

Examples of static optimization

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optimization formulation

maximize (or minimize) $\rightarrow f$ objective

by changing x variables

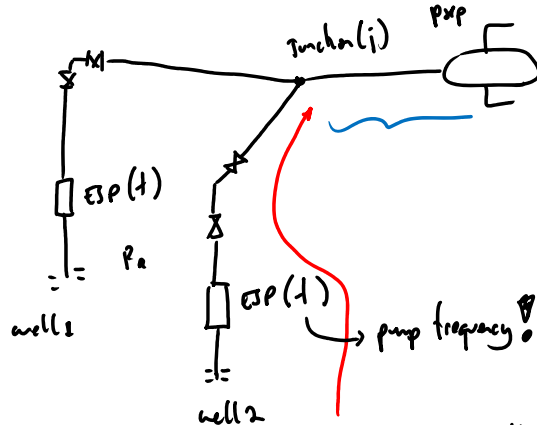
subjected to : constraints

method

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Setting up the optimization: optimizer «outside» the model

2 well ESP linked in a network

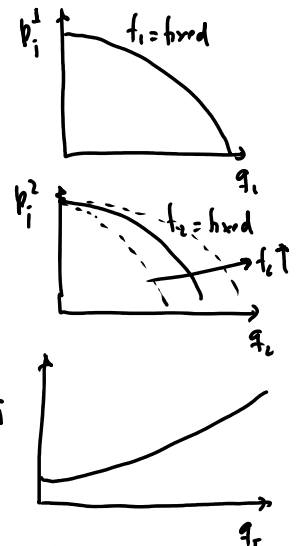


$$p_i^1 = F_1(q_1, f_1)$$

F : IPR, TPR, ESP, FPR

$$p_i^2 = F_2(q_2, f_2)$$

$$p_i = F_3(q_1 + q_2)$$



How to solve this system given f_1, f_2

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Setting up the optimization: optimizer «outside» the model

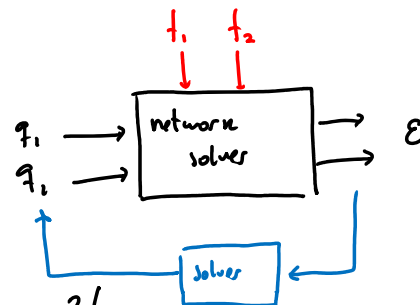
all p_i must be equal !

given f_1, f_2

change q_1, q_2 to drive

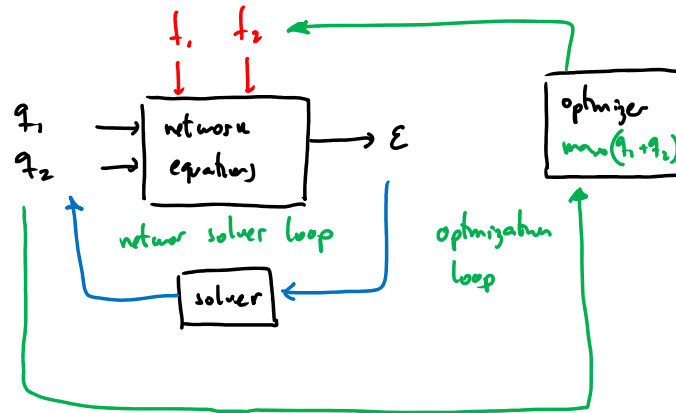
$$\left\{ \underbrace{\left(F_1(q_1, f_1) - F_2(q_2, f_2) \right)^2}_{p_i^1 = p_i^2} + \underbrace{\left(F_3(q_1 + q_2) - F_2(q_2, f_2) \right)^2}_{p_i = p_i^2} \right\} \rightarrow 0$$

$\mathcal{E}$ (error)



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Setting up the optimization: optimizer «outside» the model



the two loops are solved sequentially
for each iteration of optimizer,
the network solver must be
converged

if the optimizer employs
for a Newton method

$$\nabla(q_1, q_2) \quad \frac{\partial q_1}{\partial f_1} \quad \frac{\partial q_1}{\partial f_2}$$

$$\frac{\partial q_2}{\partial f_1} \quad \frac{\partial q_2}{\partial f_2}$$

not typically output by
network solver

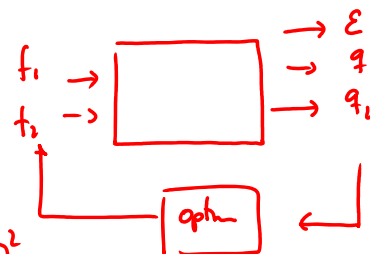
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Details on optimization setup

- Model + optimizer together

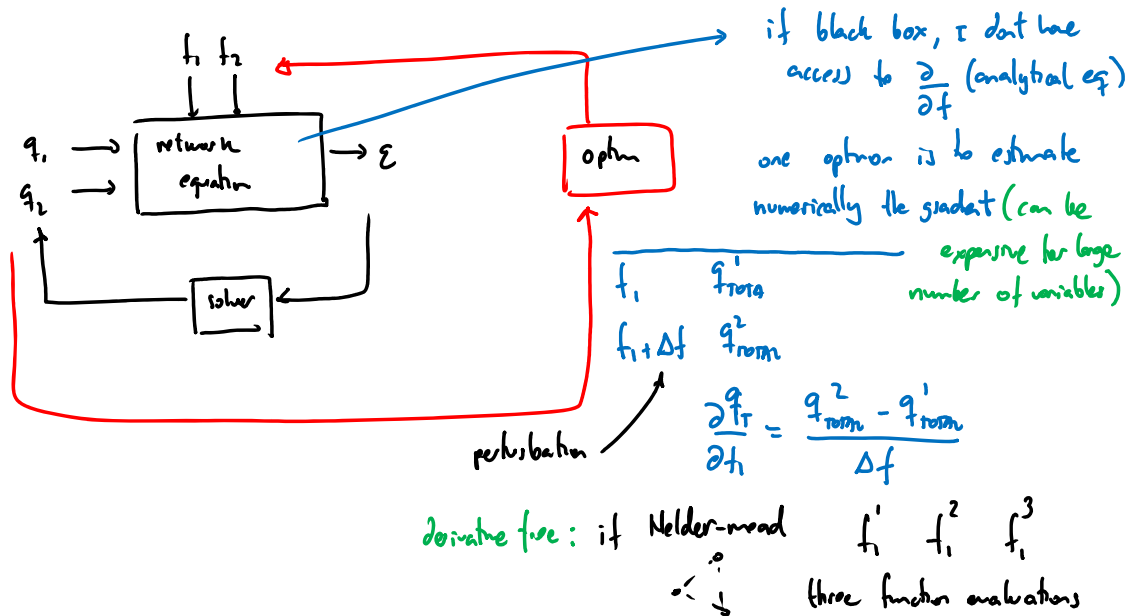
max $q_1 = q_1 + q_2$
by changing f_1, f_2, q_1, q_2
subject to constraint: $\epsilon = 0$

$$\left[F_1(q_1, f_1) - F_2(q_1, f_2) \right]^2 + \left[F_3(q_1, q_2) - F_4(q_2, f_1) \right]^2 = 0$$



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«Black-box» optimization (optimizer outside)

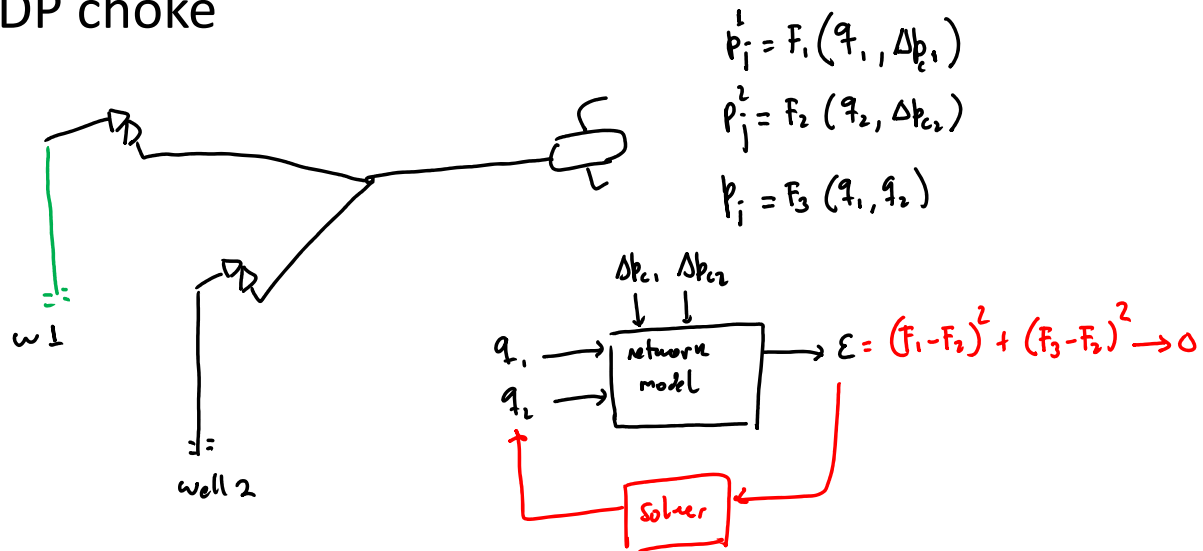


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Effect of optimization formulation

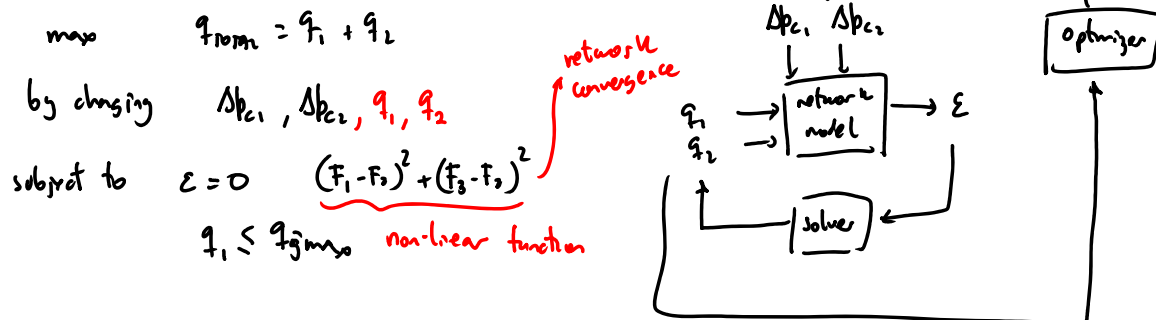
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2. Two gas wells in a network – Optimization with DP choke



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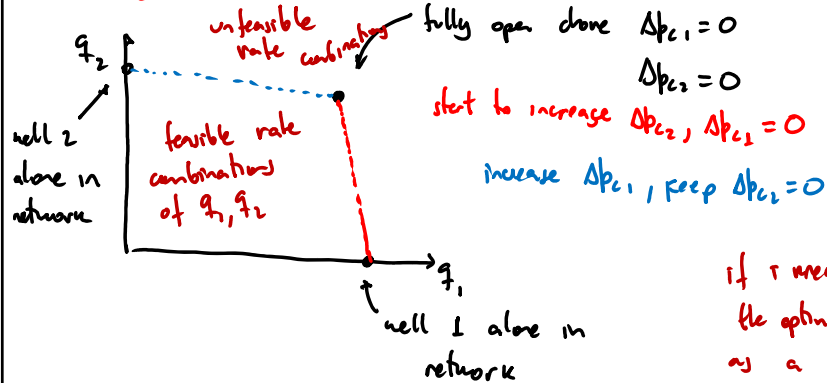
2. Two gas wells in a network – Optimization with gas rates



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2. Two gas wells in a network - Differences when formulating the problem

let's try to reformulate the problem as a linear problem

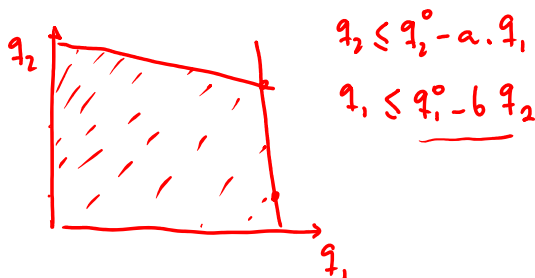


if I knew this area before hand, then the optimization can be re-formulated as a linear problem

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2. Two gas wells in a network - Differences when formulating the problem

$$\begin{aligned} \max \quad & q_1 + q_2 = q_T \quad \text{linear problem!} \\ \text{subject to} \quad & q_1 \leq q_{T\max} \end{aligned}$$



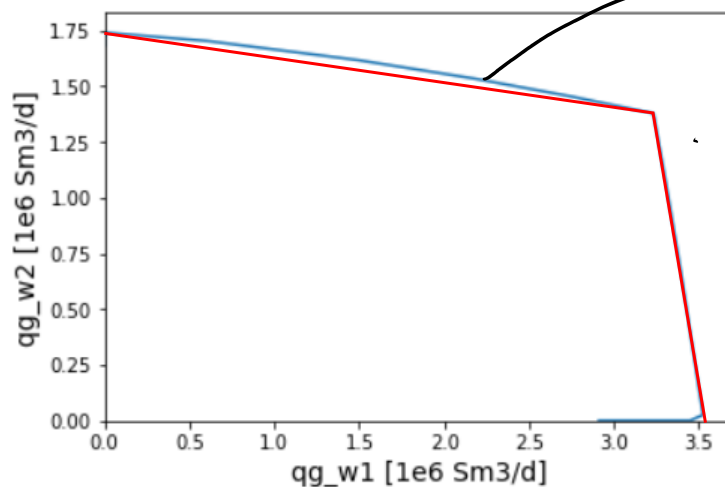
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2. Two gas wells in a network - Differences when formulating the problem

```
#ESTIMATING FEASIBLE OPERATING REGION, qg1, qg2
qg1=[]
qg2=[]
dp2=0
DP=np.linspace(250,0,10)
for dp1 in DP:
    x=minimize(error,qg,args=(pR,CR,n,CT,S,Cp1,Cf1,psep,[dp1,dp2]),method='Nelder-Mead')
    qg1=np.append(qg1,x.x[0])
    qg2=np.append(qg2,x.x[1])
DP=np.linspace(0,250,10)
dp1=0
for dp2 in DP:
    x=minimize(error,qg,args=(pR,CR,n,CT,S,Cp1,Cf1,psep,[dp1,dp2]),method='Nelder-Mead')
    qg1=np.append(qg1,x.x[0])
    qg2=np.append(qg2,x.x[1])
plt.plot(qg1/1e06,qg2/1e06)
plt.xlabel('qg_w1 [1e6 Sm3/d]',fontsize=14)
plt.ylabel('qg_w2 [1e6 Sm3/d]',fontsize=14)
plt.xlim(0)
plt.ylim(0)
plt.show()
```

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2. Two gas wells in a network - Differences when formulating the problem



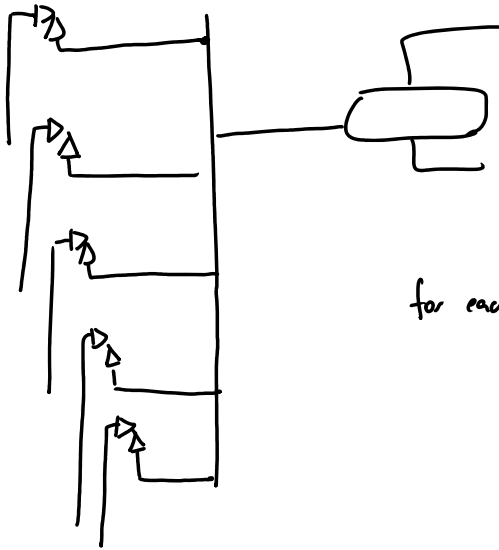
deviation between linear approximation
and real behavior:

$$q_2 \leq q_1^0 - a q_1 - b q_1^2$$

this is non-linear !

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3. Well routing – class exercise



wells have different GOR, WC
find how much to produce from
each well, to maximize
total oil production and
be below constraints

q_{wmax}
 q_{smax}

for each well $q_o^i = f(\Delta p_c^i)$ non linear function!
IPR, TPR, clone eq.

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3. Well routing – class exercise

one option
max $q_o^T = \sum_{i=1}^5 q_o^i$ — $q_o^i = f(\Delta p_c^i)$ is non-linear!

by using Δp_c^i for $i=1 \dots N$

subject to $\sum_{i=1}^N q_o^i \leq q_{smax}$

$\sum_{i=1}^N q_{wi} \leq q_{wmax}$

A different approach ... to make it linear

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3. Well routing – class exercise

$$\max q_o = q_{o1} + q_{o2} + q_{o3} + q_{o4} + q_{o5}$$

by changing $q_{o1}, q_{o2}, q_{o3}, q_{o4}, q_{o5}$

subject to

$$\sum_{i=1}^N q_{gi}^i \leq q_{gmax}$$

$$\sum_{i=1}^N q_{wi}^i \leq q_{wmax}$$

$$q_{gi}^i = q_{oi}^i \cdot GOR^i$$

$$q_{wi}^i = q_{oi}^i \cdot \frac{WC^i}{(1-WC^i)}$$

$q_{o1} \leq q_{o1,max}$ ← fully open chime } either from model or from field test

$q_{o2} \leq q_{o2,max}$ $q_{o4} \leq q_{o4,max}$

$q_{o3} \leq q_{o3,max}$ $q_{o5} \leq q_{o5,max}$

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3. Well routing – class exercise

Well	q_{max} Sm ³ /D	WC fraction	GOR Sm ³ /m ³	qo Sm ³ /D	qg Sm ³ /D	qw Sm ³ /D
1	636	0.20	142	635.6	90255.2	158.9
2	795	0.43	214	698.1966	149134.8	526.7097
3	477	0.31	267	50	13350	22.46377
4	636	0.47	356	50	17800	44.33962
5	318	0.10	249	50	12460	5.555556
qototal [Sm ³ /d]				1483.797	283000	757.9687

Variable	Constraint	Value
qo	No Limit Sm ³ /d	Maximize oil production
qw	795 Sm ³ /d	
qg	283.0E+3 Sm ³ /d	
qo min	50 Sm ³ /d	

Solver Parameters

Set Objective:

To: ☒ Max ☐ Min ☐ Value Of:

By Changing Variable Cells:

Subject to the Constraints:

- $\$E\$5:\$E\$9 \leq \$E\$5:\$E\9
- $\$E\$5:\$E\$9 \geq \$E\16
- $\$E\$10 \leq \$E\15
- $\$G\$10 \leq \$G\14

☒ Make Unconstrained Variables Non-Negative

Select a Solving Method:

Solving Method: Select the GRG Nonlinear engine for Solver Problems that are smooth nonlinear. Select the LP Simplex engine for linear Solver Problems, and select the Evolutionary engine for Solver problems that are non-smooth.

Buttons: Help, Solve, Close

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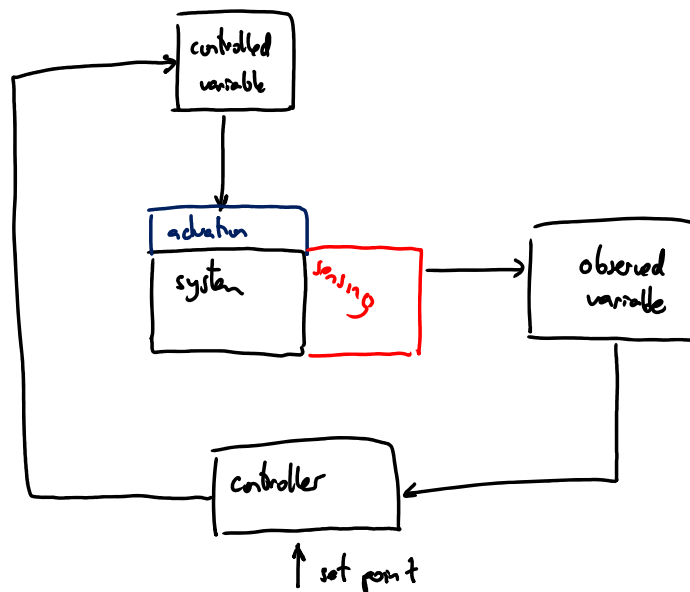
Optimization types

- Parametric (static) – using a model
- **Dynamic (control)** – using a model, physical system, or a combination of both

https://en.wikipedia.org/wiki/Simulation-based_optimization

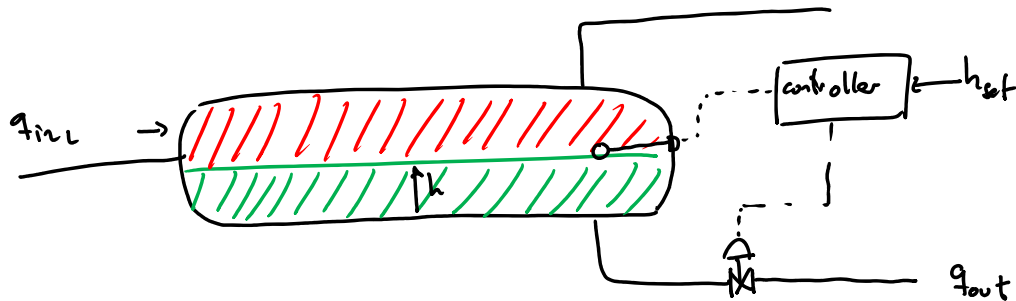
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Dynamic optimization (control)

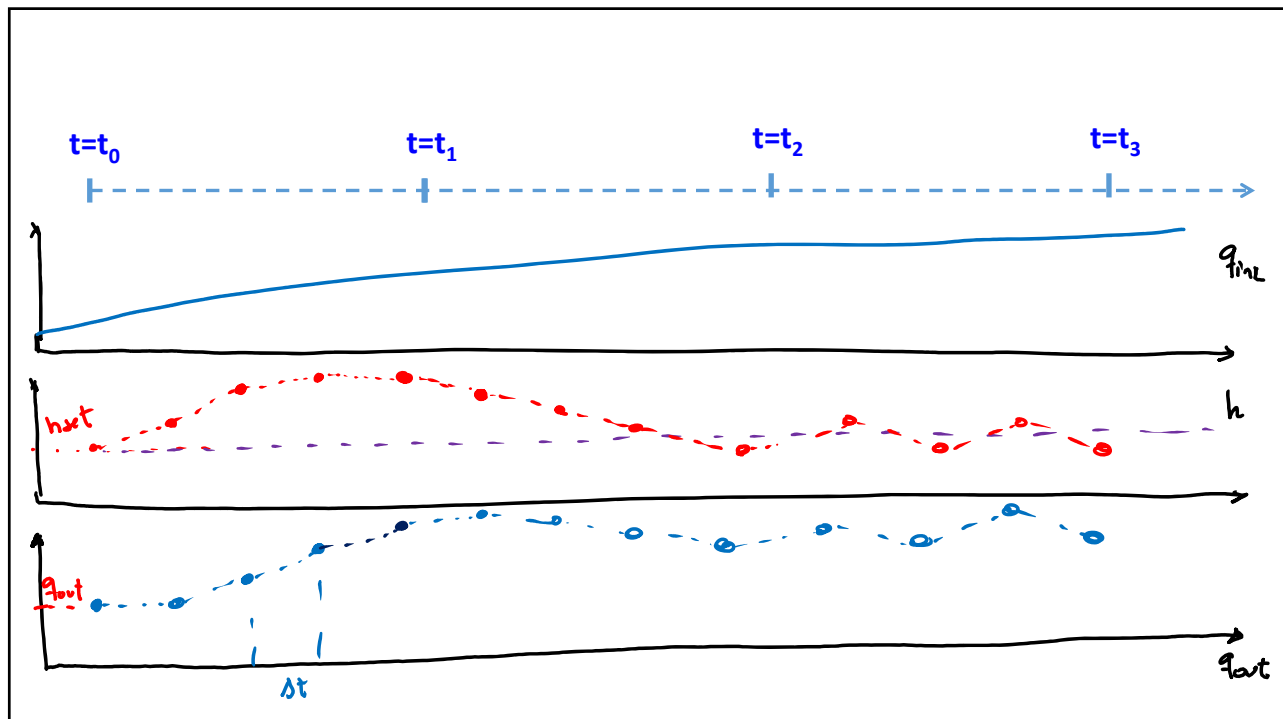


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Dynamic optimization (control): gas-liquid separator



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Dynamic optimization (control)

to calculate $h(t)$ we need $\leadsto$ model (transient model)
 $\leadsto$ measurement on physical system

but we can also apply control using a steady state model. for example

in the gas lift case $q_o = f(q_{inj}^1, q_{inj}^2)$

we evaluate the function in each time, depending on the value of q_{inj}^1 and q_{inj}^2

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Dynamic optimization (control)



$\uparrow$ check q_o^* $\rightarrow$ controller $\rightarrow q_{inj}^1, q_{inj}^2$

then on t_3 , evaluate $q_o = f(\quad, \quad)$, then

$q_o^{**} \rightarrow$ controller $\rightarrow q_{inj}^1, q_{inj}^2$

one approach to have the controller optimize is to done

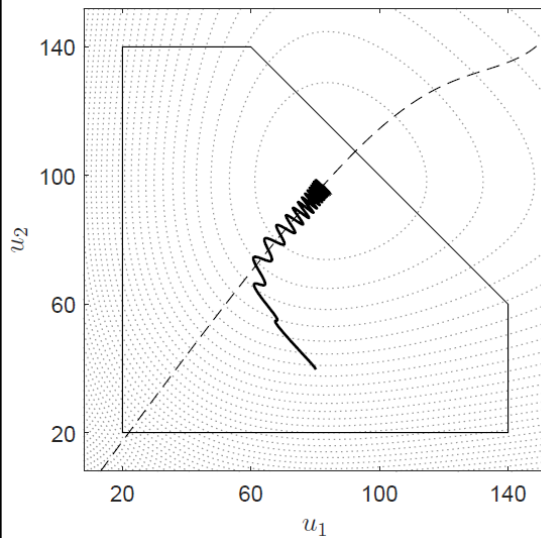
$$\frac{\partial q_o}{\partial q_{inj}^1} = 0$$

$$\frac{\partial q_o}{\partial q_{inj}^2} \rightarrow 0$$

$$\frac{\partial q_o}{\partial q_{inj}^1} = \frac{\partial q_o}{\partial q_{inj}^2}$$

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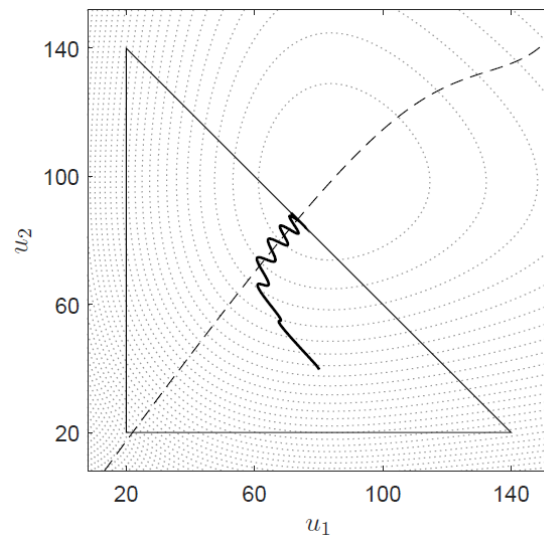
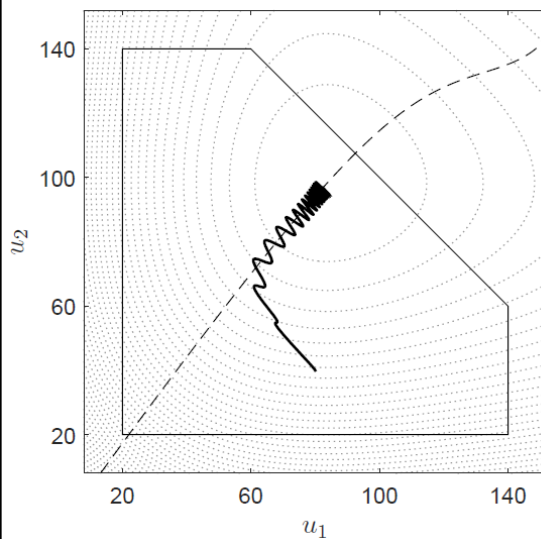
Dynamic optimization (control)



Practical extremum-seeking control for gas lifted oil production – Pavlov et al

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Dynamic optimization (control)



Practical extremum-seeking control for gas lifted oil production – Pavlov et al

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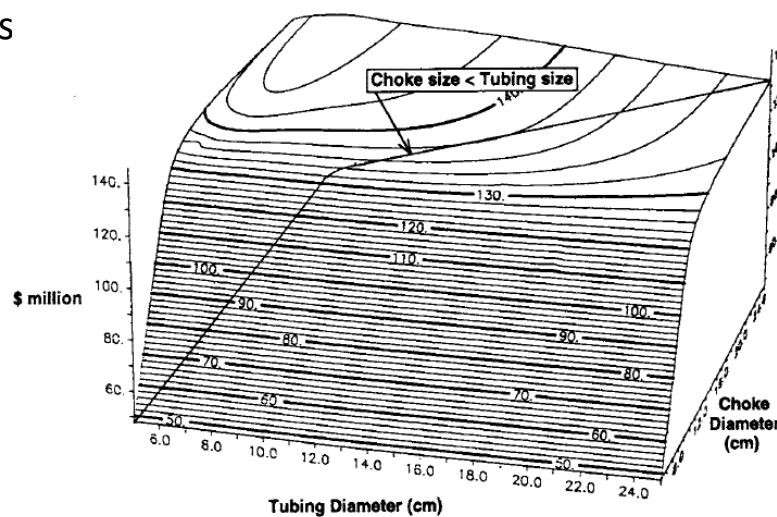
Limitations and pitfalls

- Model fidelity
- Is it actually possible to change the decision settings?:
 - Is the equipment/actuator functional and available?
 - Am I allowed to operate the control element?
 - Actuator response time

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Limitations and pitfalls

- Flat peak of optimum- more efforts give less res

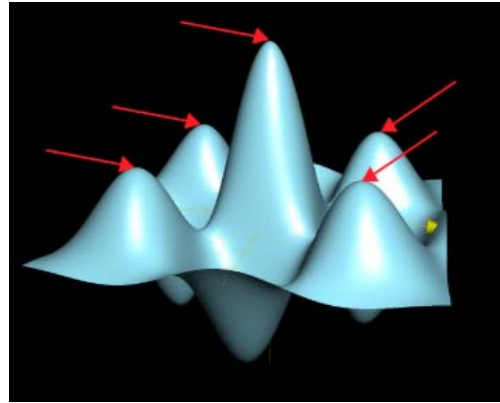


SPE-166027-MS Multivariate optimization of production systems optimization Carroll and Horne

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Limitations and pitfalls

- Local optima
- Starting point
- Running time
- Short term versus long term optimization



(Khan academy)

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Limitations and pitfalls

- Short term versus long term optimization

Maximize NPV
By changing $q_o(t)$

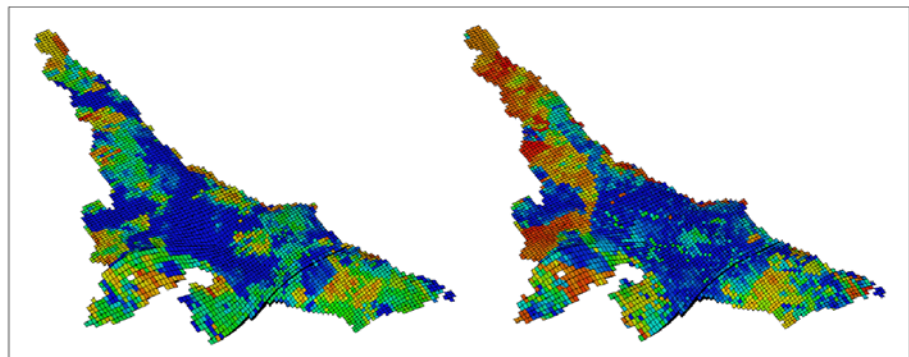


Figure 3: Permeability (left) and porosity (right) distributions of the south wing.

SPE-166027-MS Decision analysis for long term and short-term production optimization Applied to the Voador field, Agus Hasan

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• Short term versus long term optimization

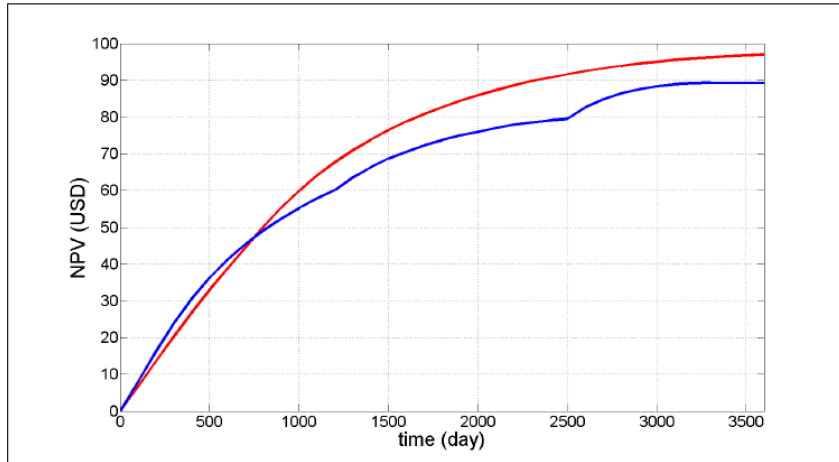


Figure 4: Normalized NPV of the long-term optimization (red) using adjoint-based optimization and short-term optimization (blue) using reactive control.

SPE-166027-MS Decision analysis for long term and short-term production optimization Applied to the Voador field, Agus Hasan

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• Short term versus long term optimization

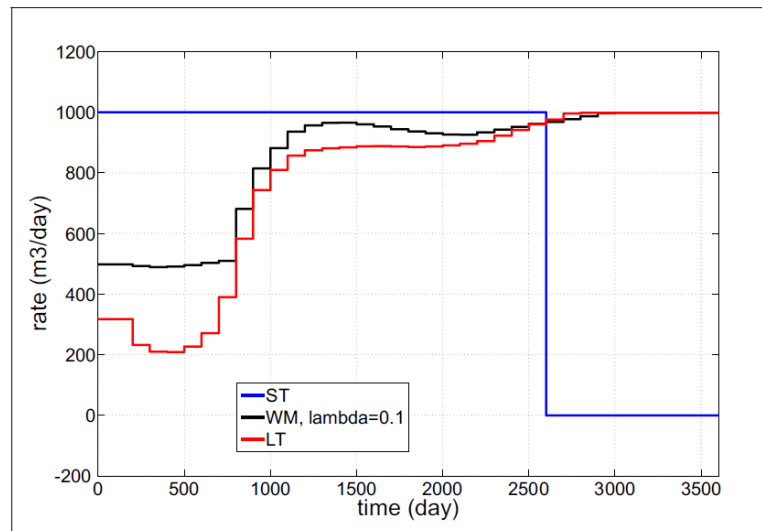


Figure 9: Oil rate from production well PROD3 using different strategies; reactive control (blue), adjoint-based optimization (red), and the weighted-sum method (black).

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Final advice:

- Look at the rest of the list first!
- Do we REALLY need to do optimization?
- Think carefully what is the main, most important, first order of magnitude problem
- Define objective, constraints and variables
- Determine relevance of constraints
- Is it realistic to modify optimization variables?
- Formulate your optimization in a smart way (choose the right variable)
- Study how your input affects your results

SLIDE 2

- Detect locations in the system with abnormally high-pressure loss and flow restrictions
- Verification of equipment design conditions vs actual operating conditions
- Identification and addressing fluid sources that have disadvantageous characteristics (e.g. high water cut, high H₂S content)
- Identify and correct system malfunctions and non-intended behavior
- Analyze and improve the logistics and planning of maintenance, replacement and installation of equipment or in the execution of field activities.
- Review the occurrence of failures and recognize patterns
- Calibration of instrumentation
- Identification of operational constraints (e.g. water handling capacity, power capacity)
- Observe and analyze the response of the system when changes are introduced
- Find control settings of equipment that give a production higher than current (or, preferably, that give maximum production possible)
- Identify Bottlenecks
- Identifying and monitoring Key Performance Indicators (KPIs)