Norwegian University of Science and Technology

Project + Guest lecture

Eksamen: 14. og 15. desember

2023-12-14 09:00	Fosmo, Pål Ivar Delphin Kværnø
2023-12-14 09:00	Foss, Peder Josef Sjøgreen
2023-12-14 09:00	Rasmussen, Vetle Skifjeld
2023-12-14 09:00	Sivarasa, Sivaranjith
2023-12-14 09:00	Sommerud, Erland Schjatvet
2023-12-14 15:00	Fjalestad, Torleiv Skovgaard
2023-12-14 15:00	Gude, Tore
2023-12-14 15:00	Langklopp, Markus
2023-12-14 15:00	Prytz, Elias
2023-12-14 15:00	Trøen, Jørgen By
2023-12-15 09:00	Haughom, Håvard Sinnes
2023-12-15 09:00	Høksnes, Håkon Skau
2023-12-15 09:00	Pedersen, Aurora Åsgård
2023-12-15 09:00	Stokkeland, Andreas
2023-12-15 09:00	Sveen, Marit Skarderud
2023-12-15 15:00	Hanisch, Halvard Hodne
2023-12-15 15:00	Løver, Sondre



Main exam topics

- Modeling of MILP problems
- Solving MILP problems: Relaxations, B&B, cutting planes (principles)
- PWL modeling (from project)

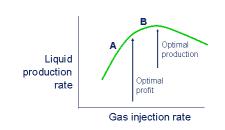
Project work

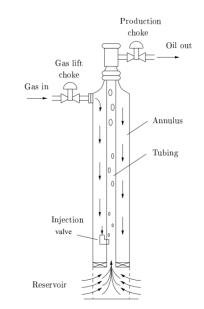
- Groups or individual
- Cooperation OK
- "Deliverable": Code + Illustration of results

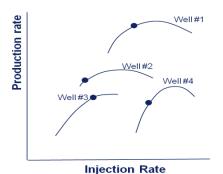
- Deadline: November 24?
 - I will set up meeting to discuss results

Gas lift optimization

- Gas lift is used for increasing production from oil wells with insufficient reservoir pressure
- A single well has typically a 'gas lift performance curve'
- An offshore oil platform has typically many wells, but not enough 'lift gas' for optimal production from each well
 - Constrained optimization problem!
- Challenge: We do not know the gas lift performance curve...
 - But we can try to measure it using test separator

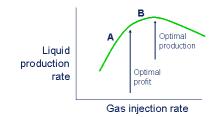






Project assignment

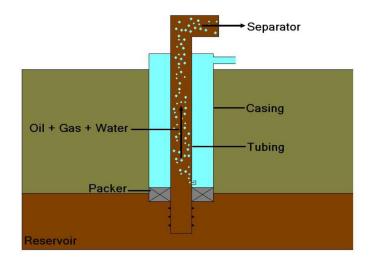
- Use 'sampled' gas lift performance curves to solve the production optimization problem using MILP
- Use piecewise linear representations to embed the gas lift performance curves in the optimization problem



 $P_1: \max \sum \widehat{q}_0^n$ s.t. $\sum q_{\rm inj}^n \le q_{\rm inj}^{\rm max}$ $\sum (q_{\mathbf{w}}^n + \widehat{q}_{\mathbf{o}}^n) \le q_{\mathbf{liq}}^{\mathbf{max}}$ $\sum \left(q_{\rm inj}^n + q_{\rm g}^n \right) \le q_{\rm g}^{\rm max}$ $\begin{cases} q_{\mathbf{g}}^{n} = \gamma_{\mathbf{g}}^{n} \cdot \widehat{q}_{\mathbf{o}}^{n} \\ q_{\mathbf{w}}^{n} = \frac{\gamma_{\mathbf{g}}^{n}}{1 - \gamma^{n}} \widehat{q}_{\mathbf{o}}^{n} \end{cases}, n \in \mathcal{N}$ $\begin{cases} \hat{q}_{o}^{n} = q_{o}^{n}(q_{\text{inj}}^{n}) \\ \hat{q}_{o}^{n} < q_{o}^{\max,n}y^{n} \end{cases}, n \in \mathcal{N}$ $q_{\text{ini}}^{\min,n} \cdot y^n \leq q_{\text{ini}}^n \leq q_{\text{ini}}^{\max,n} \cdot y^n, n \in \mathcal{N}$ $y^n \in \{0, 1\}, n \in \mathcal{N}$

Piecewise-Linear Approximation

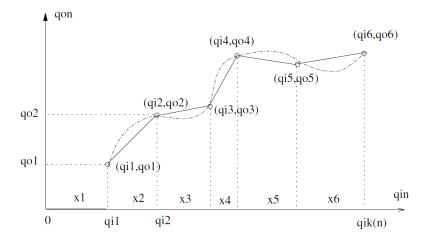
Models are obtained from linear (affine) combination of input-output data: $q_{oil}(q_{inj})$.





Piecewise-Linear Approximation

- Models are obtained from linear (affine) combination of input-output data: $q_{oil}(q_{ini})$.
- ▶ Data: $\{(q_{inj}^1, q_{oil}^1), (q_{inj}^2, q_{oil}^2), \dots, (q_{inj}^n, q_{oil}^n)\}.$



Convex Combination (CC)

Givens: $\{(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)\}.$

$$x = \sum_{i=0}^{n} \lambda_i x_i$$

$$1 = \sum_{i=0}^{n} \lambda_i$$

$$y = \sum_{i=0}^{n} \lambda_i y_i$$

$$\lambda_i \geq 0, \ i = 0, \dots, n$$

$$1 = \sum_{i=1}^{n} z_i \qquad z_i \in \{0, 1\}, \ i = 1, \dots, n$$

$$\lambda_0 \leq z_1$$
 $\lambda_n \leq z_n$

$$\lambda_0 \leq z_1$$
 $\lambda_i \leq z_i + z_{i+1}, i = 1, \ldots, n-1$

Remark: $z_i = 1$ if $x \in [x_{i-1}, x_i]$.

Piecewise-Linear Model Based on SOS2

Givens: $\{(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)\}.$

$$x = \sum_{i=0}^{n} \lambda_i x_i$$

$$y = \sum_{i=0}^{n} \lambda_i y_i$$

$$1 = \sum_{i=0}^{n} \lambda_i$$

$$\lambda_i \geq 0, i = 0, \ldots, n$$

$$\{\lambda_i\}_{i=0}^n$$
 is SOS2

