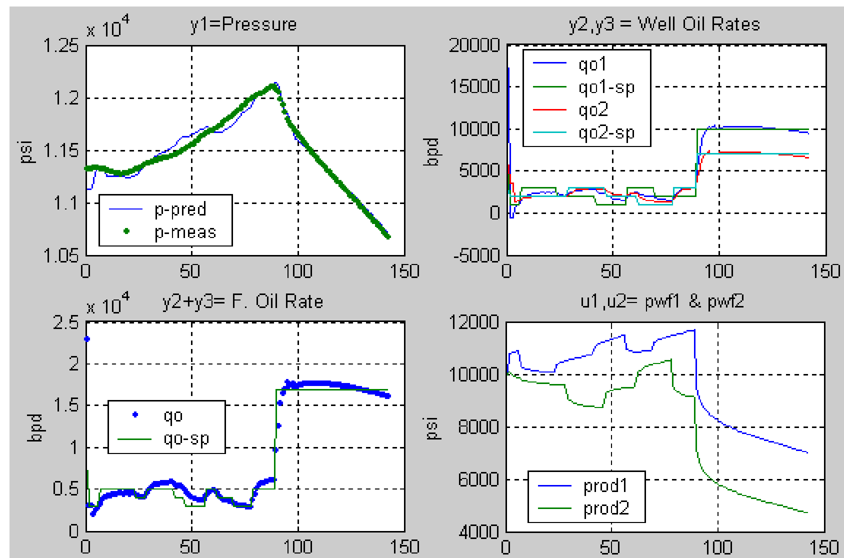
Model Predictive Control

At time ***k*** future predictions of the output ***y*** can be made as

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

Minimization Problem to solve

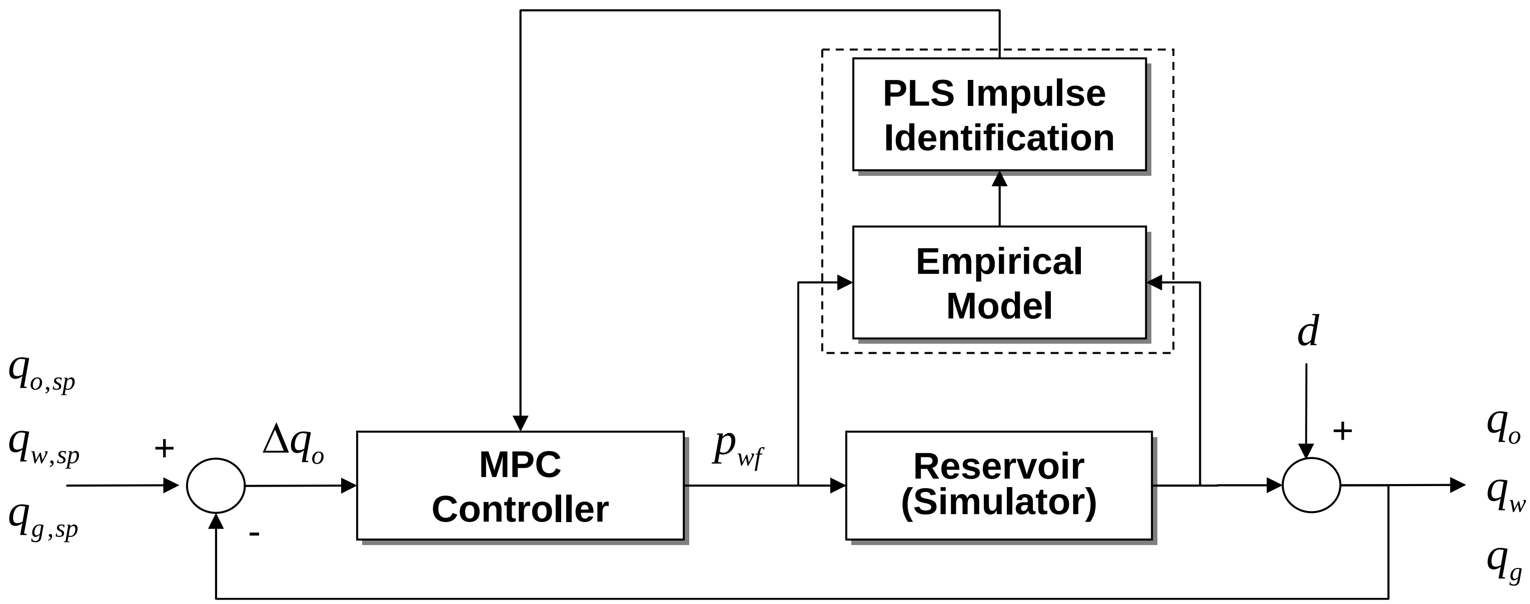
$$\left[\begin{array}{ll} \min \left\{ \sum_{j=1}^{p} \left(\hat{y}_{k+n+j|k} - y^{SP} \right)^2 + R \sum_{j=1}^{m} \Delta u^2_{k+j-1|k} \right\} & \\ s.t. & \\ y_{\min} \le \hat{y}_{k+n+j|k} \le y_{\max} & j = 1, \cdots, p \\ u_{\min} \le u_{k+j-1|k} \le u_{\max} & j = 1, \cdots, m \\ u_{k+i|k} = u_{k+m-1|k} & i = m, \cdots, p-1 \end{array}\right]$$

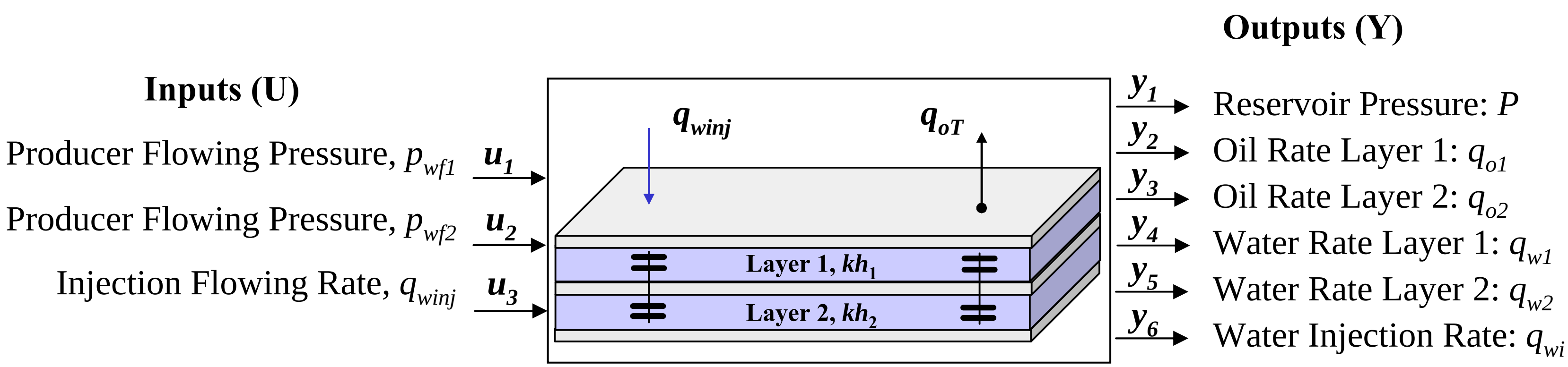


Set Point Tracking Example
All Variables normalized so that They have zero mean and Std. Dev = 1

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

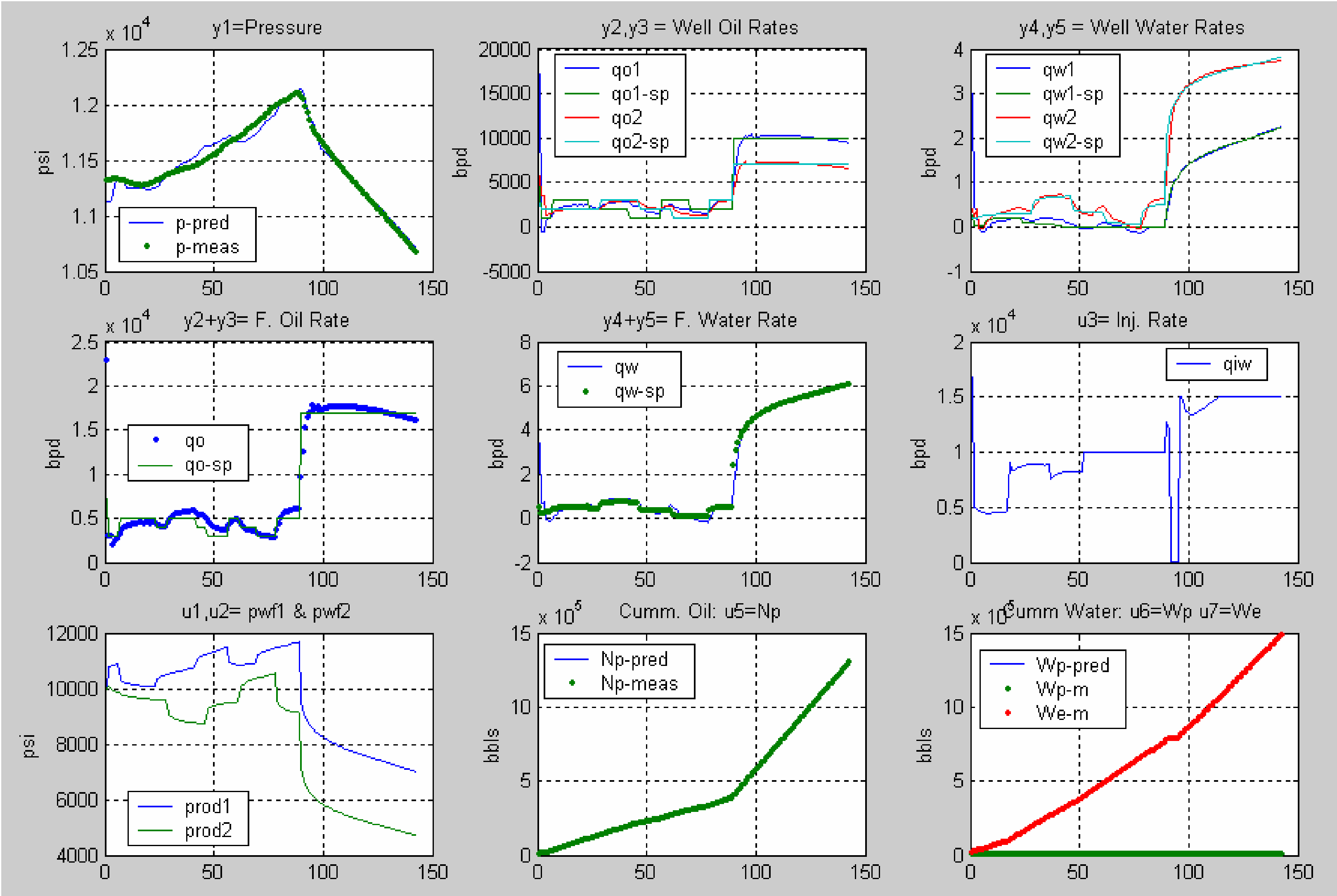
Example for Control and Block Diagram



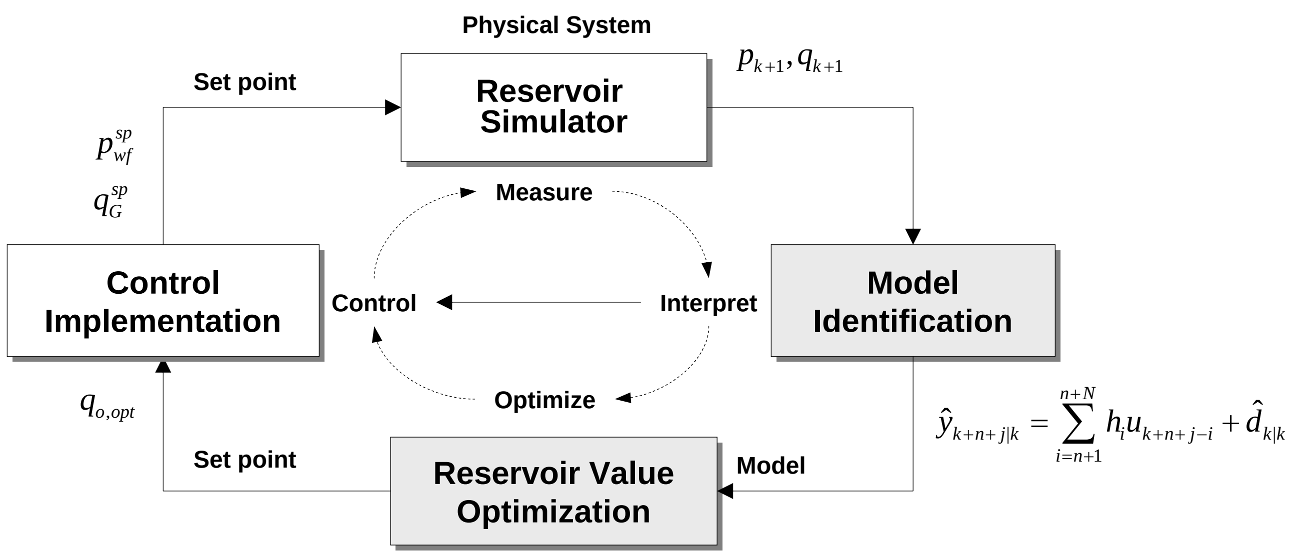


MPC minimizes future prediction error by satisfying input constraints

Model Predictive Control Response



New Self-learning Reservoir Management Technique



LP Optimization Loop

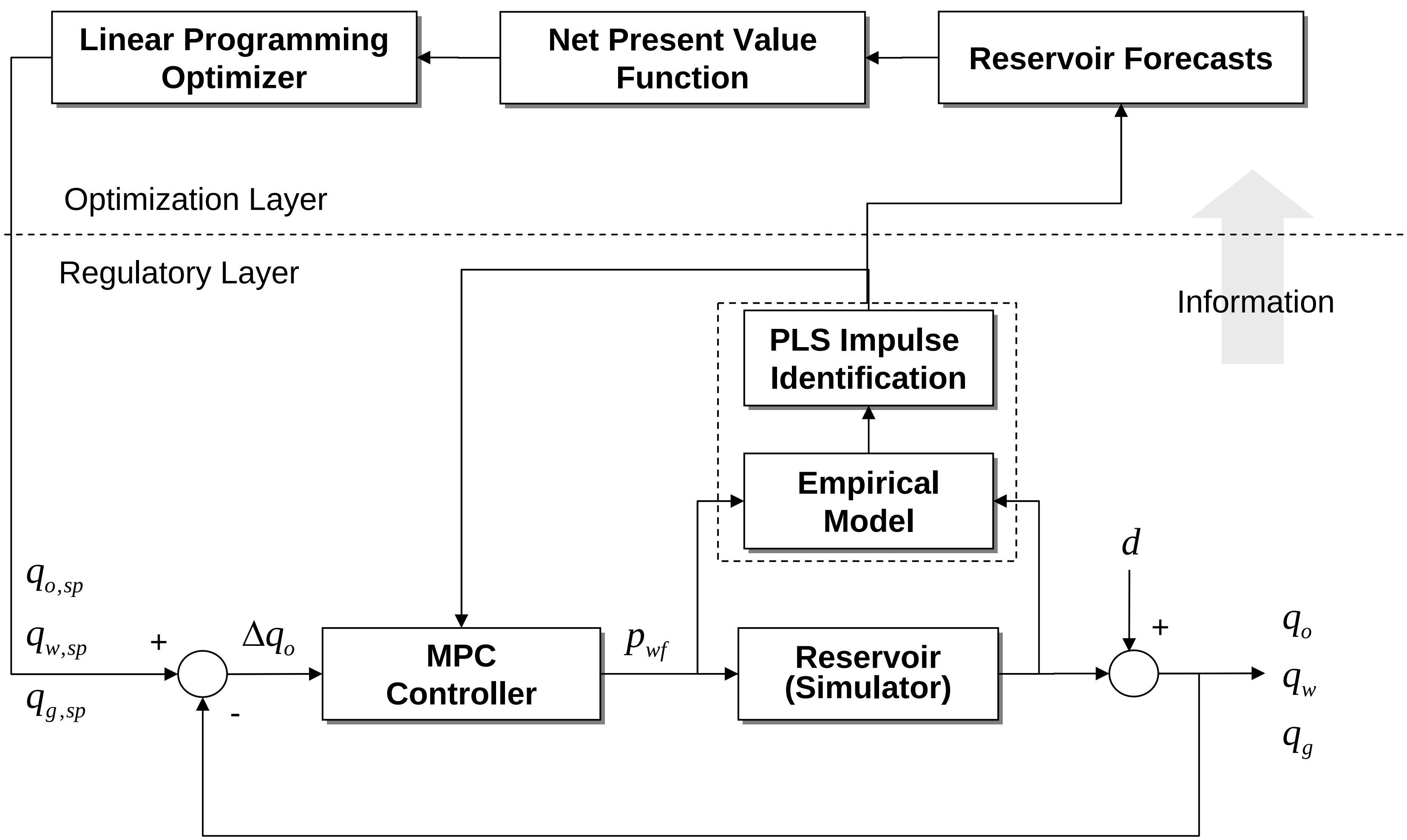
$$\max_{q_o, q_w, q_g} \left\{ \mathbf{NPV} = \sum_{1}^{N} f\left(q_o, q_w, q_g, \$, \Delta T\right) \right\}$$

$$\text{s.t.} \quad \begin{cases} p_{\min} \le p_{k+p,k} \le p_{\max} \\ q_{\min} \le q_{k+p} \le q_{\max} \end{cases}$$

$$\Leftrightarrow \left\{ \hat{q}_{o,opt}, \hat{q}_{g,opt}, \hat{q}_{w,opt} \right.$$

Upper optimization layer passes the best operating point to lower layer

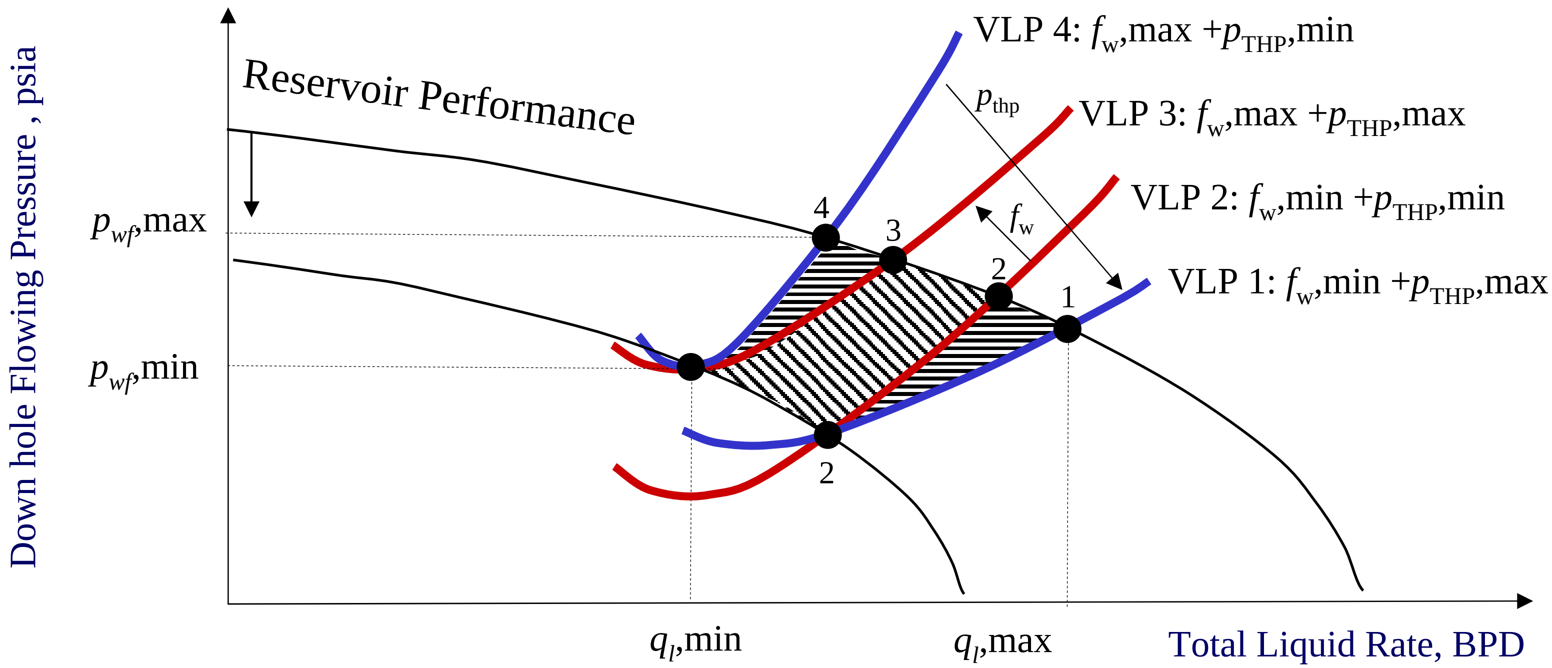
Multilayer Reservoir Control Model



Linear Optimization Problem

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

$$NPV = \sum_{k=1}^{N} \frac{\left[\left(q_o^k P_o + q_g^k P_g - q_{wp}^k C_{wp} - q_{wi}^k C_{wi}\right)\Delta T_k - I_T^k - C_F^k\right]\left(1 - r^k\right)}{\left(1+i\right)^{\frac{k \cdot \Delta T_k}{365}}}$$



Injector-producer Management Problem Results

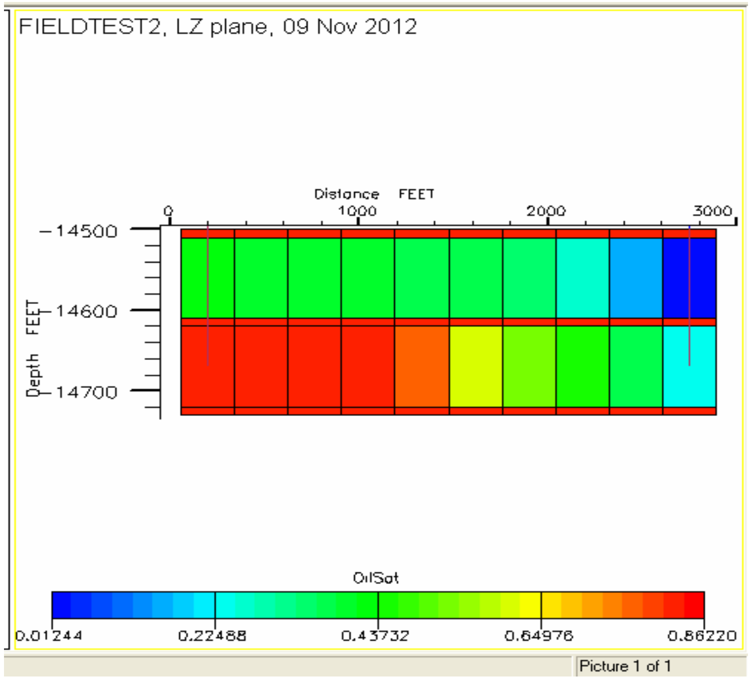
Experimental Base: History-matched Model from El Furrial, HPHT, deep onshore, light oil

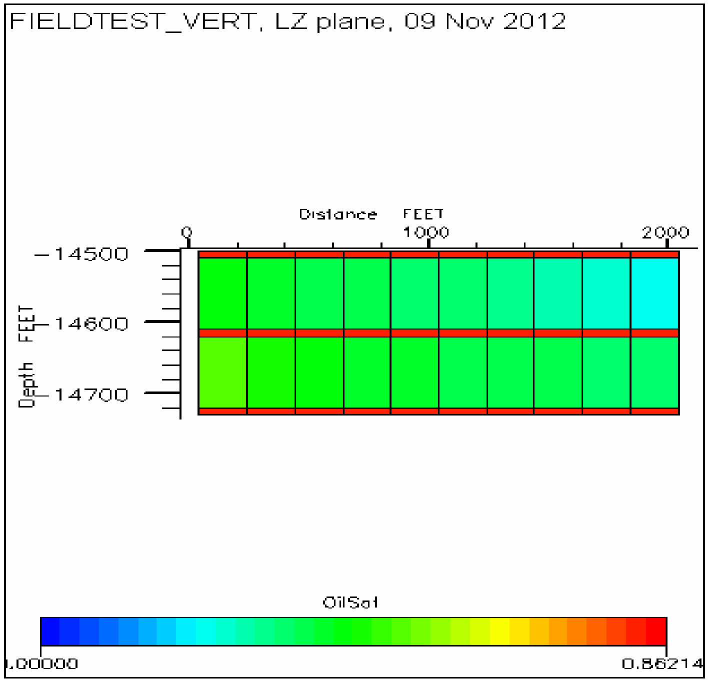
Base Case No control

- **Early water irruption reduced**
- **High water cut reduced well's vertical lift**
- **Further recovery possible at a greater cost**

Self Learning Case

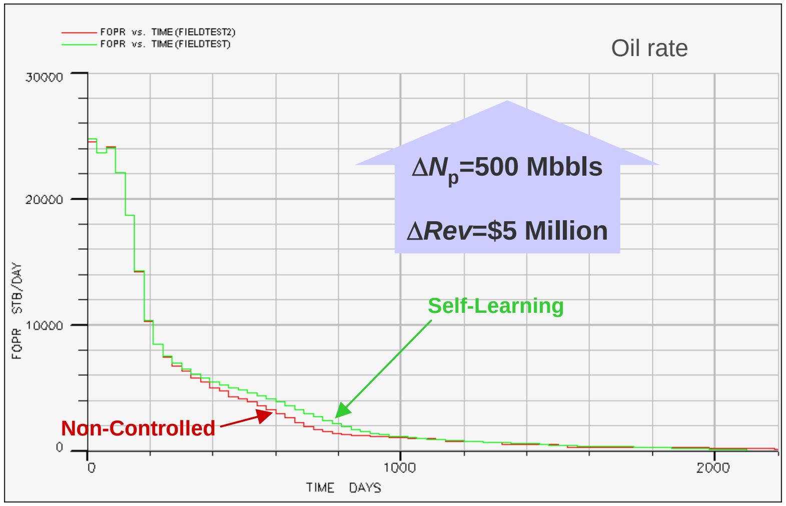
- **Water irruption detected and controlled**
- **Zone shut off permitted better well's vertical lift**
- **Recovery accelerated at a minimum cost**

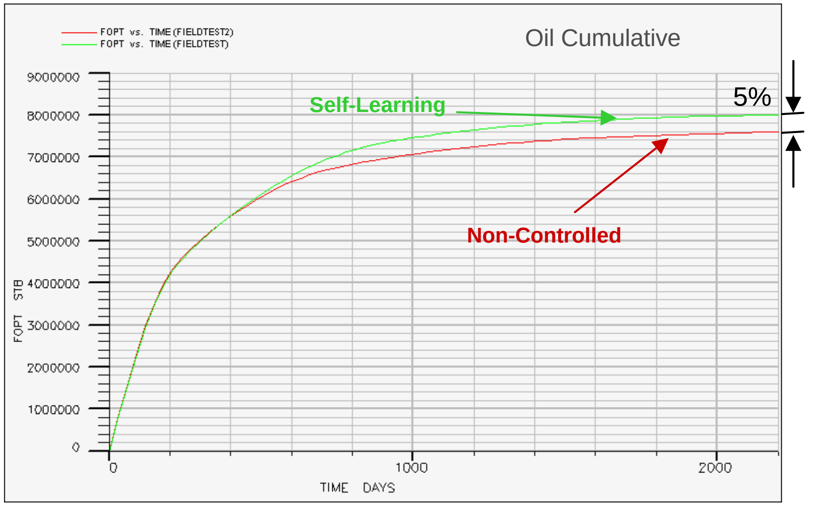


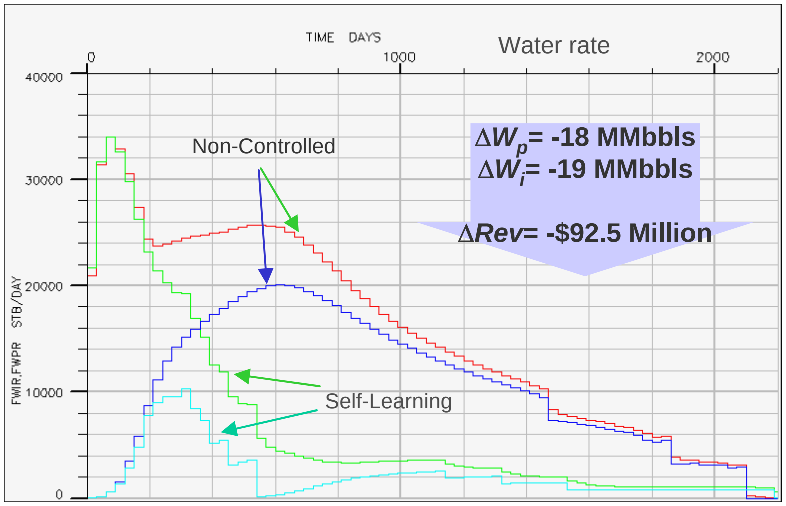


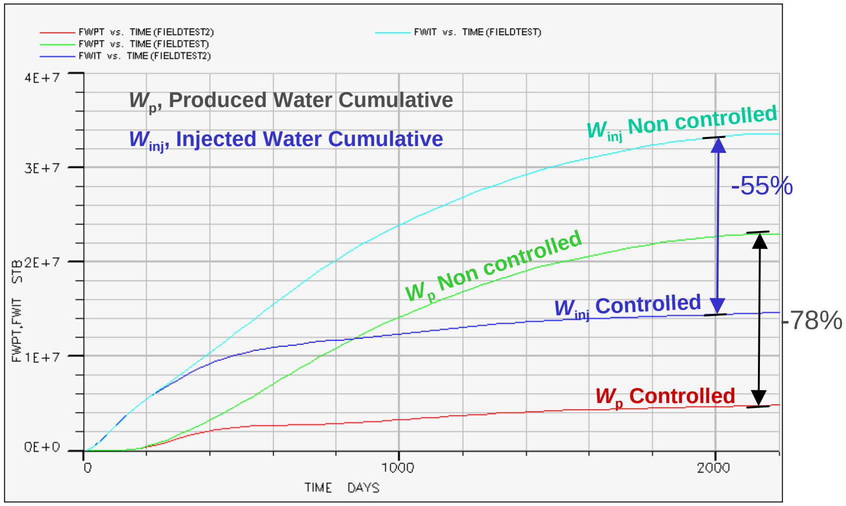
Clear benefits from extra little oil but with a lot less effort.

Field-wide life cycle comparison Results

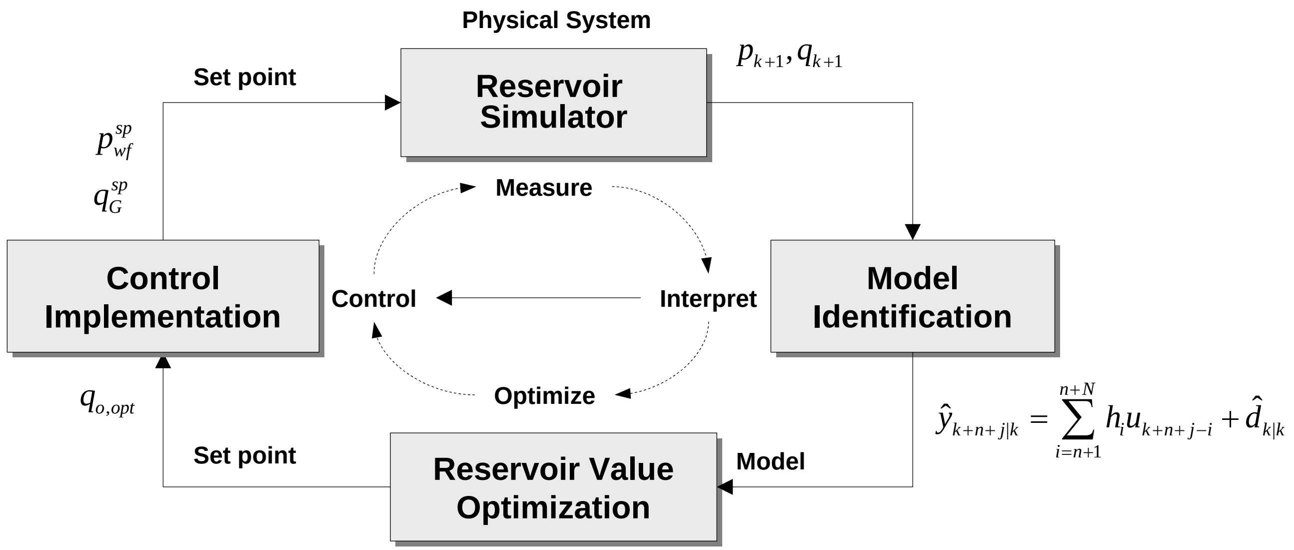








New Self-learning Reservoir Management Technique



QP Optimization Loop

$$\min_{\Delta u}\left\{\sum_{j=1}^{p}\left(\hat{y}_{k+j}-y^{SP}\right)^2+R\sum_{j=1}^{m}\Delta u_{k+j}^2\right\}$$

s.t.

$$y_{\min}\le\hat{y}_{k+j|k}\le y_{\max};\ j=[1,p]$$

$$u_{\min}\le u_{k+j|k}\le u_{\max};\ j=[1,m]$$

$$u_{k+i|k}=u_{k+m-1|k};\ i=[m,p]$$

LP Optimization Loop

$$\max_{q_o,q_w,q_g}\left\{\mathbf{NPV}=\sum_{1}^{N} f\left(q_o,q_w,q_g,\$,\Delta T\right)\right\}$$

$$\text{s.t.}\ \begin{cases} p_{\min}\le p_{k+p,k}\le p_{\max} \\ q_{\min}\le q_{k+p}\le q_{\max}\end{cases}$$

$$\Leftrightarrow\left\{\hat{q}_{o,opt},\hat{q}_{g,opt},\hat{q}_{w,opt}\right.$$

LS Optimization Loop

$$\hat{\mathbf{Y}}=\mathbf{X}\hat{\boldsymbol{\theta}}+\mathbf{e}$$

$$\min_{a,b}\left\{\sum_{i=1}^{\infty}\mathbf{e}_i^2\right\}\Rightarrow\left(\mathbf{X}^{\mathrm{T}}\mathbf{X}\right)^{-1}\mathbf{XY}$$

$$\Leftrightarrow\begin{cases} q_{o,g,w}=f_1\left(p^k,p^{k-1}\ldots\quad q_T^k,q_T^{k-1},\ldots\right) \\ p_{res}=f_n\left(p^k,p^{k-1}\ldots\quad q_T^k,q_T^{k-1},\ldots\right)\end{cases}$$

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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