DEEP LEARNING TECHNIQUES FOR GAS WELL PRODUCTION OPTIMIZATION

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DYNAMIC PROCESSES

- **Start-up**
  - Well storage effect.
  - Liquid entering the well; liquid film build-up.
  - Pressure profile build-up in reservoir.

- **Production**
  - Loading/flooding.
  - Intermittent production.

- **Shut-in**
  - Liquid film drainage.
  - Liquid injection into reservoir.
  - Gas pressurization in well.
  - Re-pressurization.
PROJECTS OVERVIEW

› Upgrade knowledge/predictability of start-up/shut-in of wells.
  › 2018: numerical modelling dynamic reservoir.
  › 2018: build multi-tank model for optimization of intermittent production.

› 2019-2020
  › Experimental validation (inflow; EoT position).
  › Experimental validation (start-up/shut-in/batch foam).
  › Data analysis field data
    › Automatic fitting tank model.
    › **Fully data-driven optimization.**
Two main activities presented in this presentation:
  - Virtual metering/back-allocation.
  - Intermittent production: data-driven production optimization.

Why Machine/Deep Learning?
  - Physical models or experimental data may not be feasible/available (complex non-linear dynamics, absence of sensors, costs…).
  - Significant amount of field data available for many processes: opportunity.

TNO is working/has worked extensively with Machine Learning for Oil and Gas.
  - Slugging prediction and characterization.
  - Data-driven slugging control.
  - Well event detection.
  - Well dynamics.
  - Virtual metering.
  - And more…
DEEP LEARNING

- Deep learning applied to our field is composed of three areas:
  - **Data Science**: gather necessary data (field/synthetic).
  - **Algorithms, workflows, software**: tools trained on gathered data: predict, forecast, detect anomalies…
  - **Domain knowledge**: interpret results, choose *not just big data, but relevant data.*

Deep Learning model

- Features: $P_{wh}$, $X_{choke}$, $GL_{pres}$
- $Q_{gas}$

Cumulative production error $= 0.21\%$
DEEP LEARNING

› **Multilayer Perceptron (MLP).**
  › Universal Function Approximator.
  › Functional mapping of inputs to outputs.
  › Can be simple yet powerful.
  › No explicit time dependency.

› **Recurrent Neural Networks (RNNs).**
  › Receives feedbacks from states in previous time step.
  › Explicit time dependency.
  › Tendency to overfit, even when regularized.
PART 1: VIRTUAL METERING AND BACK-ALLOCATION

Part 1: Virtual metering and back-allocation.

Part 2: Intermittent production optimization.
1.A. VIRTUAL METERING

Part 1: Virtual metering and back-allocation
  1.a. – Virtual metering.
  1.b. – Back-allocation.

Part 2: Intermittent production optimization.
  2.a. $Q_{gas}$ current time step monitoring.
  2.b. - $Q_{gas}$ future time steps prediction.
VIRTUAL FLOW METERING & BACK-ALLOCATION

- Multiphase flowrates:
  - Periodic: individual well tests, separator tests.
  - Continuous: total production rates (back-allocation).

- How to monitor liquid/gas rates in the absence of (multiphase) meters?

- Current approaches:
  - Physical models (reservoir, well and choke).
  - Multiphase choke model.
  - Well dynamics at well shut-in and start-up.
  - Pressure drop and vibrations over a U-bend.
  - Pressure drop over a choke valve.
  - Choke noise.

- Can we use Deep Learning to construct a virtual flow meter?
VIRTUAL FLOW METERING USING DEEP LEARNING

- Accurate, fast and robust method for multiphase flow rate estimation.
- Dynamics production (changes in GOR, LGR, WCT, reservoir depletion, additional skin and resistances (due scaling, deposits, ...).
- Pilot in several gas wells in the North-Sea.

- MLP under-predicts the liquid rate but RNN was accurate in predicting the liquid rate (relative error < 1%).
1.B. BACK-ALLOCATION

- Part 1: Virtual metering and back-allocation
  - 1.a. – Virtual metering.
  - 1.b. – Back-allocation.

- Part 2: Intermittent production optimization.
  - 2.a. $Q_{gas}$ current time step monitoring.
  - 2.b. $Q_{gas}$ future time steps prediction.
DATA-DRIVEN BACK-ALLOCATION (1/2)

Challenge:

- Determine the production rate of individual wells based on the total asset production rates (export line).

Available data:

- Continuous: P, T, Choke data each well, total production rate.
- Periodic: test separator or well test data.

Approach:

- Training artificial neural networks to predict the total production rates.
- Simplified approach to determine the back-allocation factors.

- 4 wells, 4 parameters per well (choke, pressure, 2 X temperature): 16 features.
DATA-DRIVEN BACK-ALLOCATION (2/2)

- ANN trained on hourly data for a period of 1 year.
- 15 neurons in the hidden layer.
- 1 Output: total gas flow rate.
- Trained model tested on 300 hours of a single well production data, even with highly transient periods.

Result:
- Simple, robust and accurate model for prediction of individual well production rates (capturing transients).
- Accurate prediction of single well flow rates (94%).
PART 2: INTERMITTENT PRODUCTION OPTIMIZATION

› Part 1: Virtual metering and back-allocation.

› Part 2: Intermittent production optimization.
INTERMITTENT PRODUCTION OPTIMIZATION

- Liquid loading can lead to decreased and/or unstable gas production.
- Well is shut-in, liquid drains back into the reservoir.
- When sufficient liquid has been drained, well can be restarted.

Several questions:

- When should we stop producing?
- How long should the shut-in last?
- Are similarly long cycles or very different lengths (e.g., short + long cycles) preferred?

Deep Learning + optimization can provide answers:

- Deep Learning model predicts future gas production.
- Optimization algorithm uses ANN models to choose the best start-up/shut-in pattern for a given timeframe.
INTERMITTENT PRODUCTION OPTIMIZATION: STEPS

- **Build knowledge step by step.**
  - 2.a. $Q_{gas}$ monitoring of current time step.
  - 2.b. Future $Q_{gas}$ prediction.
    - Constant start-up/shut-in.
    - Variable start-up/shut/in.
    - Variable + liquid loading/meta-stable regimes.

- Synthetic data (OLGA-ROCX).
- MLP network.
  - Simple ANNs (1-2 layers, 20-40 neurons each).
  - Trained using around 60 days of data.
2.A. $Q_{gas}$ CURRENT MONITORING

- Part 1: Virtual metering and back-allocation
  - 1.a. – Virtual metering.
  - 1.b. – Back-allocation.

- Part 2: Intermittent production optimization.
  - 2.a. $Q_{gas}$ current time step monitoring.
  - 2.b. - $Q_{gas}$ future time steps prediction.
NAIVE APPROACH MIGHT NOT WORK

- **Step 1:** monitor $Q_{gas}$ at current time step using well pressures and choke opening.

- Dataset: constant start-up/shut-in times (1 day).

- Train ANN with 60% of data.

- Naive approach does not capture dynamics.
  - Meta-stable region was not seen in training, ANN thinks that it should keep producing.
DOMAIN KNOWLEDGE IS KEY

- Baseline ($PFL + PDH + PWH + X_{choke}$).
- Best so far (Baseline + $\sqrt{PFL} + t_{cum_{shut\,in}} + Q_{gas_{cum}} + Q_{gas_{cum\,cycle}}$).

Domain knowledge significantly improves results.

Testing phase, prediction of 0 samples ahead
2.B. $Q_{gas}$ FUTURE PREDICTION

Part 1: Virtual metering and back-allocation

1.a. – Virtual metering.
1.b. – Back-allocation.

Part 2: Intermittent production optimization.

2.a. $Q_{gas}$ current time step monitoring.
2.b. - $Q_{gas}$ future time steps prediction.
STEP 2: WHAT ABOUT PREDICTING THE FUTURE?

› Goal: predict future cumulative gas production for a given timeframe.

› Predicting the future can be challenging:
  › Pressure information is not available.
  › Only choke opening can be prescribed.

› ANN input: prescribed choke opening for a given period (e.g. 50 days).
› ANN output: cumulative production for that period.

Goal:

Predicting the future can be challenging:
- Pressure information is not available.
- Only choke opening can be prescribed.

ANN input: prescribed choke opening for a given period (e.g. 50 days).
ANN output: cumulative production for that period.

Step 2:
Cumulative production future prediction

Inputs:
- $X_{c1:end}$
- $Q_{gas}$
- $Q_{gas_{cum}_{k-1}}$
- Others (cycle, cumulative)

ANN (feedforward)

Output:
- $Q_{gas_{cum}_k}$

Loop from $t = 1$ to end of period
CONSTANT START-UP/SHUT-IN

- Proof-of-concept with constant opening/shut-in times.
- Model trained with 80% of data, we let it predict the next 18 days.
- Very good fit, 0.21% of total production error.
VARIABLE START-UP/SHUT-IN

- Being fair, it was a case a bit too easy.
- What about having different cycle lengths?
  - Train/test cycle lengths are now different.
- **ANN keeps performing well:**
  - While peak just at start-up not captured…
  - **Cumulative production error around 0.4%.**
Tests before did not show significant liquid loading and decreased production.

How does our ANN behave with **noisy data with significant liquid loading**?

- New dataset between liquid loading and meta-stable regimes.
- ANN is able to capture the physics, regressing over the noisy data.

**Cumulative production error of around 1.3%**.
CONCLUSIONS
CONCLUSIONS

Virtual flow metering and back-allocation:

RNN predicts liquid flowrates with less than 1% of relative error, time-dependencies are important.

Back-allocation:

ANNS predict single well flowrates with 94% accuracy.

Intermittent production optimization:

Current time step monitoring:

Domain knowledge is key: naive approach might result in significant overfit/non-physical results.

Future time steps forecasting:

1.3% of cumulative gas production error for liquid loading/meta-stable dataset.
ONE MORE THING...
ONE MORE THING...
2.C. – FULLY DATA-DRIVEN OPTIMIZATION

› Part 1: Virtual metering and back-allocation
  › 1.a. – Virtual metering.
  › 1.b. – Back-allocation.

› Part 2: Intermittent production optimization.
  › 2.a. - $Q_{gas}$ current time step monitoring.
  › 2.b. - $Q_{gas}$ future time steps prediction.
  › 2.c. – Fully data-driven intermittent production optimization.
ONE MORE THING...

For a given time period, **what is the optimum amount of cycles and their length distribution to maximize production?**

- Couple ANN with numerical optimizer and obtain optimum $X_{\text{choke}}$ adding physical constraints.
- **Current work in progress.**
First test (50 days optimization) using OLGA-ROCX dataset with liquid loading/meta-stable regimes.

Around 17% increase in production (in this case) in only 50 days for adding more (shorter) cycles.

Last, but not least... **test this algorithm on field data.**
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