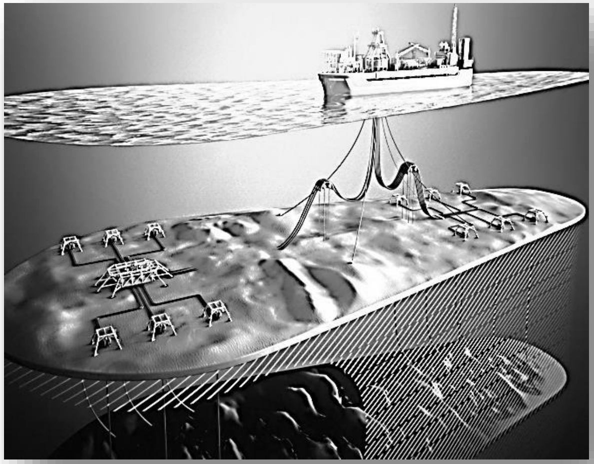
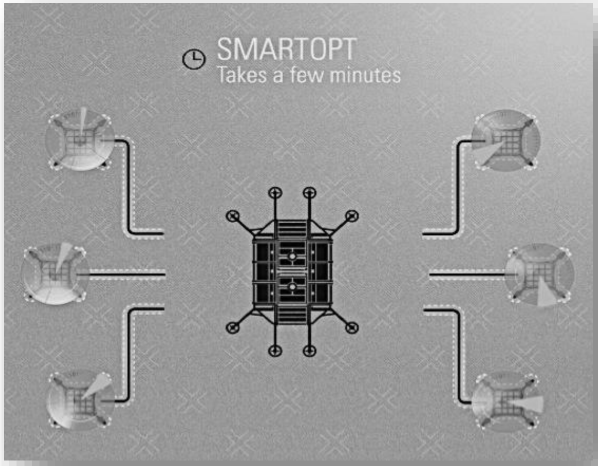
Course module

Daily production optimization methods





Fall 2014

Stine Ursin-Holm, Vidar Gunnerud & Bjarne Foss NTNU

IO Center

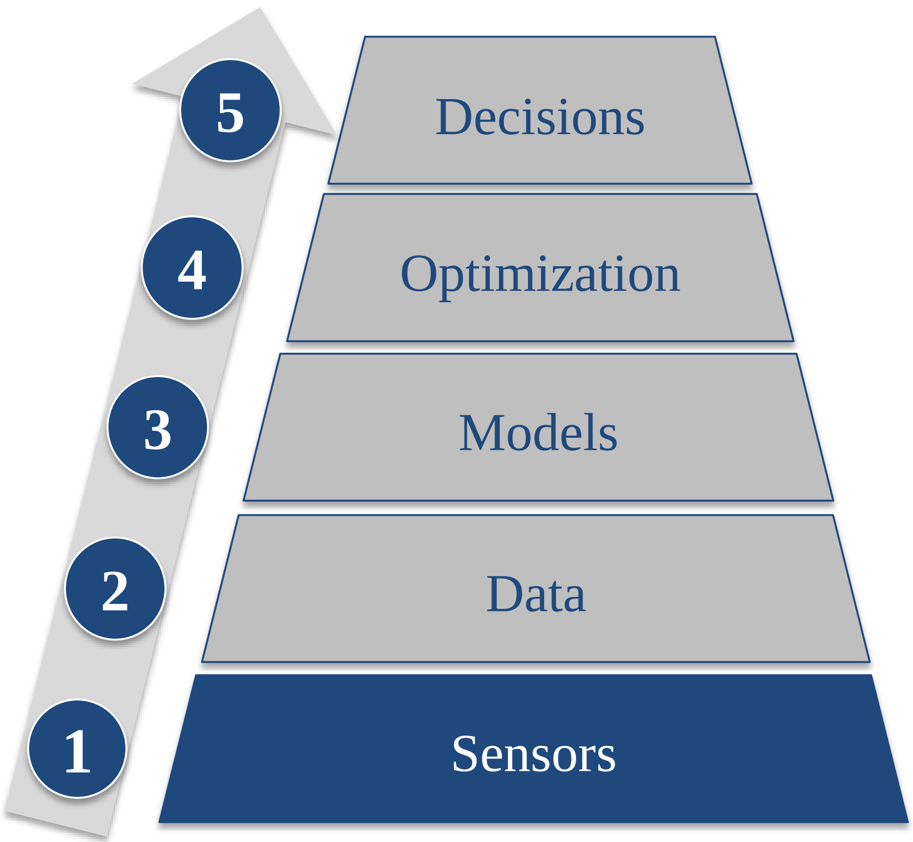
Outline

1. Introduction
2. Mathematical optimization
3. SmartOpt approaches
4. Case
5. Results
6. Conclusion

Outline

Decision support systems for operational decisions can be divided into a sequence of components

From sensors to decisions



Automation level within process industry

- Arriving at a decision is still the task of an **experienced engineer**
- Computer models help the engineers **analyse and reason** about the systems behaviour
- However, the methods often **fail to provide satisfactory results**
- Increased level of automation can **improve the efficiency and quality** of the decisions made

CENTER

Simulators have entered many engineering disciplines, due to their contribution in modelling complex systems

Simulation-based optimization

<u>The industry uses simulators in a variety of ways:</u>

- "What-if" analyses of different solutions or alternative courses of action
- Sensitivity analyses, if derivatives are available
- Optimization approaches that can build directly on simulators, as the models usually scale up well

<u>The IO Center approach:</u>

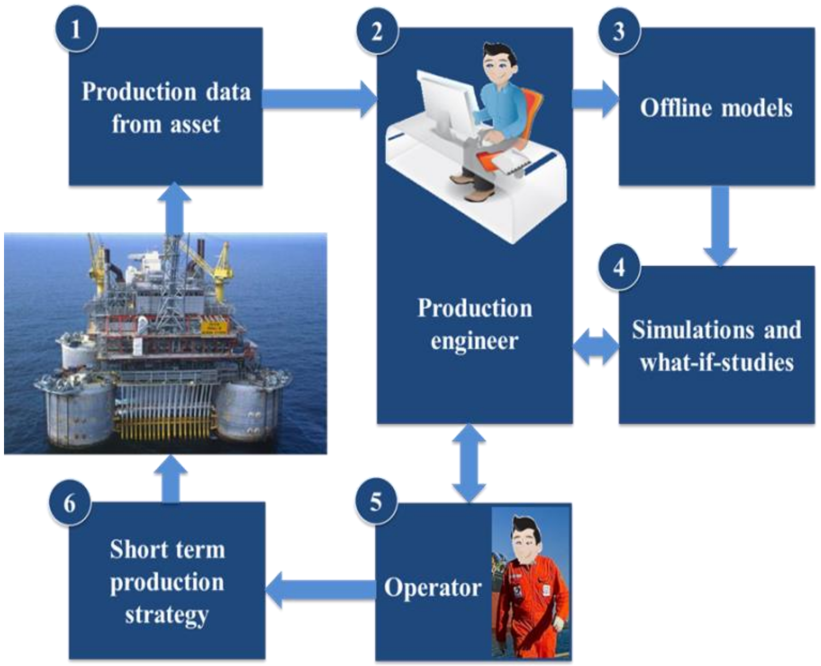
- Combine simulators with state-of-the-art optimization techniques
- Add optimization functionality onto simulators with certain structural properties

CENTER

A key challenge in offshore petroleum field operations is to decide on the optimal day-to-day production strategy

Daily production optimization process

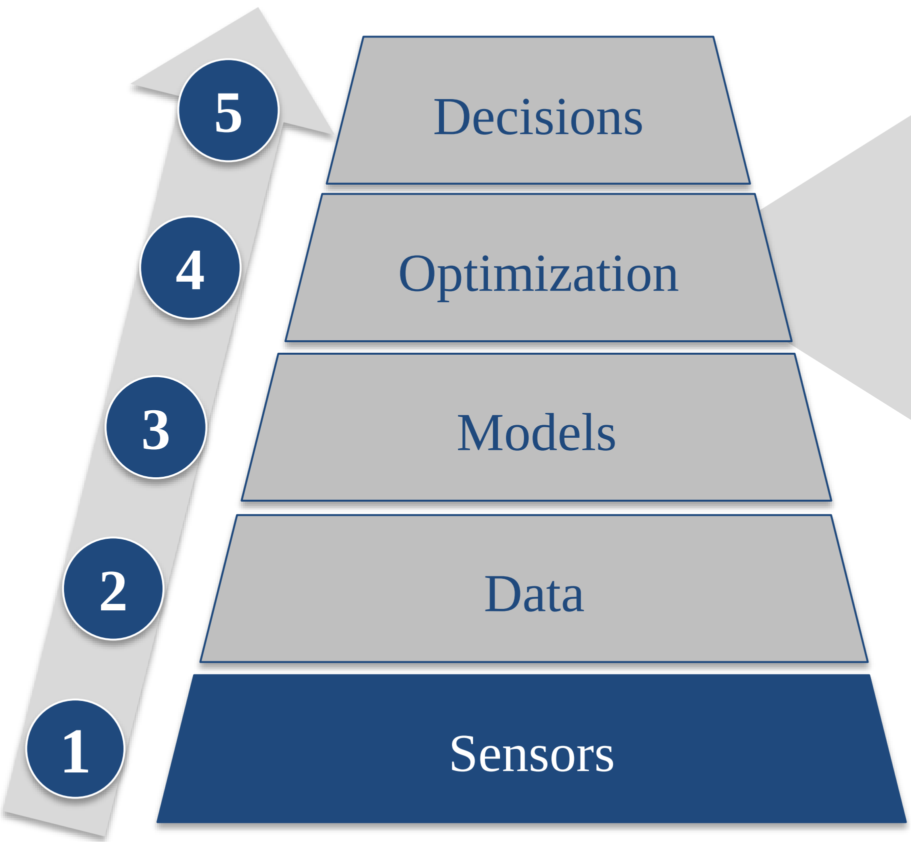
- Several **tools and individuals** are involved in the process
- The time horizon are equal to a period where **changes in the reservoir are negligible (days up to a week)**
- State-of-the-art decision support tools are **frequently imprecise and slow** at computing recommendations
- We present efficient simulation-based optimization strategies that provide **reliable suggestions to optimal production strategies**



CENTER

A key challenge in offshore petroleum field operations is to decide on the optimal day-to-day production strategy

"The decision pyramid for short-term production optimization"



State of the art

- ❑ A significant amount of manual work
- ❑ Software tools are imprecise and slow

New IO Center techniques:

- ❑ Enable optimization of larger and complex systems
- ❑ Substantial reduction in solution time
- ❑ On the fly recommendations

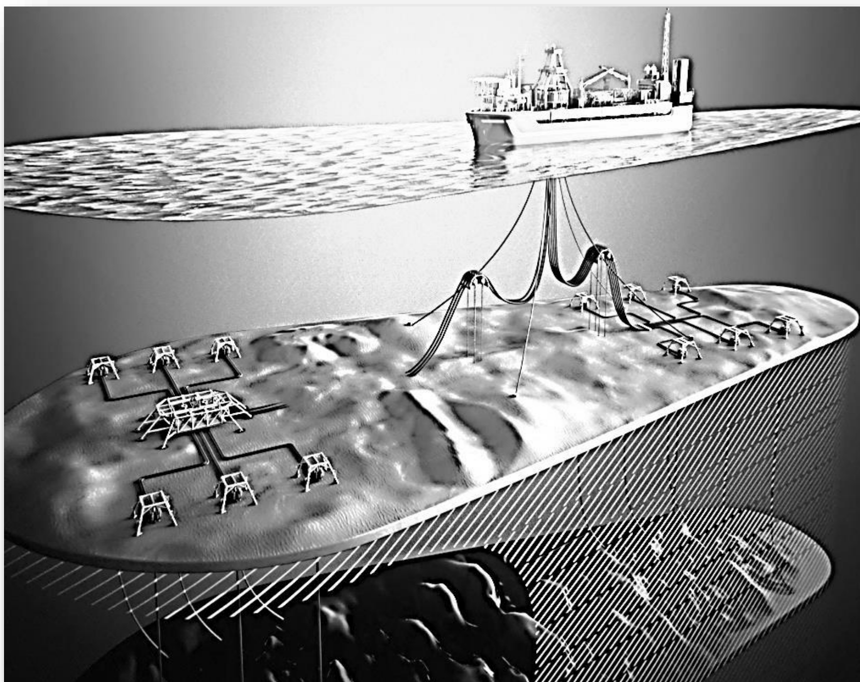
CENTER

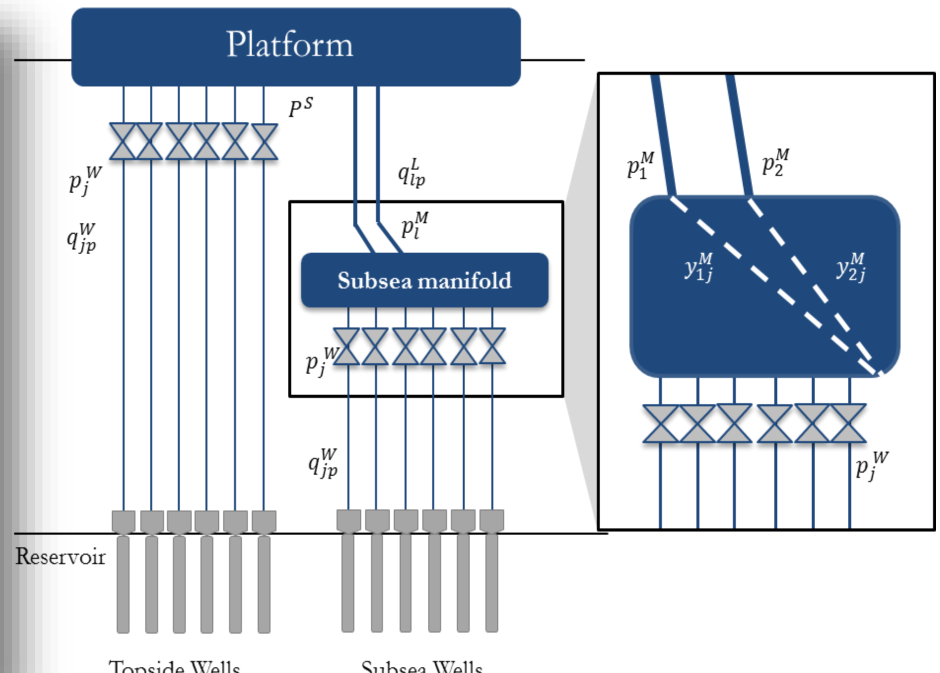
Outline

1. Introduction
2. Mathematical optimization
3. SmartOpt approaches
4. Case
5. Results
6. Conclusion

12 well production system with artificial gas lift 6 subsea wells and 6 satellite wells

Case example

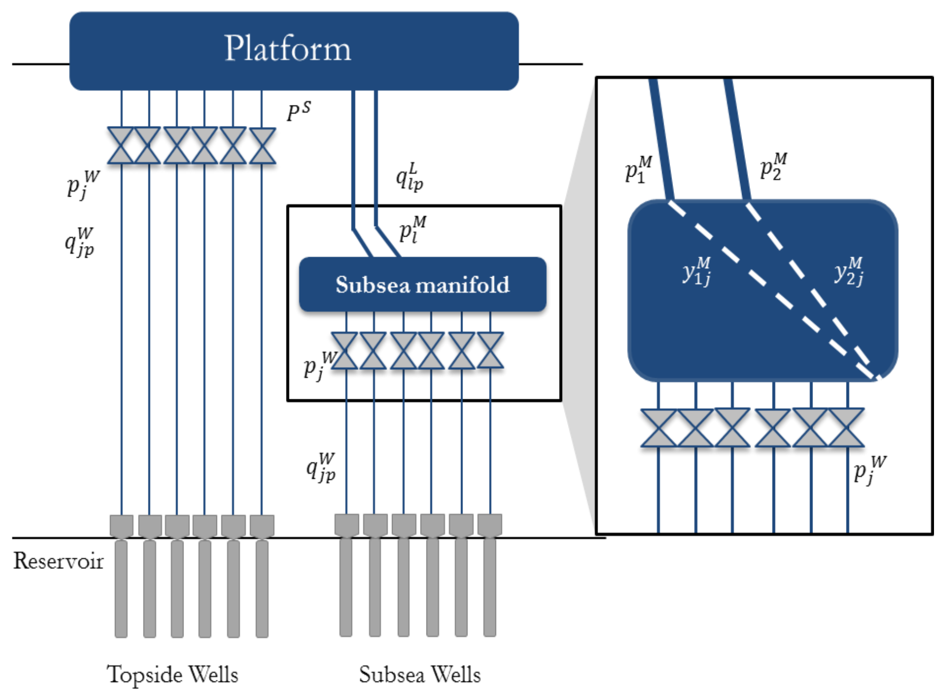




The production optimization problem aim to find the optimal operating plan for a production asset

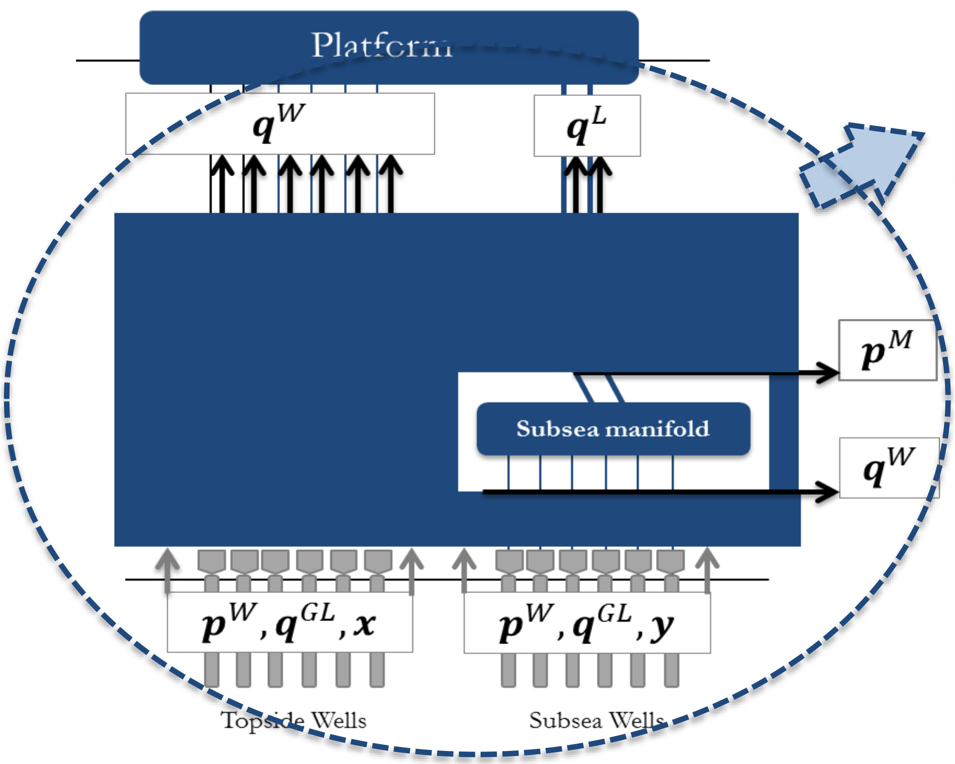
About the optimization problem

- The production optimization problem aims to **find the best short term production strategy**
- Thus, it will provide optimal values on **the relevant variables**
- While at the same time fulfilling the requirements of **mass balances, capacities and pressure constraints**
- The time horizon should be equal to a period where **changes in the reservoir are negligible, and pipeline dynamics can be assumed steady-state**



The Black box simulator is a complex calculator giving output values based on some input values

The Black box simulator in details



The whole network simulated as one simulator:

$$\left(\mathbf{q}^W, \mathbf{q}^L, \mathbf{p}^M\right) = f^{BB}\left(\mathbf{p}^W, \mathbf{q}^{GL}, \mathbf{x}, \mathbf{y}\right)$$

***Inputs*:**

- Wellhead pressures, $\mathbf{p}^W$
- Gas lift $\mathbf{q}^{GL}$
- Routing of all wells, $\mathbf{x}$ and on/off $\mathbf{y}$

Outputs:

- Production rates from all wells, $\mathbf{q}^W$
- Pipeline pressures at the subsea manifold, $\mathbf{p}^M$
- Pipeline flow rates, $\mathbf{q}^L$

Production optimization problem, objective and relevant variables and constraints depends on the case

Alternative participants of an optimization problem

Objectives

- Maximize oil production
- Maximize NPV (Net Present Value)
- Minimize operational cost

Variables

- Production choke opening
- Gas lift flow rate
- Well routing
- ESP speed

Constraints

- Pressure constraints
- Water, gas, liquid and gas lift capacities
- Erosion or velocity constraints
- Pressure-Temperature envelope - hydrates

Mass balances and discrete decisions handled inside the box, pressure balances and capacity constraints treated outside

"The Black box optimization problem"

Objective function

$$\max \sum_{l \in L} q_{lo}^{L} + \sum_{j \in J_t} q_{jo}^{W}$$

Black box simulator

$$\left(\boldsymbol{q}^{W}, \boldsymbol{q}^{L}, \boldsymbol{p}^{M}\right) = f^{BB}\left(\boldsymbol{p}^{W}, \boldsymbol{q}^{GL}, \boldsymbol{x}, \boldsymbol{y}\right)$$

Capacity constraints

$$\sum_{l \in L} q_{lp}^{L} + \sum_{j \in J_t} q_{jp}^{W} \leq C_p$$

$$\sum_{j \in J_s} \sum_{l \in L} q_j^{GL} y_{jl} + \sum_{j \in J_t} q_j^{GL} x_j \leq C^{GL}$$

Pressure balances

$$p_l^{M} \leq p_j^{W} \quad j \in J_s$$

$$P^{S} \leq p_j^{W} \quad j \in J_t$$

Routing

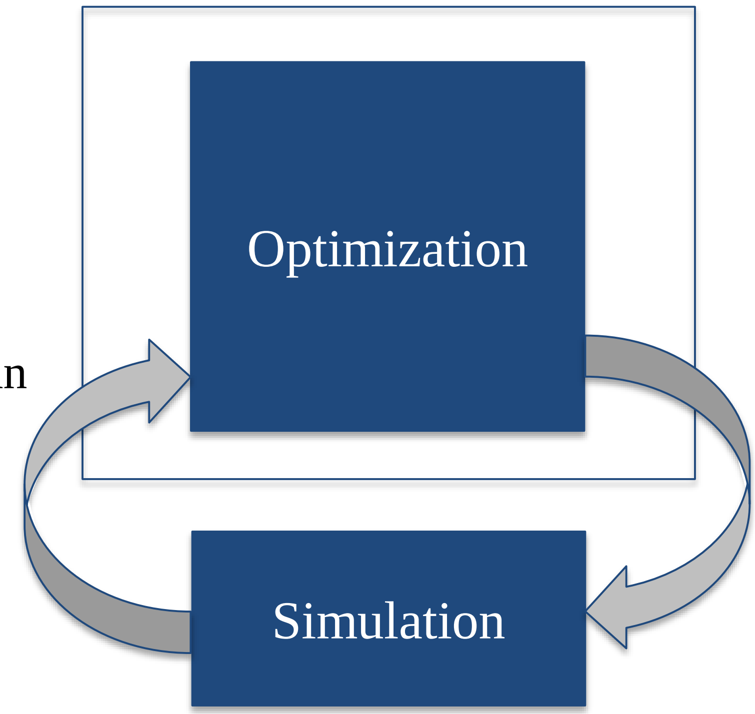
$$\sum_{l \in L} y_{jl} \leq 1 \quad j \in J_s$$

CENTER

The traditional method optimize by simulate the network as one large black box

An overview of the Black box approach

- A black box simulator represent the whole network
- Routing decisions are handled inside the black box simulator
- Additional constraints represent the boundary conditions
- Black box simulators usually only allow an optimization algorithm to make queries with discrete values on routing and on/off decisions
- Therefore it is only possible to get gradients for continuous variables
- The problem must then be solved with derivative-free algorithms

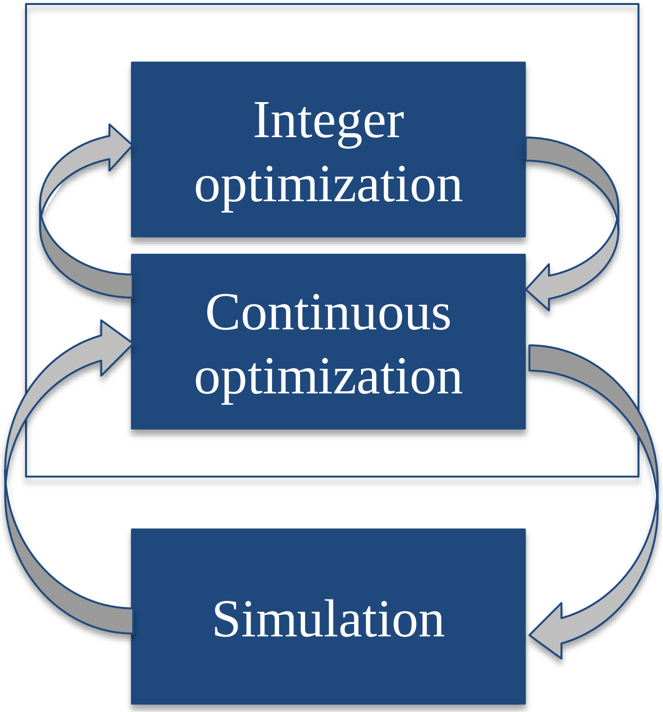


2-layer approach enables production optimization for complex systems by decomposing the problem and simulator

Splitting the decision space

2-layer approach

- The decision space is split in one integer subspace and one continuous subspace
- Still the mathematical formulation stays similar to the traditional approach
- However, it facilitates the use of optimization algorithms in two layers
- A derivative-free algorithm decides upon the routing and on/off decisions
- For each iteration of the derivative-free algorithm, a gradient-based algorithm communicates with the network simulator to find the optimal solution of the continuous subspace

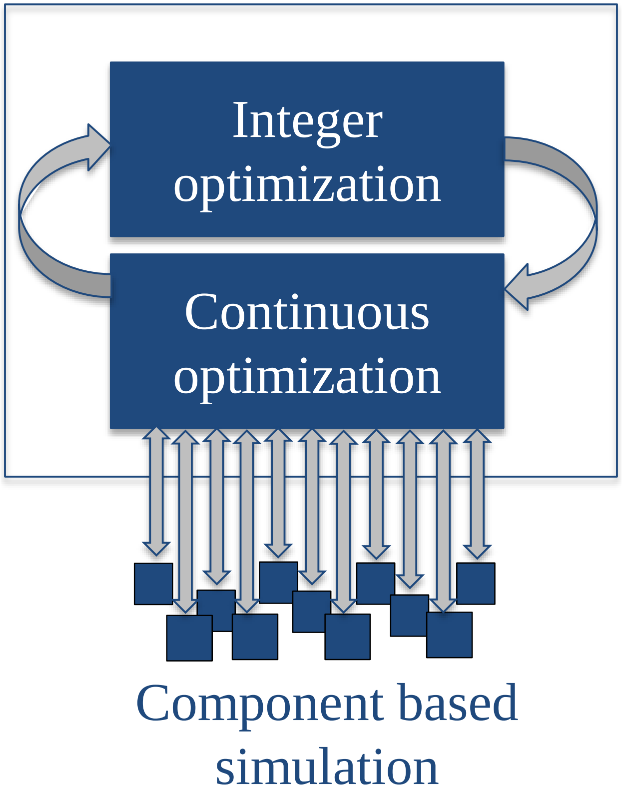


The SmartOpt approach enables production optimization for complex systems by decomposing the problem and simulator

Splitting up the decision space and the network simulator

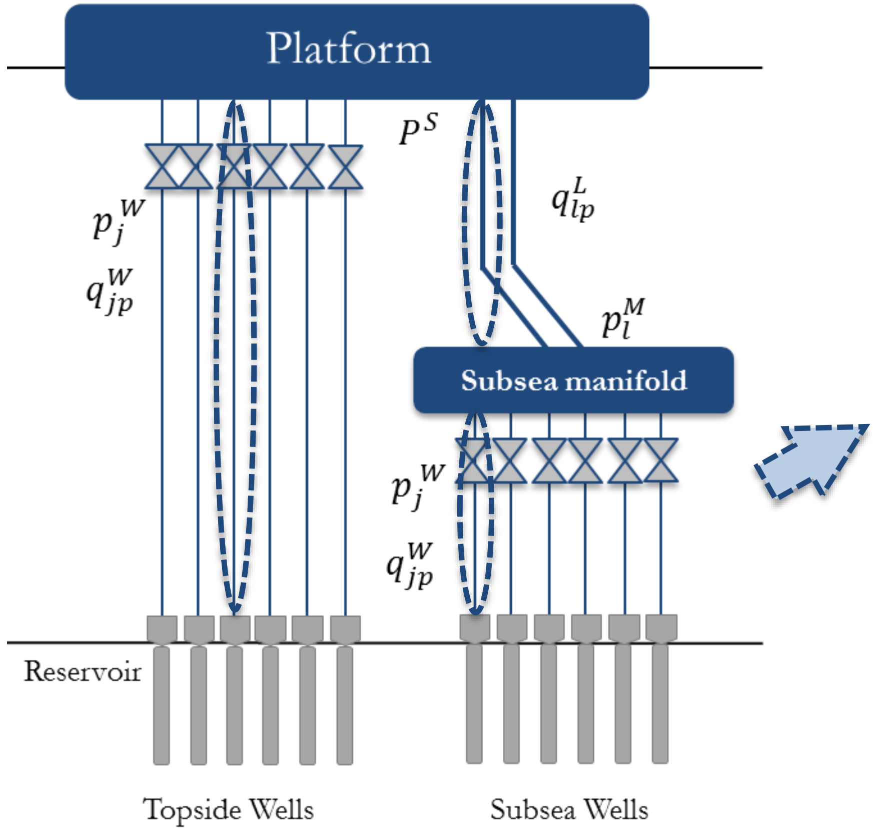
SmartOpt

- The decision space is first split into integer and continuous subspaces
- It utilizes the information in the network structure and the simulator is decomposed into component simulators for wells and pipelines
- Mass and pressure balances can be treated inside the optimization algorithm
- The decomposition enables relaxation of all integer variables
- And facilitate the utilization of Branch & Bound and gradient based search algorithms



SmartOpt utilizes the production network structure and separates the simulations into smaller parts, one for each well and pipeline

SmartOpt simulation strategy



Splits network into simulators for each well and pipeline...

- Well $q^W = f^W(p^W, q^{GL})$
- Pipeline $p^M = f^L(q^L)$

...while mass balance and pressure relations are treated as explicit algebraic constraints

IO CENTER

By splitting up the simulator, discrete decisions are treated in analytical constraints, enabling Brach & Bound

"The SmartOpt problem"

Objective function

$$\max \sum_{l \in L} q_{lo}^{L} + \sum_{j \in J_t} q_{jo}^{W} x_j$$

Capacity constraints

$$\sum_{l \in L} q_{lp}^{L} + \sum_{j \in J_t} q_{jp}^{W} x_j \le C_p$$

$$\sum_{j \in J_s} \sum_{l \in L} q_j^{GL} y_{jl} + \sum_{j \in J_t} q_j^{GL} x_j \le C^{GL}$$

Pressure and mass balance

$$\sum_{j \in J_s} q_{jp}^{W} y_{jl} = q_{lp}^{L} \qquad \sum_{l \in L} y_{jl} \le 1 \qquad j \in J_s$$

$$p_l^M y_{jl} \le p_j^W \qquad j \in J_s$$

$$x_j P^S \le p_j^W \qquad j \in J_t$$

Well and pipeline

$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^W, q_j^{GL}\right)$$

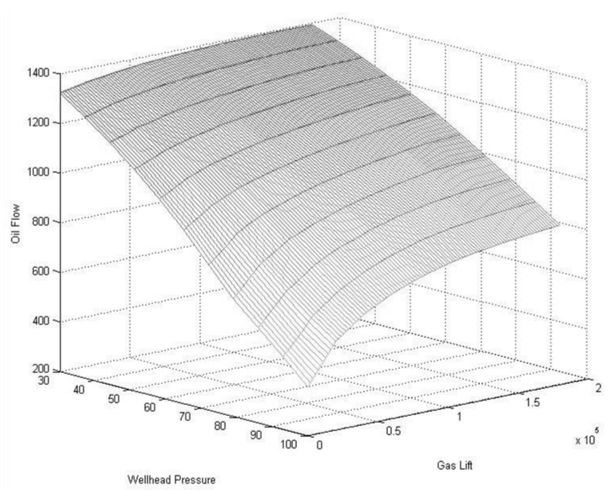
$$p_l^M - P^S = f_l^L(q_{lo}^L, q_{lg}^L, q_{lw}^L)$$

The simulators for each well and pipeline is of much lower dimension than the complete network simulator

Well and pipeline simulator data

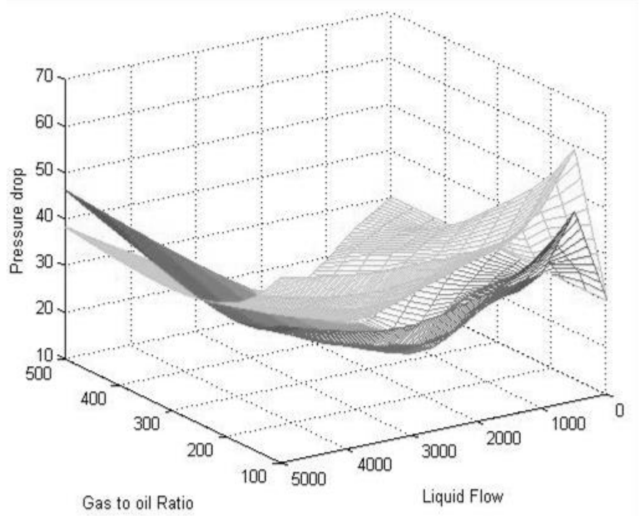
Oil production from well:

$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^{W}, q_j^{GL}\right)$$



Pressure drop over pipeline:

$$p_l^{M} - P^{S} = f_l^{L}\left(q_{lo}^{L}, q_{lg}^{L}, q_{lw}^{L}\right)$$

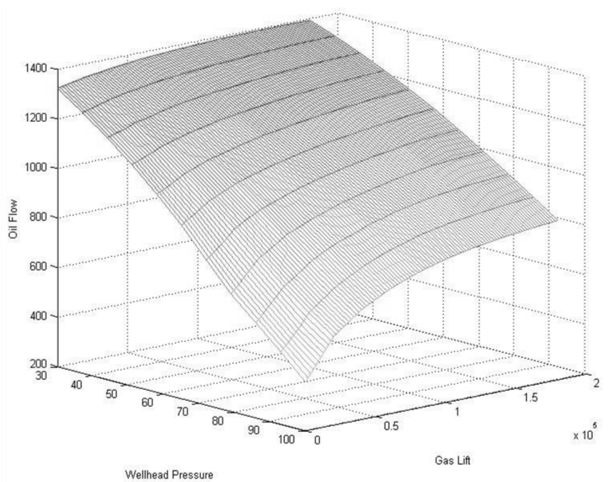


Gas and water production rates from each well are calculated using the GOR, WC and oil production rate

Gas and water production equations

Oil production from well:

$$q_{jo}^{W} = f_{jo}^{W}\left(p_{j}^{W}, q_{j}^{GL}\right)$$



Gas and water production:

$$q_{jg}^{W} = GOR_{j}^{W} q_{jo}^{W} + q_{j}^{GL}$$

$$q_{jw}^{W} = q_{jo}^{W}\left(\frac{WC_{j}^{W}}{1 - WC_{j}^{W}}\right)$$

The gas-to-oil ratio (GOR) and the water cut (WC) are assumed constant for each well…

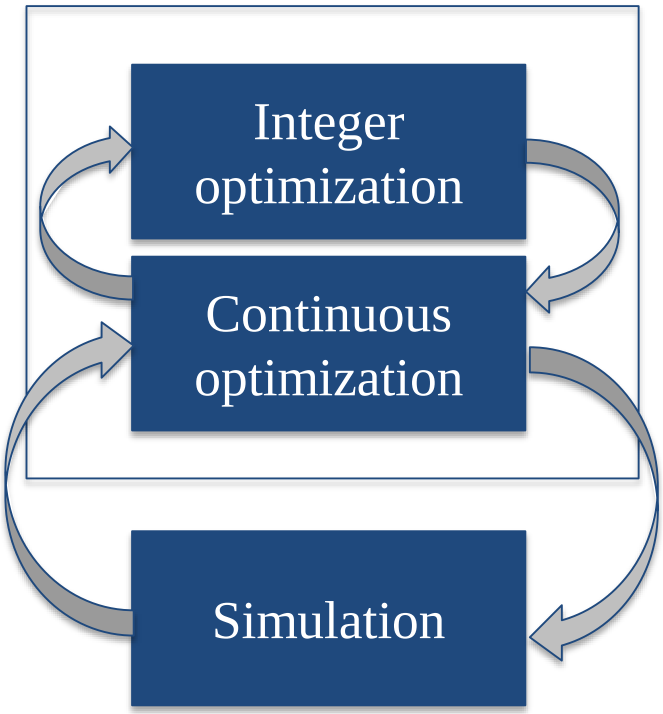
Outline

1. Introduction
2. Mathematical optimization
3. SmartOpt approaches
4. Case
5. Results
6. Conclusion

The simplest 2-layer approach divides the search space in a derivative free master problem and a continuous sub-problem

Recap 2-layer approach

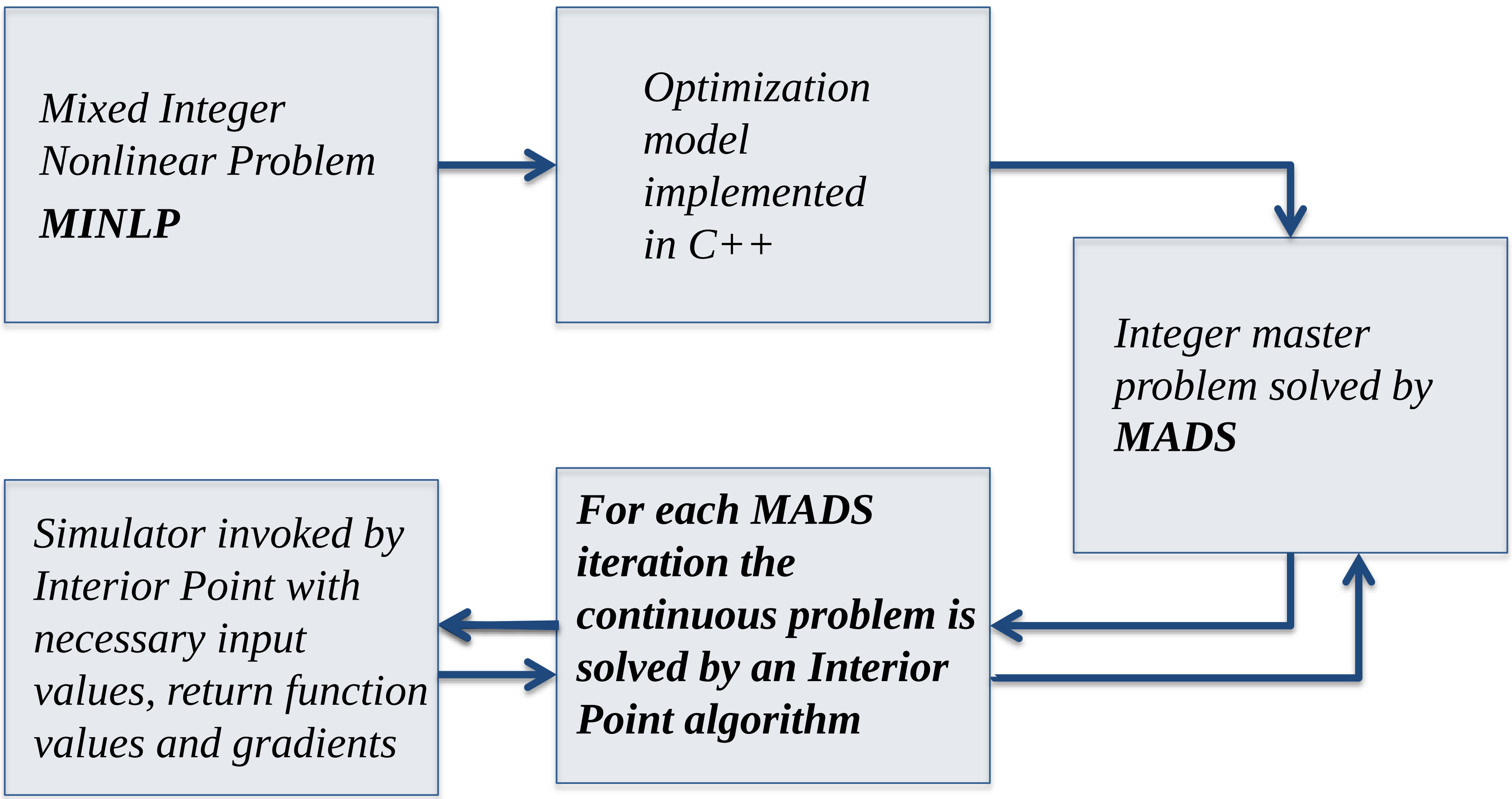
- One integer subspace and one continuous subspace
- Mathematical formulation similar to the traditional approach
- Optimization algorithms in two layers
- A **derivative-free algorithm** solves the integer master-problem
- For each iteration of the derivative-free algorithm, a **gradient-based algorithm** solves the continuous sub-problem



CENTER

SmartOpt 2-layer method includes the network simulator, the algorithm does not see what happens in the simulator

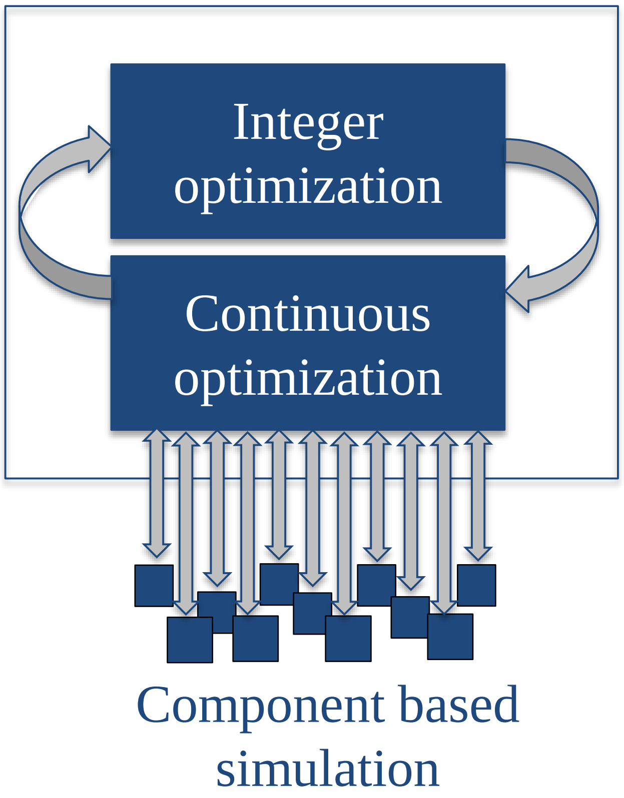
How wells and pipes are simulated, modeled and optimized



The more “sophisticated” SmartOpt approach further utilize the network structure to decompose the simulator

Recap SmartOpt

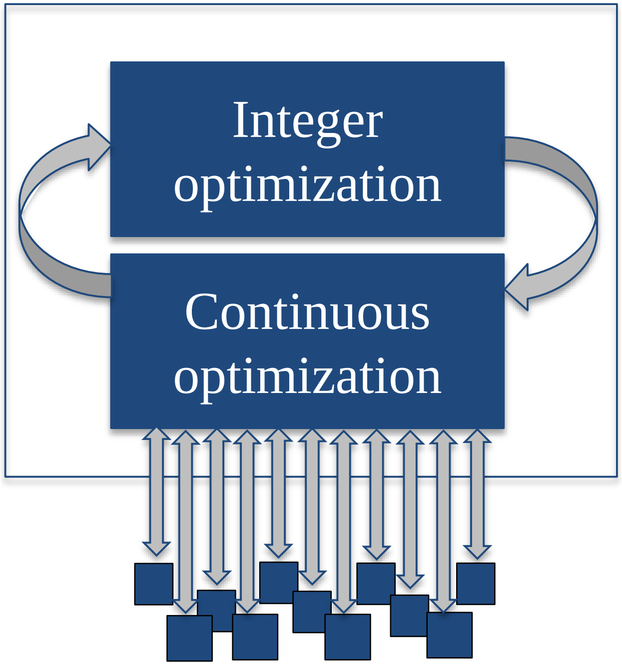
- The decision space is split into integer and continuous subspaces
- The network simulator is decomposed into component simulators for wells and pipelines
- Mass and pressure balances are treated inside the optimization algorithm
- This facilitate the utilization of Branch & Bound and gradient based search algorithms



The more "sophisticated" SmartOpt approach further utilize the network structure to decompose the simulator

Recap SmartOpt

- It is more efficient to call the specific component simulator as one needs information of that part of the system, than to call the entire network simulator each time
- This also opens up to the possibility of sampling the simulators prior to running the optimization algorithm, and use data tables and/or proxy models during the optimization
- Several representations of the component simulators will be presented

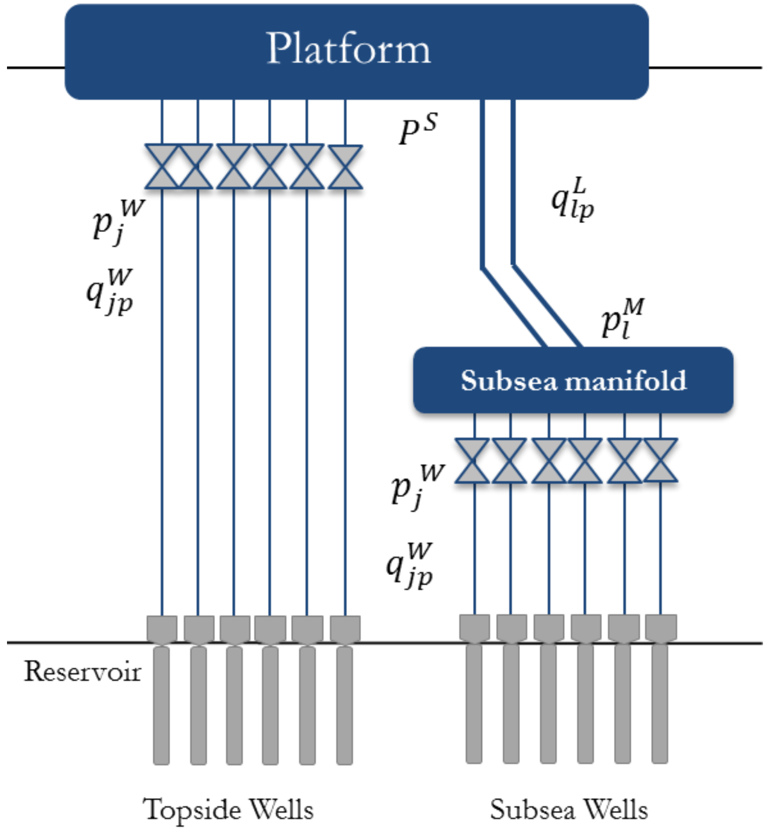


Play SmartOpt movie..

CENTER

Well and pipeline simulators can be represented in several ways, either simulated directly or through approximations

SmartOpt simulation strategies



SmartOpt
Simulation

SmartOpt
Interpolation

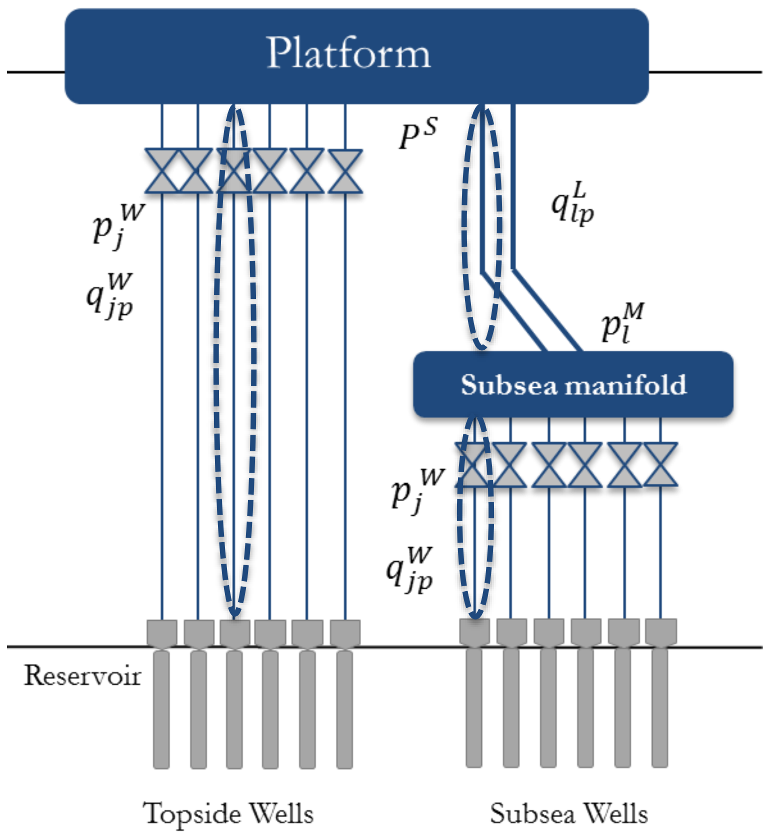
SmartOpt
Algebraic

SmartOpt
SOS2

CENTER

Well and pipeline simulators can be represented in several ways, either simulated directly or through approximations

SmartOpt simulation strategies



SmartOpt
Simulation

SmartOpt
Interpolation

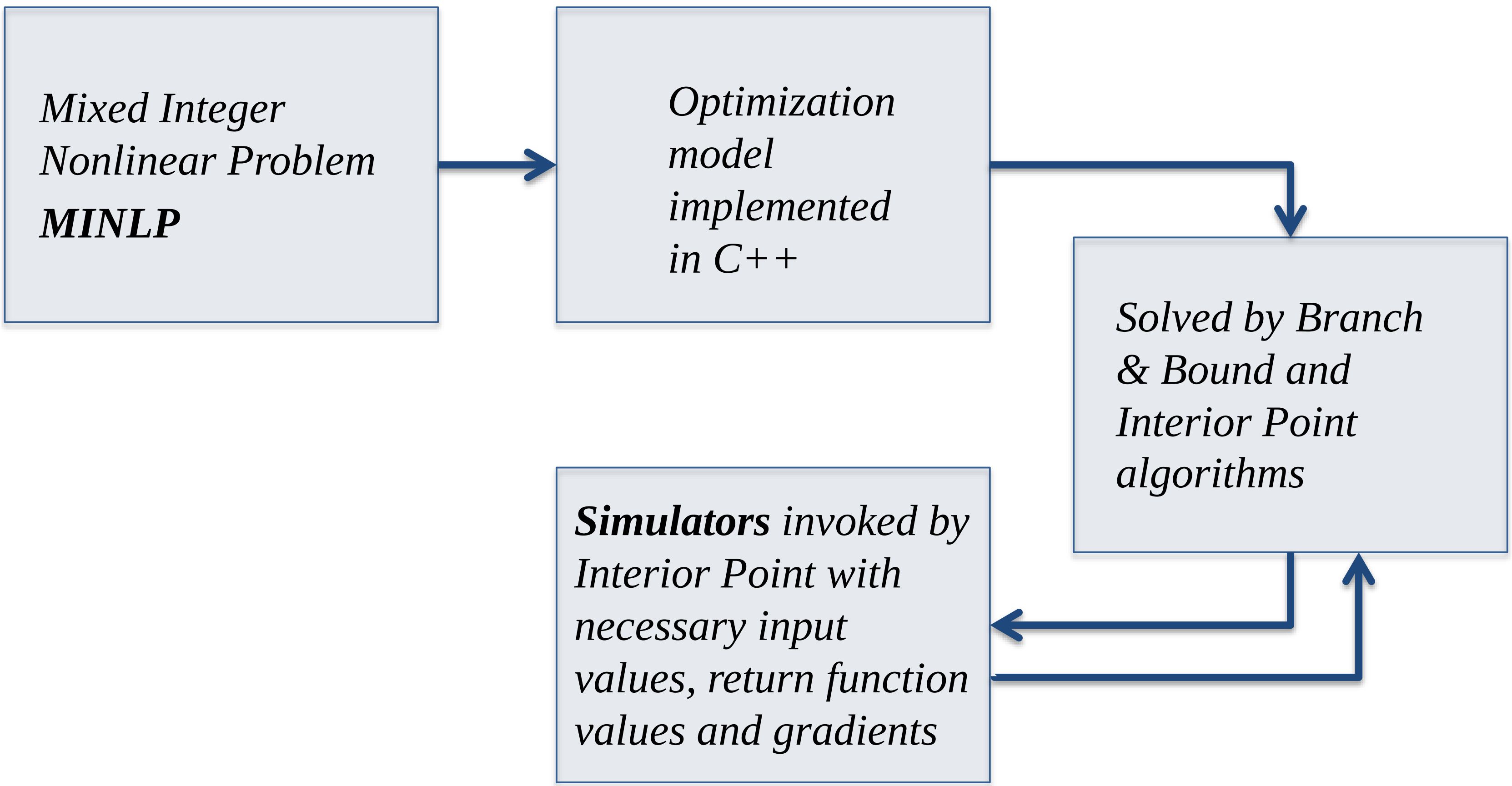
SmartOpt
Algebraic

SmartOpt
SOS2

CENTER

SmartOpt simulation method includes simulators - the algorithm does not see what happens inside the simulator

How wells and pipes are simulated, modeled and optimized



By splitting up the simulator, discrete decisions are treated in analytical constraints, enabling Brach & Bound

"The SmartOpt problem"

Objective function

$$\max \sum_{l \in L} q_{lo}^{L} + \sum_{j \in J_t} q_{jo}^{W} x_j$$

Capacity constraints

$$\sum_{l \in L} q_{lp}^{L} + \sum_{j \in J_t} q_{jp}^{W} x_j \le C_p$$

$$\sum_{j \in J_s} \sum_{l \in L} q_j^{GL} y_{jl} + \sum_{j \in J_t} q_j^{GL} x_j \le C^{GL}$$

Pressure and mass balance

$$\sum_{j \in J_s} q_{jp}^{W} y_{jl} = q_{lp}^{L} \qquad \sum_{l \in L} y_{jl} \le 1 \qquad j \in J_s$$

$$p_l^{M} y_{jl} \le p_j^{W} \qquad j \in J_s$$

$$x_j P^{S} \le p_j^{W} \qquad j \in J_t$$

Well and pipeline

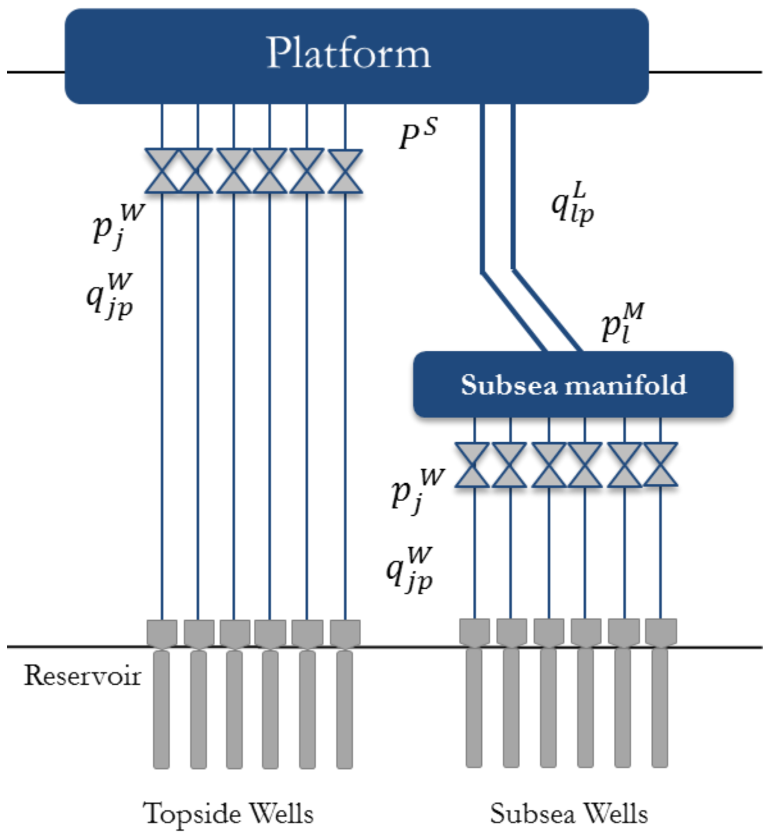
$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^{W}, q_j^{GL}\right)$$

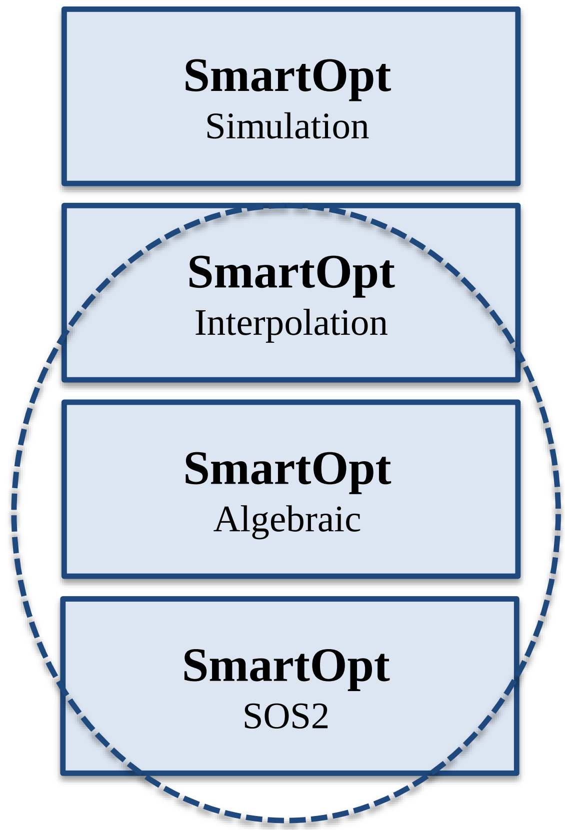
$$p_l^{M} - P^{S} = f_l^{L}(q_{lo}^{L}, q_{lg}^{L}, q_{lw}^{L})$$

Simulators are called directly; function value and gradients are returned

Well and pipeline simulators can be represented in several ways, either simulated directly or through approximations

SmartOpt simulation strategies





CENTER

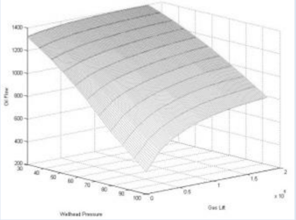
The SmartOpt enables use of pre-generated data tables and interpolation techniques to reduce evaluation time

How wells and pipes simulators can be represented

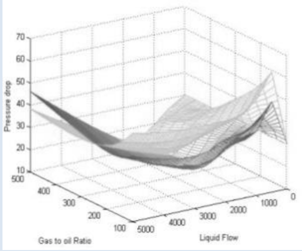
- The SmartOpt formulation decomposes the network simulator into smaller component simulators
- With the model parameters fixed, the well and pipeline simulator only have 2 or 3 degrees of freedom left
- Due to few variables the component simulators can be sampled and represented as data tables
- The data tables can be used for interpolation or pre-generation of proxy models

Wells and pipelines

$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^{W}, q_j^{GL}\right)$$



$$p_l^{M} - P^{S} = f_l^{L}(q_{lo}^{L}, q_{lg}^{L}, q_{lw}^{L})$$



CENTER

Including real simulators will affect the evaluation times, an alternative is to approximate the simulator

How wells and pipes are simulated, modeled and optimized

Simulators

$$q_{jp}^{W} = F_{jp}^{W}\left(p_{j}^{W}, q_{j}^{GL}, m_1, \dots, m_n\right)$$

- The parameters $m_1, \dots, m_n$ are describing the plant.
- They introduce complexity in F_{jo}.
- $m_1, \dots, m_n$ are known and constant during optimization.

A numerical solver will only be faced with

$$q_{jp}^{W} = f_{jp}^{W}\left(p_{j}^{W}, q_{j}^{GL}\right)$$

- Desirable to create a analytical replacement $\hat{f}_{jp}$, that is easily integrated in a optimization software and has short evaluation times.

Approximation

$$\hat{q}_{jp}^{W} = approx\ \hat{f}_{jp}^{W}\left(p_{j}^{W}, q_{j}^{GL}\right) \cong f_{jp}^{W}\left(p_{j}^{W}, q_{j}^{GL}\right)$$

By splitting up the simulator, discrete decisions are treated in analytical constraints, enabling Brach & Bound

“*The SmartOpt problem*”

Objective function

$$\max \sum_{l \in L} q_{lo}^{L} + \sum_{j \in J_t} q_{jo}^{W} x_j$$

Capacity constraints

$$\sum_{l \in L} q_{lp}^{L} + \sum_{j \in J_t} q_{jp}^{W} x_j \leq C_p$$

$$\sum_{j \in J_s} \sum_{l \in L} q_j^{GL} y_{jl} + \sum_{j \in J_t} q_j^{GL} x_j \leq C^{GL}$$

Pressure and mass balance

$$\sum_{j \in J_s} q_{jp}^{W} y_{jl} = q_{lp}^{L} \qquad \sum_{l \in L} y_{jl} \leq 1 \qquad j \in J_s$$

$$p_l^M y_{jl} \leq p_j^W \qquad j \in J_s$$

$$x_j P^S \leq p_j^W \qquad j \in J_t$$

Well and pipeline

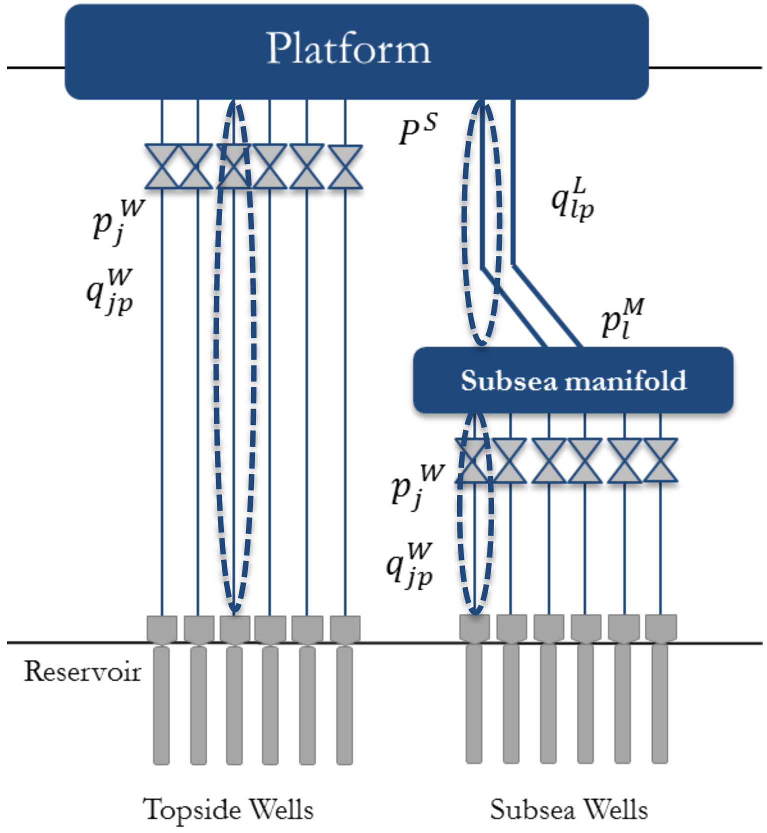
$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^W, q_j^{GL}\right)$$

$$p_l^M - P^S = f_l^L(q_{lo}^L, q_{lg}^L, q_{lw}^L)$$

Simulators are approximated, and a surrogate model returns function value and gradients

Well and pipeline simulators can be represented in several ways, either simulated directly or through approximations

SmartOpt simulation strategies



SmartOpt
Simulation

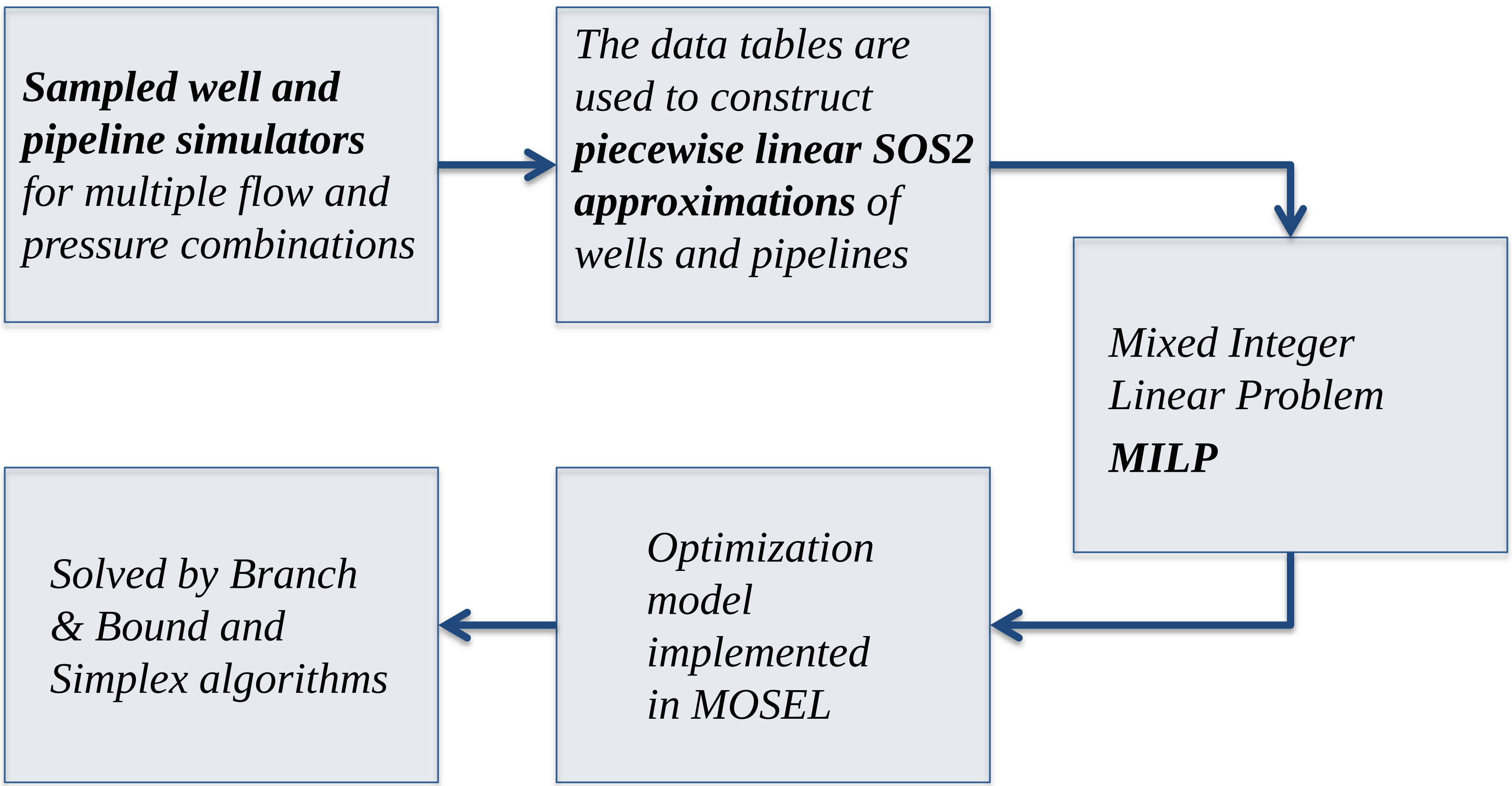
SmartOpt
Interpolation

SmartOpt
Algebraic

SmartOpt
SOS2

SmartOpt SOS2 becomes a linear and convex formulation of the production optimization problem

How wells and pipes are simulated, modeled and optimized



To obtain a linear model all nonlinear constrains must be reformulated; by "Big M" and SOS2

"The SmartOpt nonlinear problem"

Objective function

$$\max \sum_{l \in L} q_{lo}^{L} + \sum_{j \in J_t} q_{jo}^{W} x_j$$

Capacity constraints

$$\sum_{l \in L} q_{lp}^{L} + \sum_{j \in J_t} q_{jp}^{W} x_j \leq C_p$$

$$\sum_{j \in J_s} \sum_{l \in L} q_j^{GL} y_{jl} + \sum_{j \in J_t} q_j^{GL} x_j \leq C^{GL}$$

Pressure and mass balance

$$\sum_{j \in J_s} q_{jp}^{W} y_{jl} = q_{lp}^{L} \qquad \sum_{l \in L} y_{jl} \leq 1 \qquad j \in J_s$$

$$p_l^M y_{jl} \leq p_j^W \qquad j \in J_s$$

$$x_j P^S \leq p_j^W \qquad j \in J_t$$

Well and pipeline

$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^W, q_j^{GL}\right)$$

$$p_l^M - P^S = f_l^L(q_{lo}^L, q_{lg}^L, q_{lw}^L)$$

To obtain a linear model all nonlinear constrains must be reformulated; by "Big M" and SOS2

"The SmartOpt SOS2 problem"

Objective function

$$max \sum_{l \in L} q_{lo}^{L} + \sum_{j \in J_t} q_{jo}^{W}$$

Capacity constraints

$$\sum_{l \in L} q_{lp}^{L} + \sum_{j \in J_t} q_{jp}^{W} \leq C_p$$

$$\sum_{j \in J} q_{j}^{GL} \leq C^{GL}$$

Pressure balance

$$p_l^M \leq p_j^W + P_l^{MAX}(1 - y_{jl}) \quad j \in J_s$$

$$P^S \leq p_j^W + P^S(1 - x_j) \quad j \in J_t$$

Pressure and mass balance

$$\sum_{l \in L} q_{jlp}^{WL} = q_{jp}^{W} \quad j \in J_s \qquad \sum_{j \in J_s} q_{jlp}^{WL} = q_{lp}^{L}$$

$$\sum_{l \in L} y_{jl} \leq 1 \quad j \in J_s \qquad q_{jlp}^{W} \leq Q_{jp}^{W} y_{jl} \quad j \in J_s$$

$$q_{jp}^{W} \leq Q_{jp}^{W} x_j \quad j \in J_t$$

Well and pipeline

$$q_{jp}^{W} = f_{jp}^{W}\left(p_j^W, q_j^{GL}\right)$$

$$p_l^M - P^S = f_l^L(q_{lo}^L, q_{lg}^L, q_{lw}^L)$$

The component simulators are represented through data tables and piecewise linear SOS2 approximations

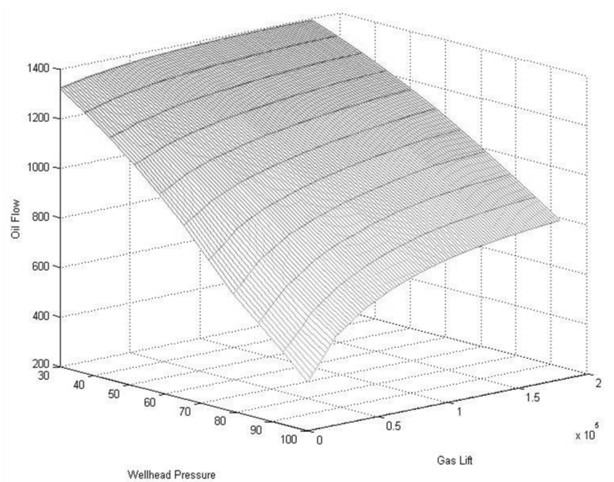
These plots is piecewise linearized

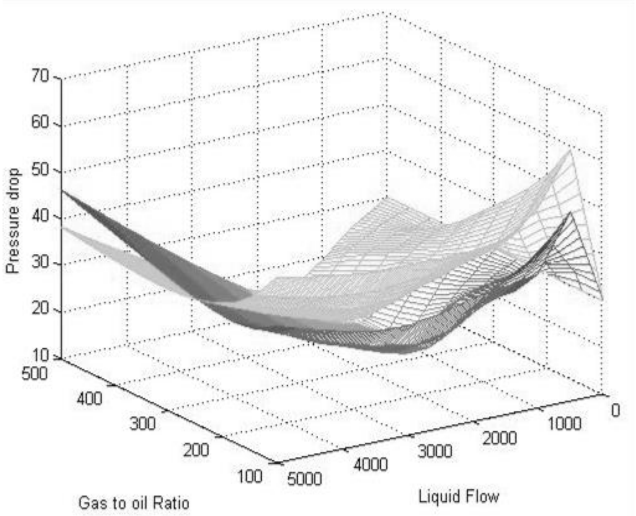
Well:

$$q_{jp}^{W} = f_{jp}^{W}\left(p_{j}^{W}, q_{j}^{GL}\right)$$

Pipeline:

$$p_{l}^{M} - P^{S} = f_{l}^{L}(q_{lo}^{L}, q_{lg}^{L}, q_{lw}^{L})$$

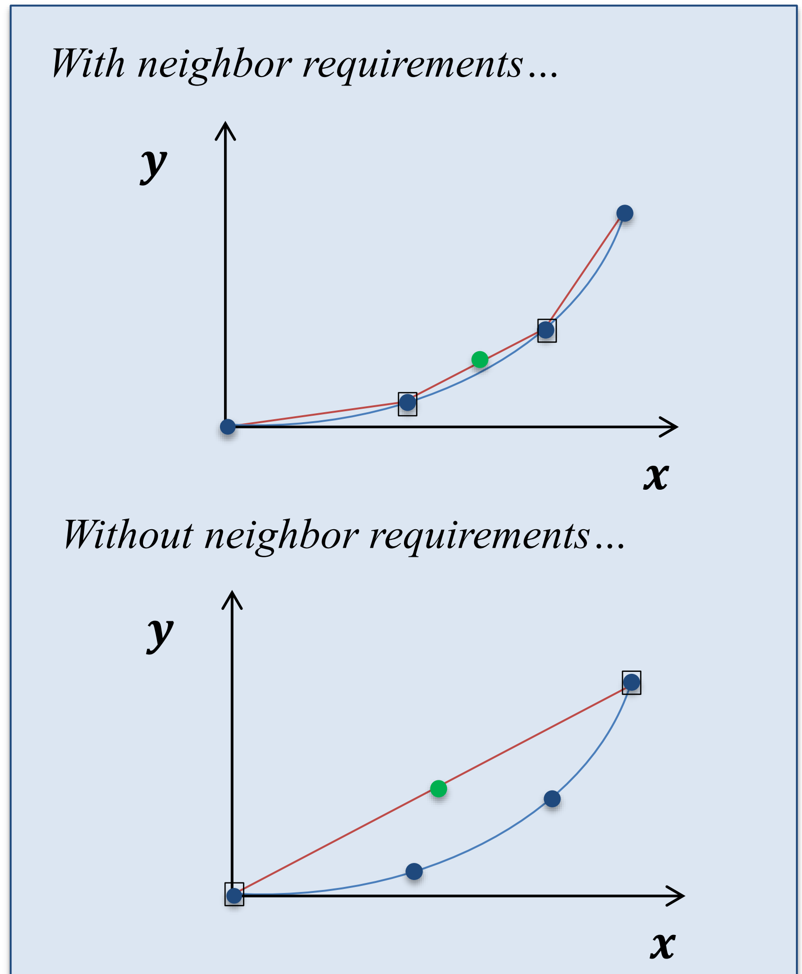




SOS 2 formulation example for a fixed number of breakpoint values for x and y given by the curve $y = x^2$

Special ordered sets of type 2

- Defining the weighting variables as SOS2 means that at most two points can be non-zero, and they have to be adjacent
- This allows for interpolation between the two associated breakpoints
- Relaxing the neighboring requirements might lead to poor function approximations as seen in the figure
- SOS 2 can also be used when linearizing multidimensional functions



Introduction to piecewise linearization through SOS2; a simple “one to one dimension” example $y=x^2$

Special ordered sets of type 2

Piecewise linearization of function $y=x^2$

$$x = 0\lambda_0 + 1\lambda_1 + 2\lambda_2 + 2.5\lambda_3$$

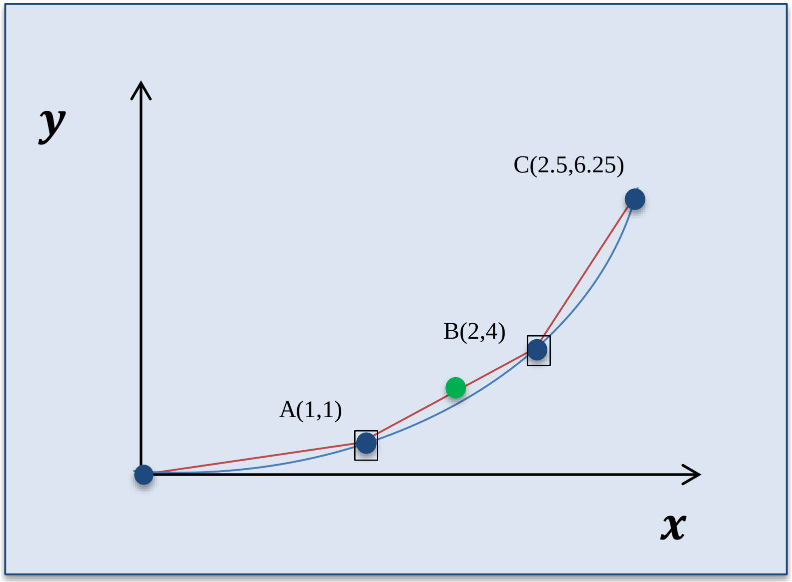
$$y = 0\lambda_0 + 1\lambda_1 + 4\lambda_2 + 6.25\lambda_3$$

$$\lambda_0 + \lambda_1 + \lambda_2 + \lambda_3 = 1$$

$$\lambda_0 \le \alpha_0$$
$$\lambda_1 \le \alpha_0 + \alpha_1$$
$$\lambda_2 \le \alpha_1 + \alpha_2$$
$$\lambda_3 \le \alpha_2$$

$$\lambda_i \in [0,1], i \in \{0, \dots, 3\}$$
$$\alpha_i \in \{0,1\}, i \in \{0, \dots, 2\}$$

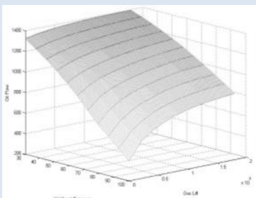
- A fixed number of breakpoint values for x and y can be defined and nonnegative weighting variables λ_i are assigned to each breakpoint i
- Linear segments can be drawn between the data points



CENTER

Well simulators are approximated through pre-generated data tables and linear pieces between the data points

"The SOS 2 formulation for the well simulator"



$$q_{jp}^{W} = f_{jp}^{W}\left(p_{j}^{W}, q_{j}^{GL}\right)$$

$$q_{jp}^{W} = \sum_{k \epsilon K} \sum_{n \epsilon N} Q_{(jp)kn}^{W} \lambda_{(j)kn}$$

$$p_{j}^{W} = \sum_{k \epsilon K} \sum_{n \epsilon N} P_{(j)k}^{W} \lambda_{(j)kn}$$

$$q_{j}^{GL} = \sum_{k \epsilon K} \sum_{n \epsilon N} Q_{(j)n}^{GL} \lambda_{(j)kn}$$

$$\sum_{k \epsilon K} \sum_{n \epsilon N} \lambda_{(j)kn} = 1$$

$$\lambda_{(j)kn} \geq 0$$

$$\eta_{(j)k}^{K} = \sum_{n \epsilon N} \lambda_{(j)kn}$$

$$\eta_{(j)n}^{N} = \sum_{k \epsilon K} \lambda_{(j)kn}$$

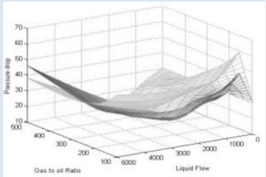
$\eta_{(j)k}^{K}$ *is SOS 2 for k*

$\eta_{(j)n}^{N}$ *is SOS 2 for n*

$$\eta_{(j)n}^{N}, \eta_{(j)k}^{K} \geq 0$$

Pipeline simulators are approximated through pre-generated data tables and linear pieces between the data points

"The SOS 2 formulation for the pipeline simulator"



$$p_l^M - P^S = f_l^L(q_{lo}^L, q_{lg}^L, q_{lw}^L)$$

$$\sum_{k \epsilon K} \sum_{n \epsilon N} \sum_{r \epsilon R} F_{(l)knr}^L \delta_{(l)knr} = P^S - p_l^M$$

$$q_{lo}^L = \sum_{k \epsilon K} \sum_{n \epsilon N} \sum_{r \epsilon R} Q_{(l)k}^O \delta_{(l)knr}$$

$$q_{lg}^L = \sum_{k \epsilon K} \sum_{n \epsilon N} \sum_{r \epsilon R} Q_{(l)n}^G \delta_{(l)knr}$$

$$q_{lo}^L = \sum_{k \epsilon K} \sum_{n \epsilon N} \sum_{r \epsilon R} Q_{(l)r}^W \delta_{(l)knr}$$

$$\sum_{k \epsilon K} \sum_{n \epsilon N} \sum_{r \epsilon R} \delta_{(l)knr} = 1$$

$$\delta_{(l)knr} \geq 0$$

$$\gamma_{(l)r}^R = \sum_{k \epsilon K} \sum_{n \epsilon N} \delta_{(l)knr}$$

$$\gamma_{(l)n}^N = \sum_{k \epsilon K} \sum_{r \epsilon R} \delta_{(l)knr}$$

$$\gamma_{(l)k}^K = \sum_{n \epsilon N} \sum_{r \epsilon R} \delta_{(l)knr}$$

$\gamma_{(l)r}^R$ is SOS 2 for r

$\gamma_{(l)n}^N$ is SOS 2 for n

$\gamma_{(l)k}^K$ is SOS 2 for k

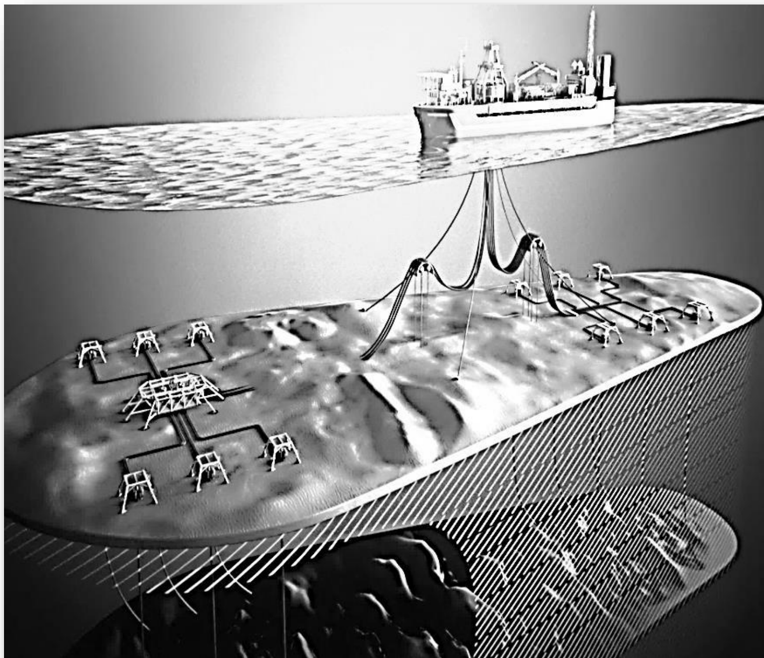
$$\gamma_{(l)r}^R, \gamma_{(l)n}^N, \gamma_{(l)k}^K \geq 0$$

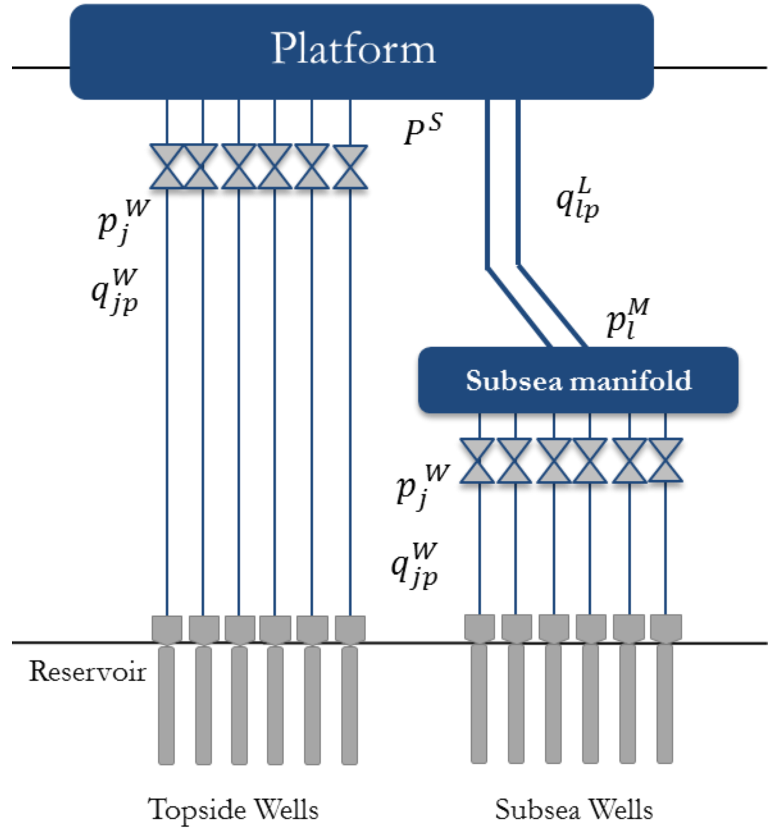
Outline

CENTER

12 well production system, 6 subsea wells and 6 satellite wells, with artificial gas lift

TEST CASE





1 base case and 5 similar cases are defined for available gas lift, gas and water handling capacities and separator pressure

OPTIMIZATION PROBLEM

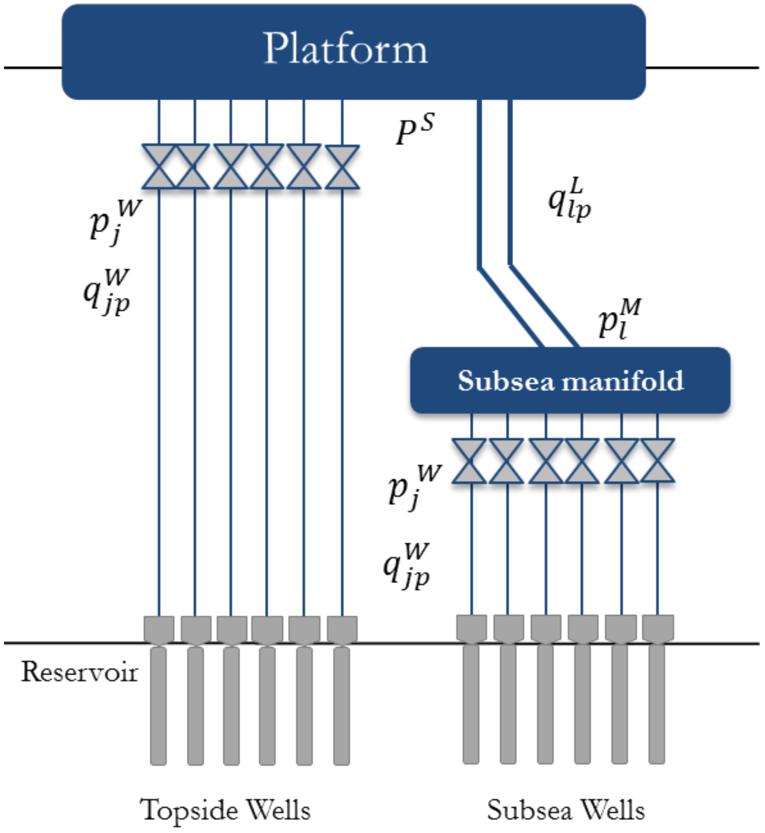
- **Maximize total oil production**

By adjusting:

- Well head pressures
- Gas lift
- Subsea well routing

And obeying:

- Total handling capacity on water and gas production
- Total gas lift compression capacity
- Minimum separator pressure



Outline

1. Introduction
2. Mathematical optimization
3. SmartOpt approaches
4. Case
5. **Results**
6. Conclusion

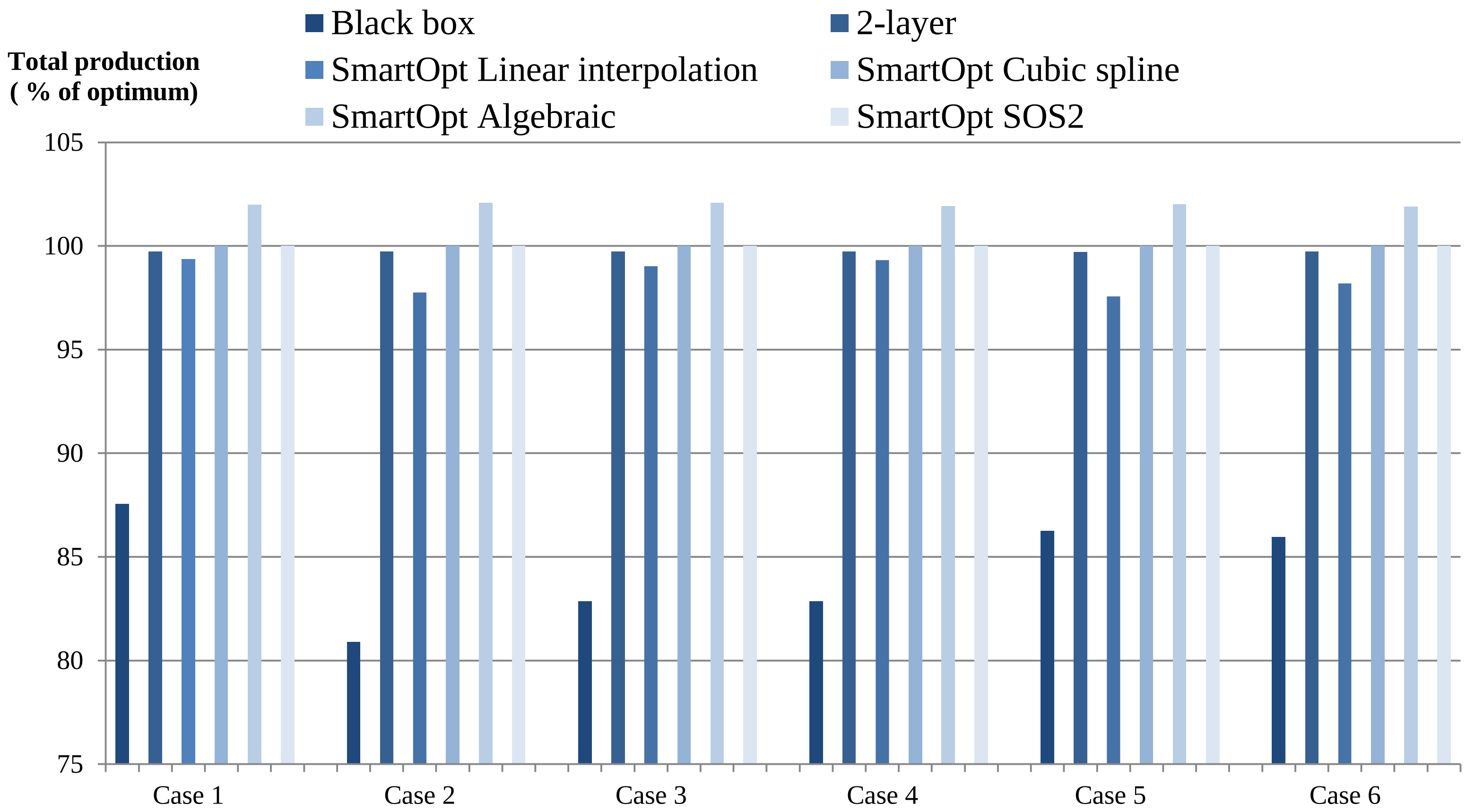
CENTER

Six of the strategies presented are demonstrated on a real petroleum production problem

	Solution approach	Description	Simulator approximation	Implementation language	Problem class	Solution algorithm
Simulation	Black- Box	Traditional method Black box simulator	Simulation	C++	MINLP "simulation"	MADS
	2-layer	One discrete and one continuous problem				MADS + Interior point
Approximation	SmartOpt Interpolation (Linear and cubic spline)	Discrete and continuous subspaces Component simulators	Interpolation algorithm Returns function value and derivatives		MINLP	Branch & Bound + Interior point
	SmartOpt Algebraic	Well and pipeline models sampled upfront	Algebraic piecewise nonlinear approximations	AMPL		
	SmartOpt SOS2	Component simulators represented by approximations	SOS2 formulations Convex problem Solutions taken as global optimum	MOSEL	MILP	Branch & Bound + Simplex

The graph present oil production from each well and indicate small differences between the methods

Base case optimal solutions in % of SOS2 solution



The SmartOpt simulation approaches are very fast, but can be sensitive to staring point if not solved globally

	Approaches	Solution time Base case	Performance Base case	Variance Base case six initial points
Simulation	Black- Box	**463 seconds**	**84.7 %**	**± 9.1 %**
Simulation	2-layer	**151 seconds**	**99.7%**	**± 18.4 %**
Approximations	**SmartOpt** Linear interpolation	**1 second**	**99.4 %**	**± 6.4 %**
Approximations	**SmartOpt** Cubic spline	**107 seconds**	**100 %**	**± 0.0 %**
Approximations	**SmartOpt** Algebraic	**14 seconds**	**102 %**	**± 0.3 %**
Approximations	**SmartOpt** SOS2	**237 seconds**	**100 %**	**± 0.0%**

CENTER

The SmartOpt simulation approaches are very fast, but can be sensitive to staring point if not solved globally

Best objective functions and variations given in % of SOS2 solution

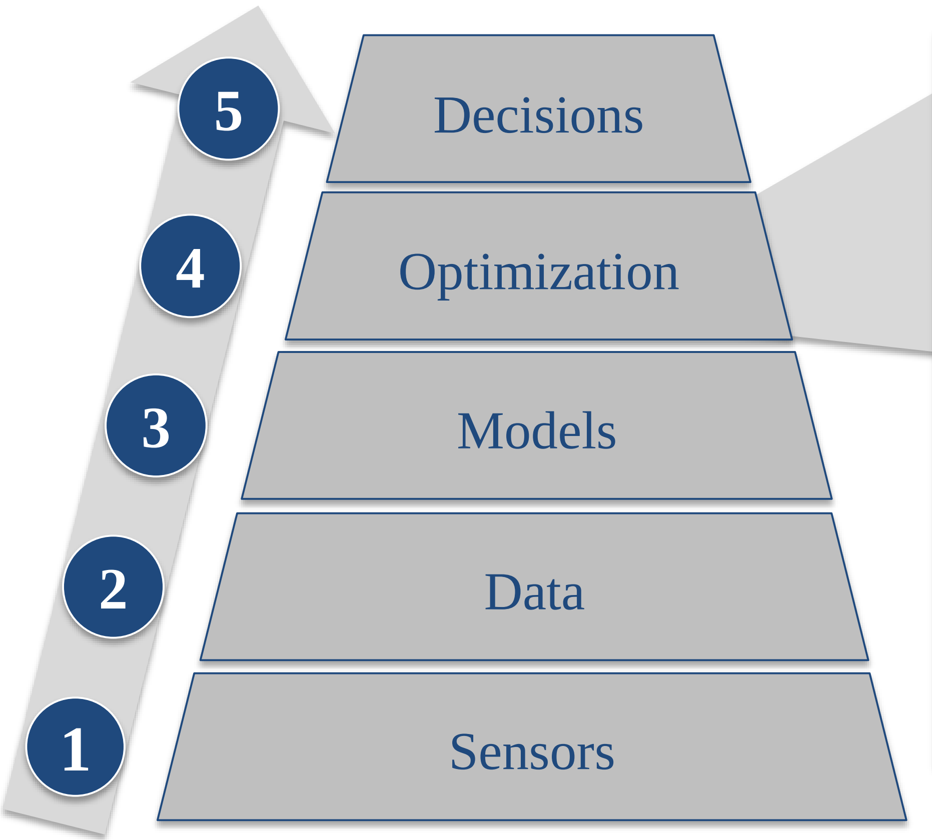
	Black- Box	2-layer	**SmartOpt** Linear int.	**SmartOpt** Cubic spline	**SmartOpt** Algebraic	**SmartOpt** SOS2
Base case	84.7± 9.1 %	99.7±18.4 %	99.4± 6.4 %	100.0±0.0 %	102.0±0.3 %	100 %
Case 1	95.0±21.5 %	99.7±18.7 %	97.8±13.1 %	100.0±0.0 %	102.1±0.2 %	100 %
Case 2	89.5±15.3 %	99.7±18.9 %	99.0± 7.3 %	100.1±0.0 %	102.1±0.0 %	100 %
Case 3	92.5±18.3 %	99.8±18.3 %	99.3± 7.8 %	100.0±0.0 %	101.9±0.0 %	100 %
Case 4	88.0±10.9 %	99.7±18.5 %	97.6± 3.2 %	100.1±0.0 %	102.0±0.1 %	100 %
Case 5	92.3±17.8 %	99.7±18.0%	98.2± 9.6 %	100.1±0.0 %	101.9±0.0 %	100 %

Outline

CENTER

Six of the strategies presented are demonstrated on a real petroleum production problem

EVALUATION CRITERIA



Evaluate and compare:

- Discrete decisions
- Solution time and scalability
- Model exactness
- Solution quality
- Robustness
- Modelling effort
- Automation

There are pros and cons to all SmartOpt approaches, witch one to choose depends on problem and preferences

DISCRETE DECISIONS

SmartOpt

- Enables the use of Branch & Bound for efficient treatment of discrete decisions
- Optimal solution two orders of magnitude faster than the Black box approach
- Facilitates instant re-optimization
- Enable production engineers to focus on other important questions

Traditional approach

- Simulators only allow the optimization algorithm to make queries with discrete values on the routing and on/off decisions
- Excludes the use of Branch & Bound based algorithms that rely on relaxing the integer requirements
- Must solve using derivative-free solution algorithms
- Leads to slow convergence and increased solution times

There are pros and cons to all SmartOpt approaches, witch one to choose depends on problem and preferences

SOLUTION TIME & SCALABILITY

SmartOpt

- The **SmartOpt** approaches sees a speed up compared to the traditional approach, thus much is gained by including explicit structural constraints
- **SmartOpt SOS2** is highly sensitive to an increase in data points and network components due to the subsequent increase in SOS2 variables
- **SmartOpt interpolation** methods scale better as the interpolation is quick
- Evaluations of more proxy models will have a noticeable effect on the solution speed of **SmartOpt algebraic**

Traditional approach

- The **Black box approach** solves the petroleum production problem with reasonable solution times
- An increase in the number of decision variables that follows a larger production network is likely to slow down the derivative-free black box approach

CENTER

There are pros and cons to all SmartOpt approaches, witch one to choose depends on problem and preferences

MODEL EXACTNESS

Simulator & interpolation based:

- **Black box, 2-layer and SmartOpt interpolation** approaches provide realistic portrayals of the production network
- The number of data point and the interpolation scheme will affect the accuracy of **SmartOpt interpolation**

Algebraic based:

- More detailed discretization will result in a **better match with the reality**
- SmartOpt SOS2 experience a trade off between **solution time and accuracy**
- **Algebraic proxy models** have been created based on visual inspections combined with least square fits. In this case the solutions are proven slightly infeasible, undermining the accuracy of the approximations used
  (Some well approximations overestimating the oil production for certain wellhead pressures and gas lift allocations, while pipeline approximations at the same time underestimate the pressure losses over the pipelines for the resulting flows)

There are pros and cons to all SmartOpt approaches, witch one to choose depends on problem and preferences

SOLUTION QUALITY

SmartOpt

- All **SmartOpt** approaches provide better solutions than the traditional approach
- **SmartOpt SOS2** provide global optimal solutions
- The **cubic spline interpolation** scheme proves very good and finds the same solutions as the SOS2 approximations, i.e. the optimal solution
- Clearly sensitive to the exactness of the proxy models the **SmartOpt algebraic** solutions surpasses the optimal values

Traditional approach

- The **Black box approach** provide inferior solutions
- The **2-layer** approach lead to a significant improvement in objective function values

There are pros and cons to all SmartOpt approaches, witch one to choose depends on problem and preferences

ROBUSTNESS

Simulator & interpolation based:

- The **SmartOpt Cubic spline** interpolation can be efficiently convexified, proves very robust
- The **SmartOpt linear interpolation** method proves dependent on starting point, this can be solved by multi start
- The **Black box** and **2-layer** methods are also highly dependent of starting point, multi start is not so attractive due to solution time

Algebraic based:

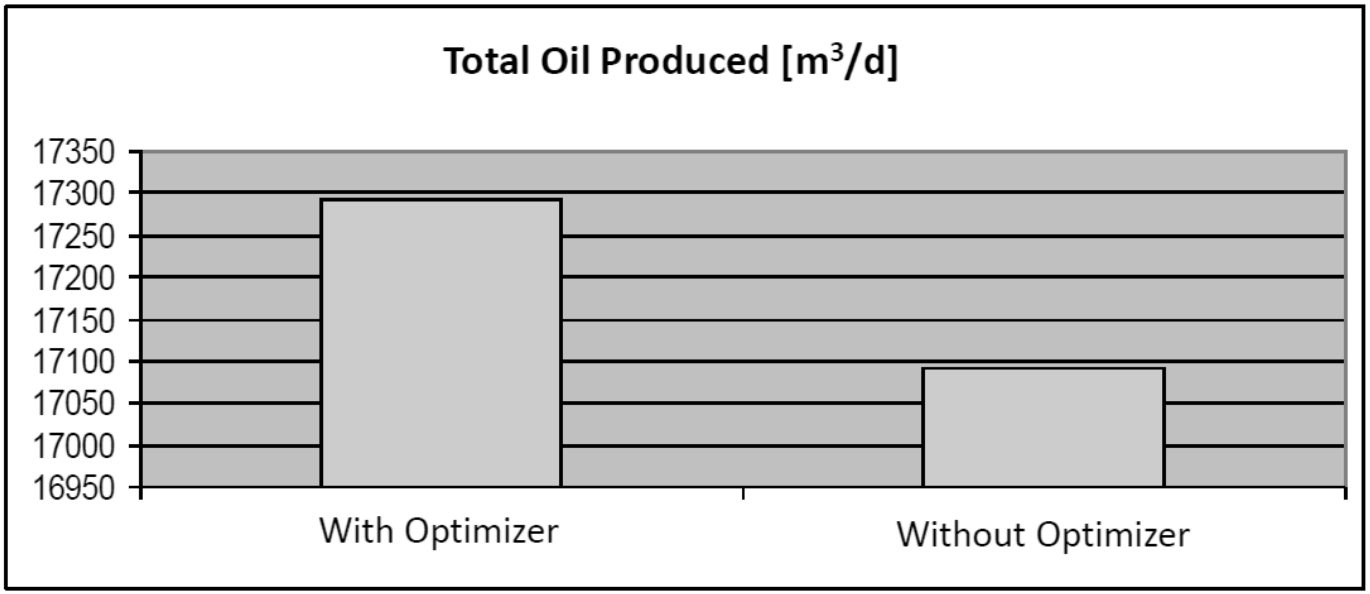
- Linearization and convexification of the optimization problem makes **SmartOpt SOS2** the most robust approach
- Almost convex proxy models makes **SmartOpt algebraic** method essentially independent of initial starting point

Computational study and results indicate that SmartOpt performs well compared to traditional approach

	Solution approach	Discrete decisions	Component simulators	Model exactness	Solution time/ scalability	Solution quality	Robustness	Modelling effort	Automation
	Black- Box	÷	÷	--	÷	+	÷	+	++
	2-layer	+	÷	--	÷	+	÷	+	++
SmartOpt	Linear interpolation	++	++	+	++	++	÷	+	++
SmartOpt	Cubic spline interpolation	++	++	++	++	++	++	+	++
SmartOpt	Algebraic	++	++	÷	+	+	++	÷	+
SmartOpt	SOS2	++	++	+	÷	++	++	++	++

Petrobras decides to implement a SmartOpt SOS2 model to optimize gas lift allocation among 13 wells

Petrobras field test of SmartOpt MILP model



Alex Teixeira 2013, Petrobras

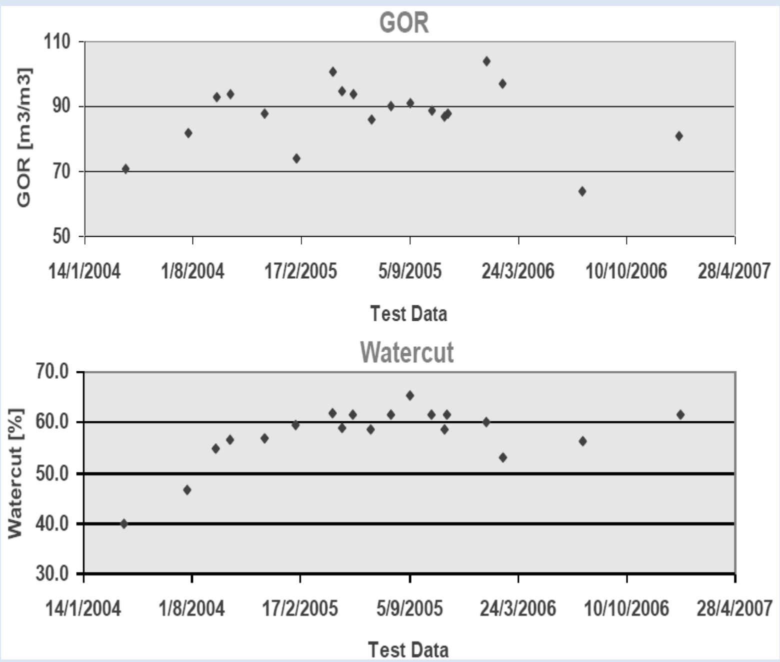
Campos basin - 1.2 % increased production

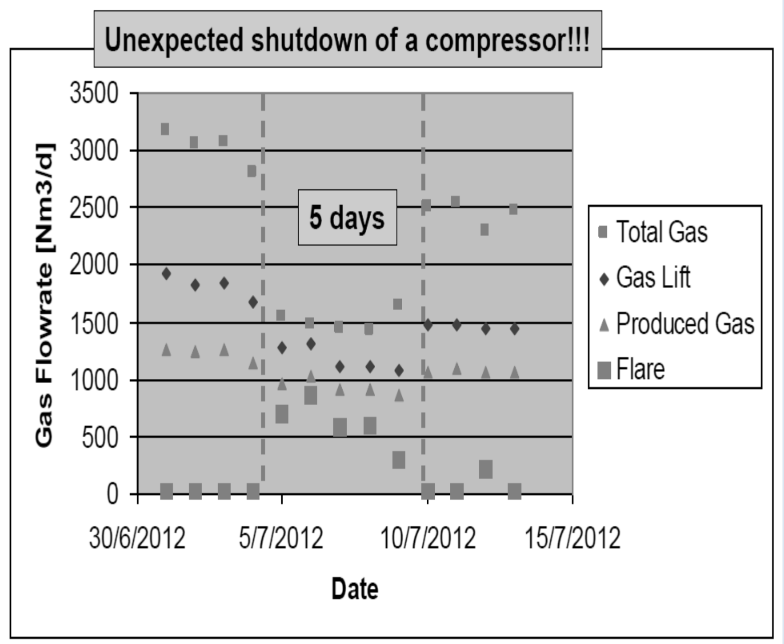
CENTER

Petrobras decides to implement a SmartOpt SOS2 model to optimize gas lift allocation among 13 wells

GOR and water cut evolution, and unexpected compressor shut downs

Why is it difficult to find the best production settings manually?





Alex Teixeira 2013, Petrobras

…because wells and operational conditions changes all the time.

IO CENTER