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DEEP LEARNING TECHNIQUES FOR GAS WELL PRODUCTION OPTIMIZATION

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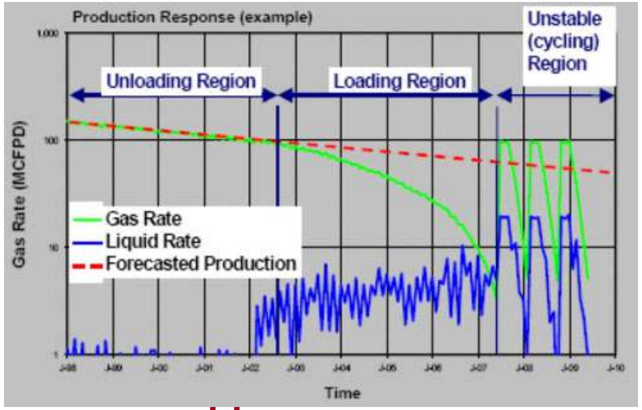
TNO innovation for life

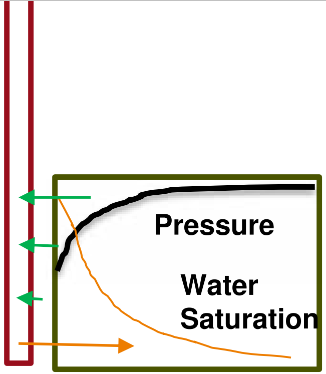
DYNAMIC PROCESSES

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

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

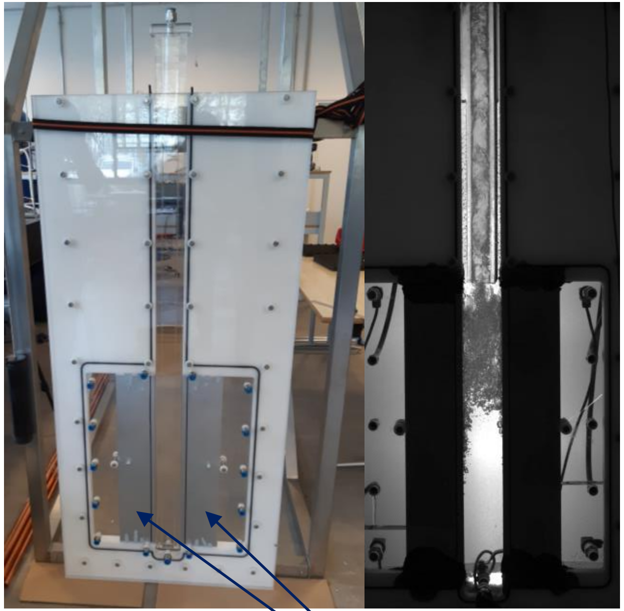
- **Shut-in**
  - Liquid film drainage.
  - Liquid injection into reservoir.
  - Gas pressurization in well.
  - Re-pressurization.





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.
      - ***<u>Fully data-driven optimization.</u>***



MACHINE/DEEP LEARNING + DOMAIN KNOWLEDGE

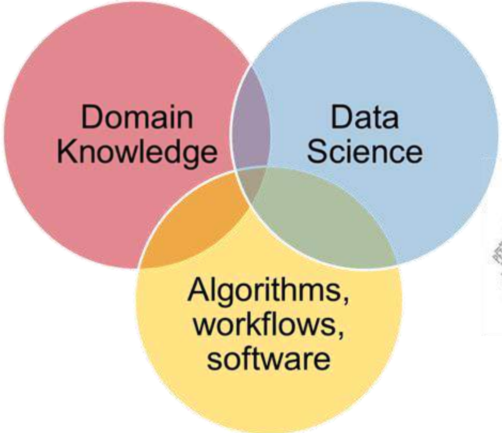
- **Two main activities presented in this presentation:**
  - Virtual metering/back-allocation.
  - Intermittent production: data-driven production optimization.

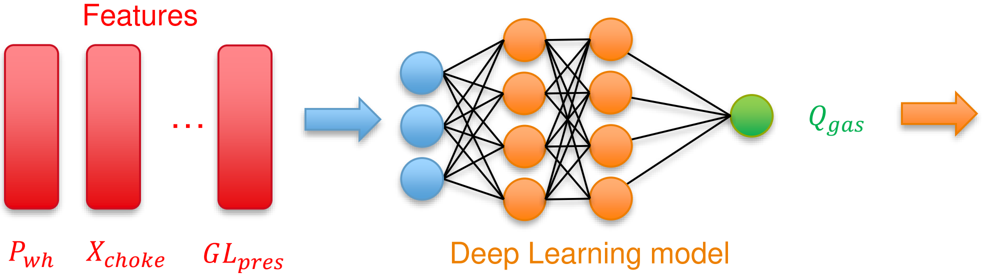
- **Why Machine/Deep Learning?**
  - Physical models or experimental data may not be feasible/available (complex non-linear dynamics, absence of sensors, costs…).
  - Significant amount of field data available for many processes: *opportunity.*

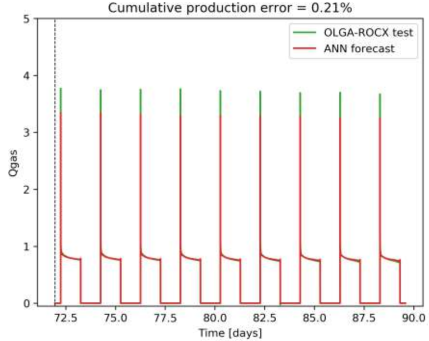
- **TNO is working/has worked extensively with Machine Learning for Oil and Gas.**
  - Slugging prediction and characterization.
  - Data-driven slugging control.
  - Well event detection.
  - Well dynamics.
  - Virtual metering.
  - And more…

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.*

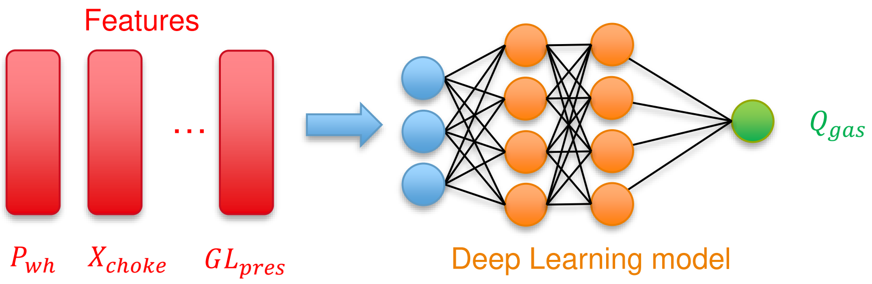




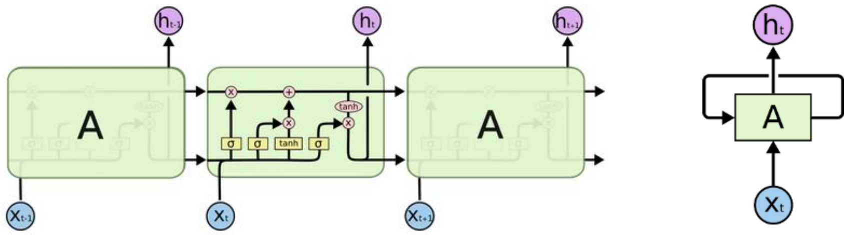


DEEP LEARNING

- **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.

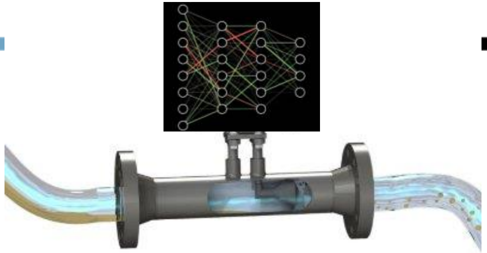
VIRTUAL FLOW METERING & BACK-ALLOCATION

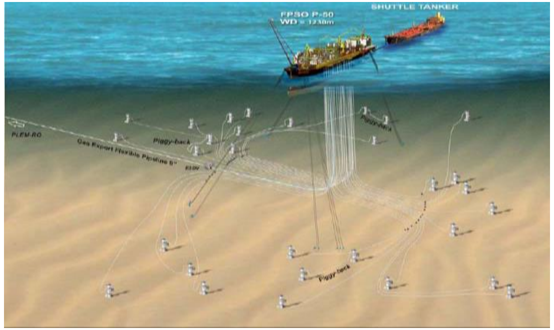
- Multiphase flowrates:
  - Periodic: individual well tests, separator tests.
  - Continuous: total production rates (back-allocation).

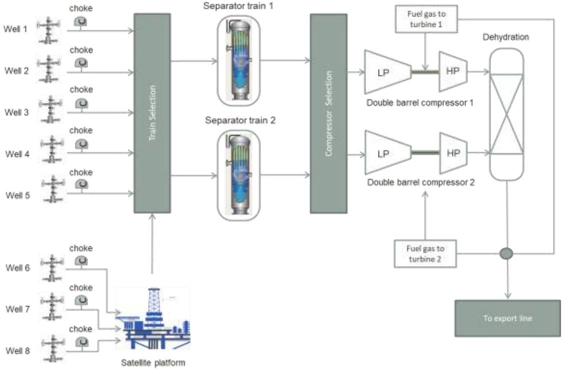
- **How to monitor liquid/gas rates in the absence of (multiphase) meters?**

- 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?***

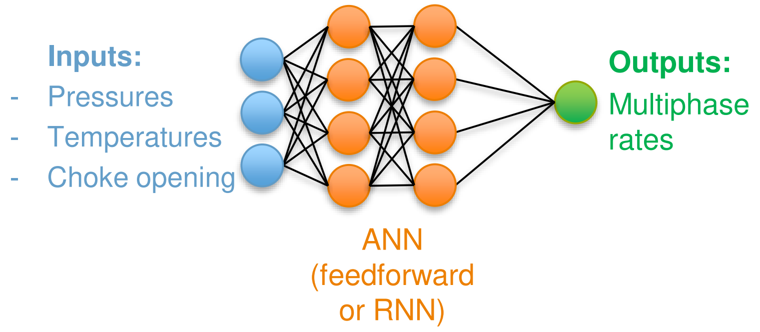


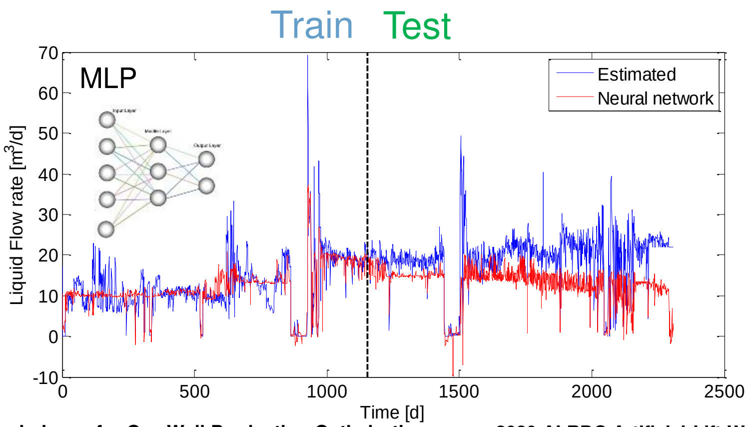


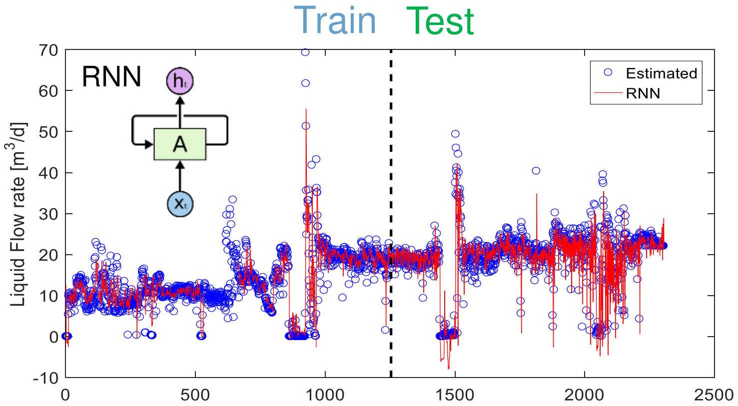


VIRTUAL FLOW METERING USING DEEP LEARNING

- 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%**).





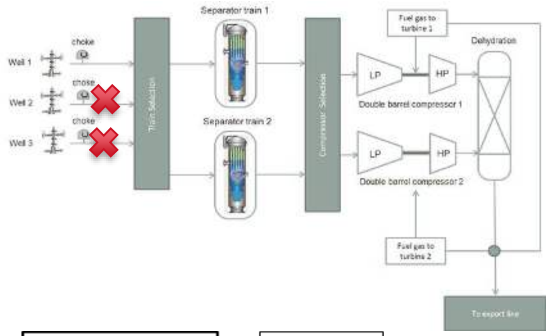


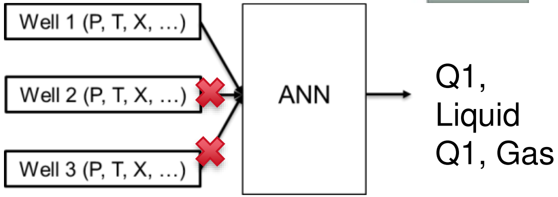
1.B. BACK-ALLOCATION

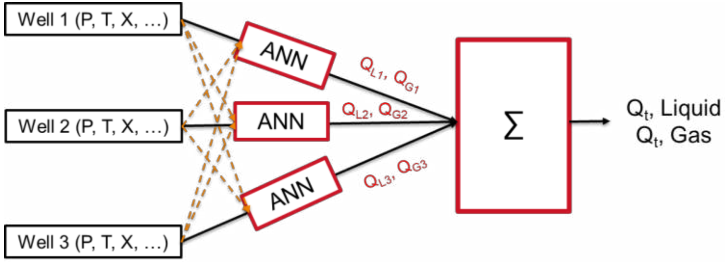
- **Part 1: Virtual metering and back-allocation**
  - 1.a. – Virtual metering.
  - 1.b. – Back-allocation.
- **Part 2: Intermittent production optimization**.
  - 2.a. Q_{gas} current time step monitoring.
  - 2.b. - Q_{gas} future time steps prediction.

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.

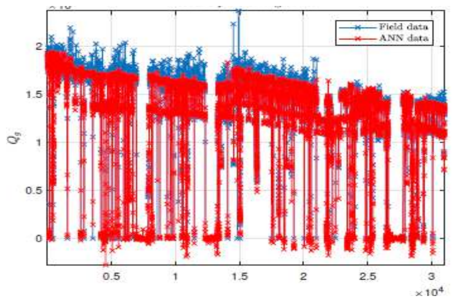


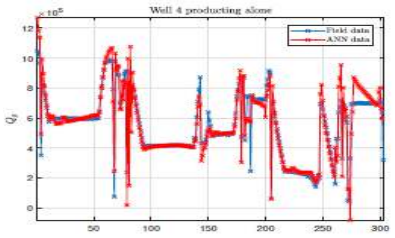


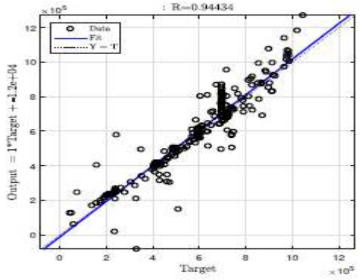


DATA-DRIVEN BACK-ALLOCATION (2/2)

- 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 (**<u>94%</u>**).

PART 2: INTERMITTENT PRODUCTION OPTIMIZATION

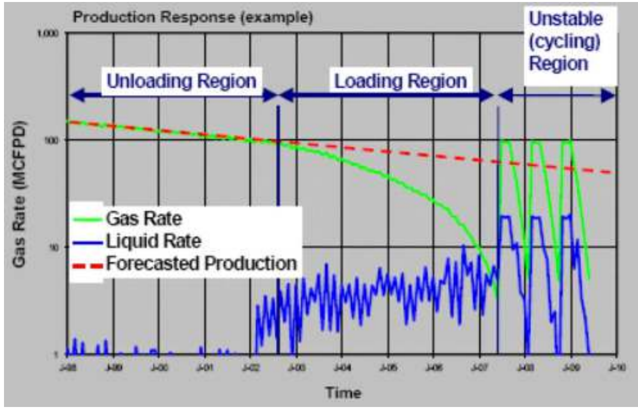
- Part 1: Virtual metering and back-allocation.
- Part 2: Intermittent production optimization.

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?*

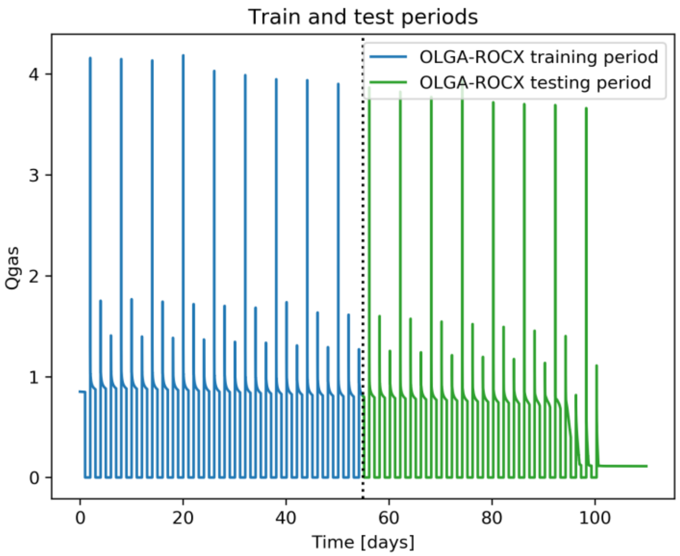
- **Deep Learning + optimization can provide answers:**
  - Deep Learning model predicts future gas production.
  - Optimization algorithm uses ANN models to choose the best start-up/shut-in pattern for a given timeframe.



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.
  - 2.c. Fully data-driven production optimization (in progress).

- Synthetic data (OLGA-ROCX).
- MLP network.
  - Simple ANNs (1-2 layers, 20-40 neurons each).
  - Trained using around 60 days of data.



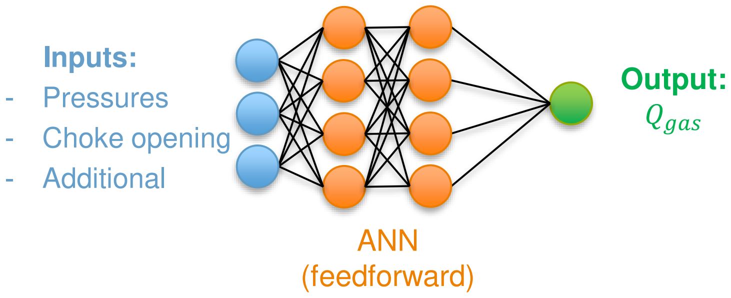
2.A. Q_{gas} CURRENT MONITORING

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

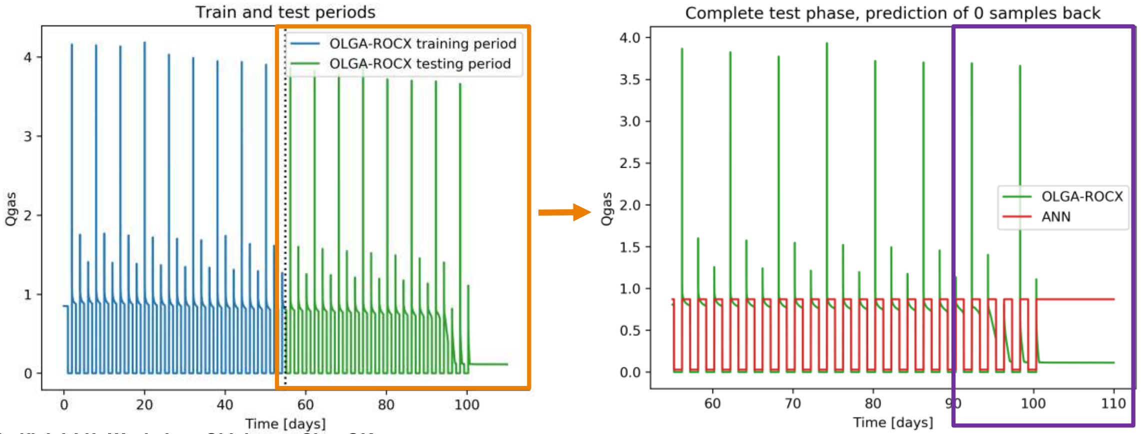
- **Part 2: Intermittent production optimization.**
  - 2.a. Q_{gas} current time step monitoring.
  - 2.b. - Q_{gas} future time steps prediction.

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.

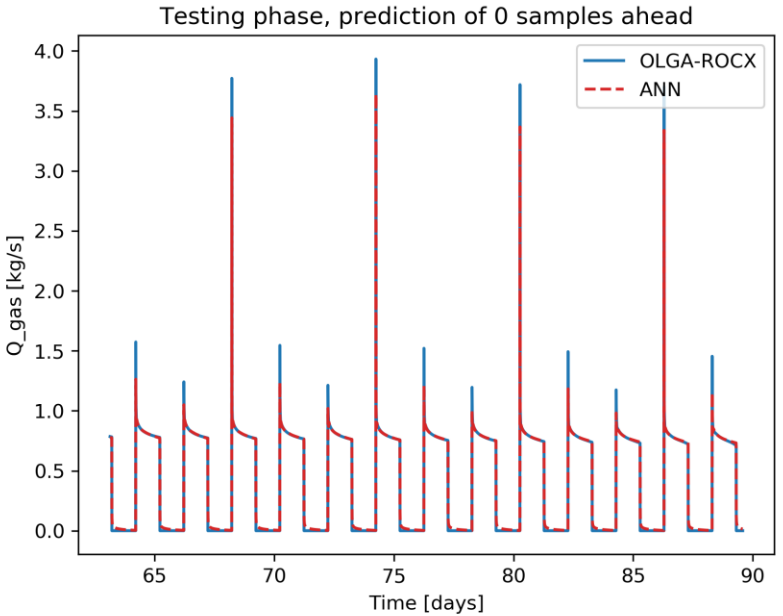


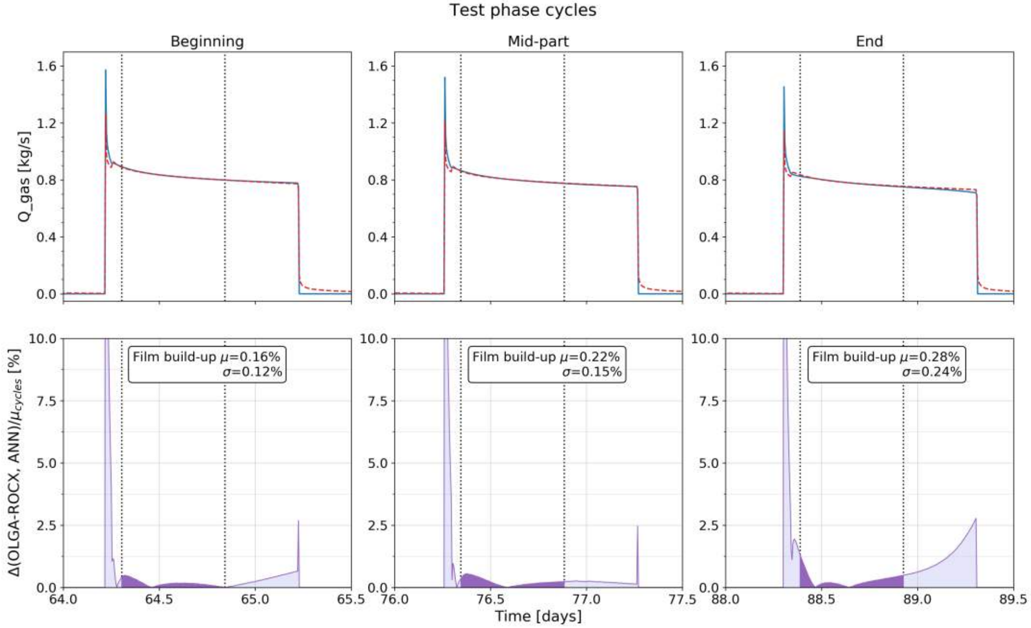
Step 1:
Monitoring of *current time step*



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.*





2.B. Q_{gas} FUTURE PREDICTION

- **Part 1: Virtual metering and back-allocation**
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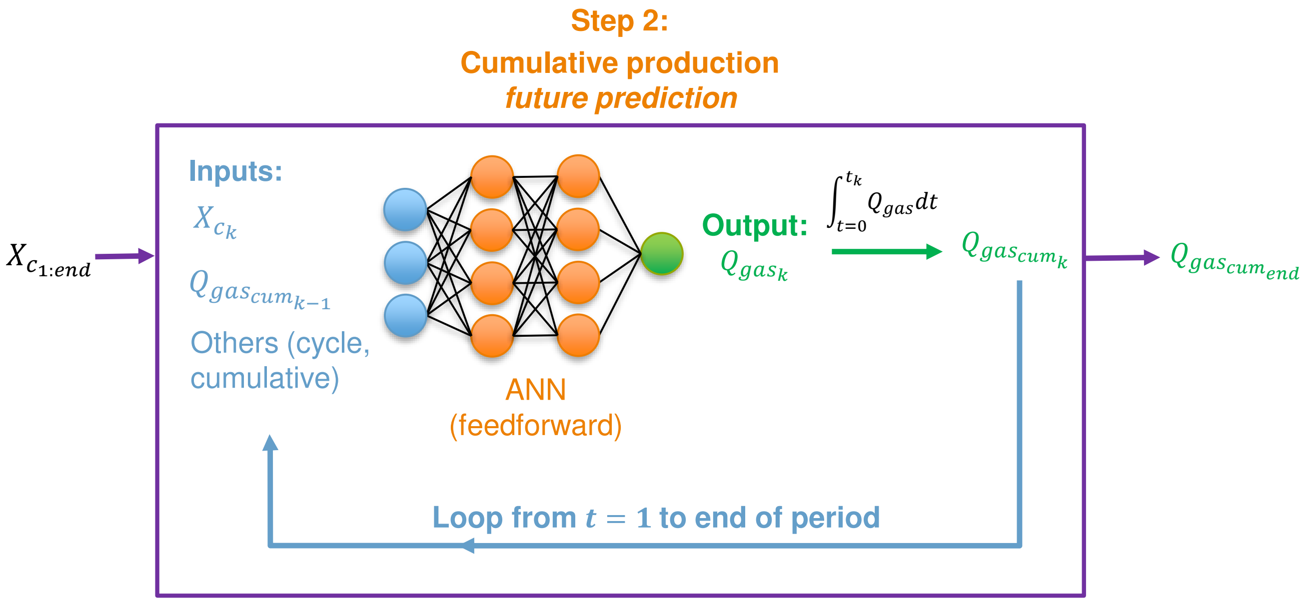
STEP 2: WHAT ABOUT PREDICTING THE FUTURE?

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

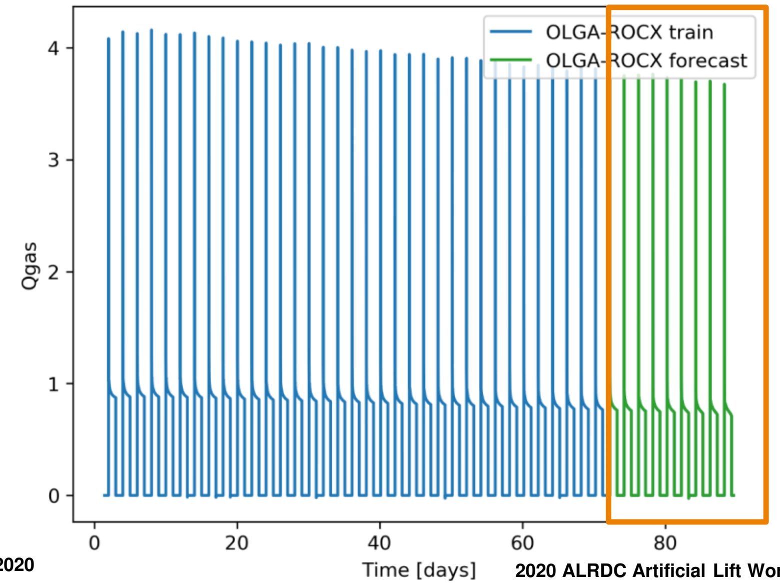
- Predicting the future can be challenging:
  - Pressure information is not available.
  - Only choke opening can be prescribed.

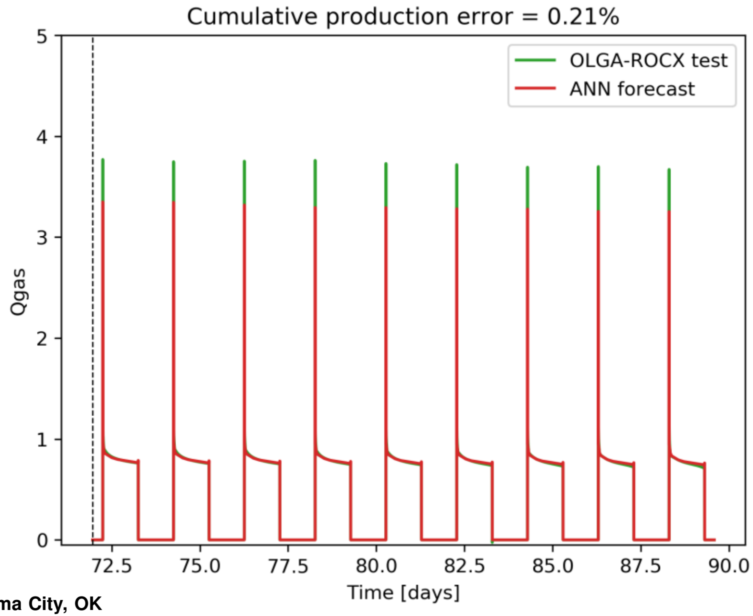
- ANN input: prescribed choke opening for a given period (e.g. 50 days).
- ANN output: cumulative production for that period.



CONSTANT START-UP/SHUT-IN

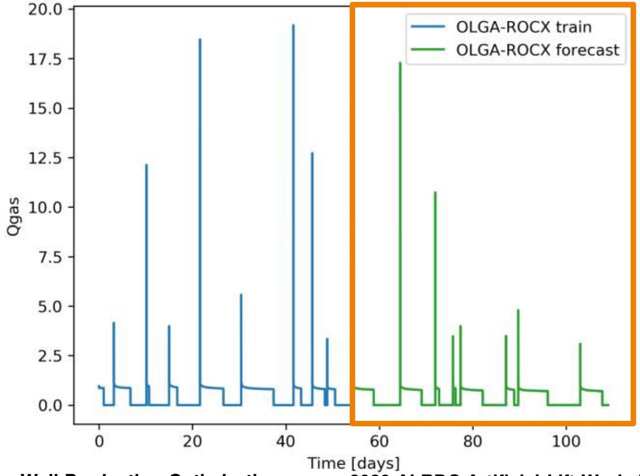
- Proof-of-concept with constant opening/shut-in times.
- Model trained with 80% of data, we let it predict the next 18 days.
- ***Very* good fit, 0.21% of total production error.**

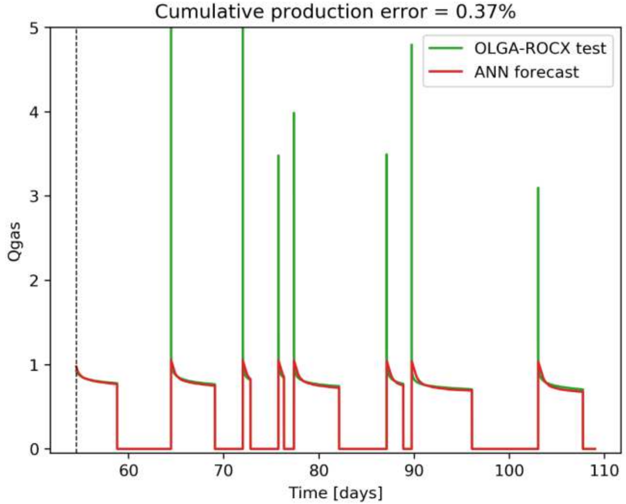




VARIABLE START-UP/SHUT-IN

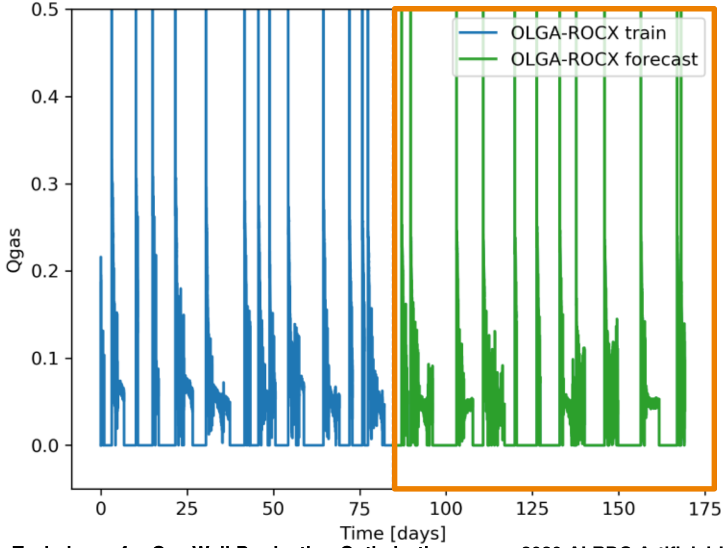
- Being fair, it was a case a bit too easy.
- What about having different cycle lengths?
  - Train/test cycle lengths are now different.
- **ANN keeps performing well:**
  - While peak just at start-up not captured….
  - **Cumulative production error around 0.4%.**

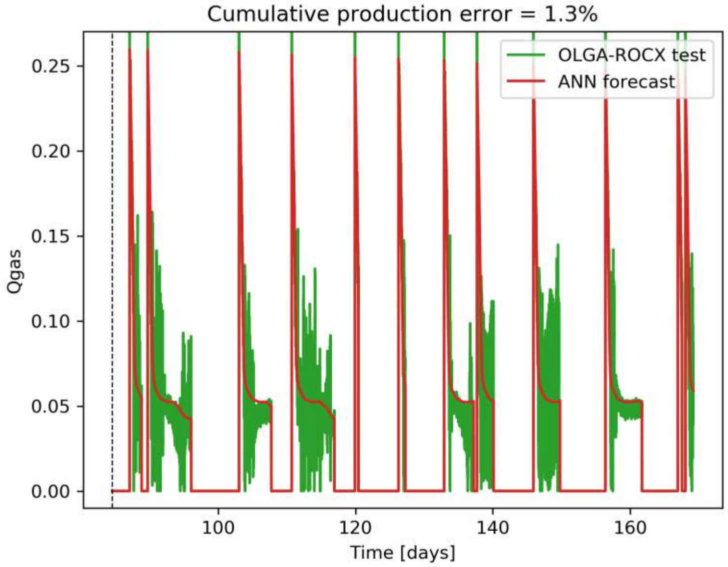




DIFFERENT FLOW REGIMES

- 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:**
  - Virtual flow metering:
    - 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
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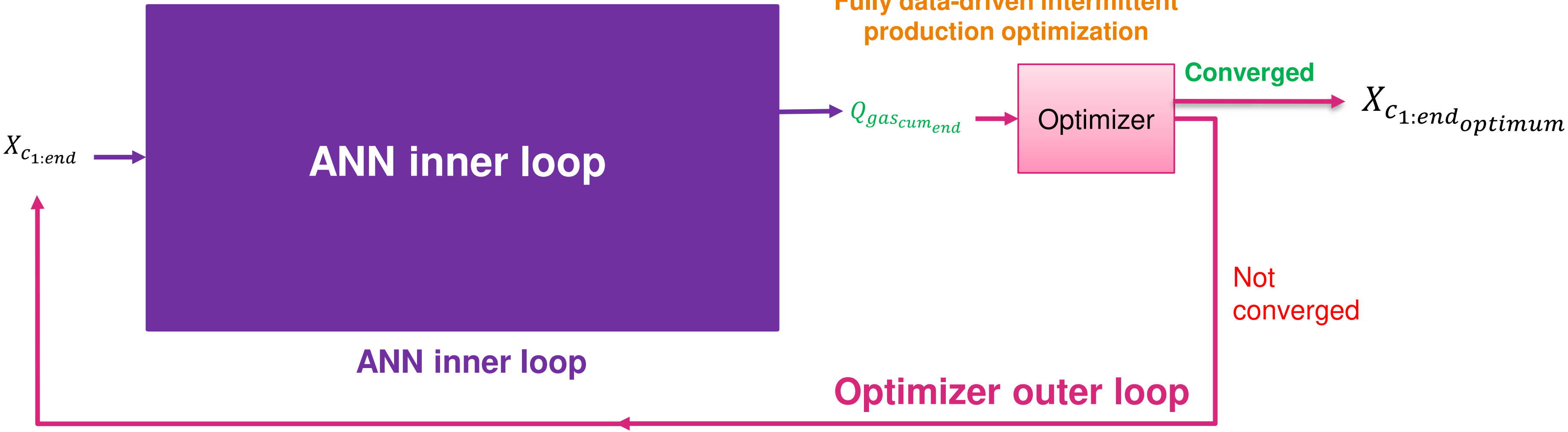
- **Part 2: Intermittent production optimization**.
  - 2.a. - Q_{gas} current time step monitoring.
  - 2.b. - Q_{gas} future time steps prediction.
  - **2.c. – Fully data-driven intermittent production optimization.**

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_{choke} adding physical constraints.
  - **Current work in progress.**

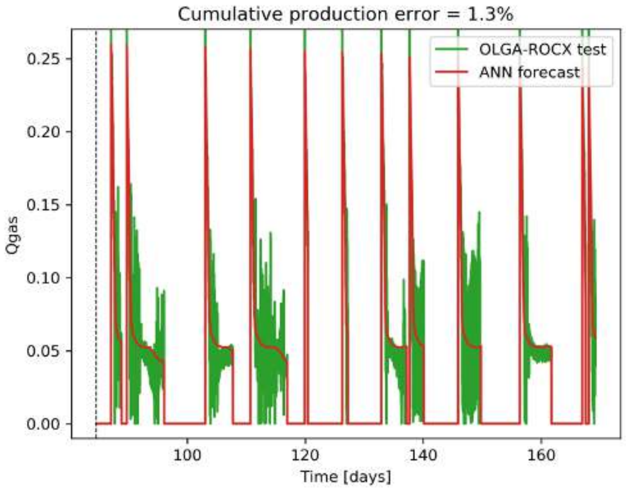
Step 3:
Fully data-driven intermittent production optimization

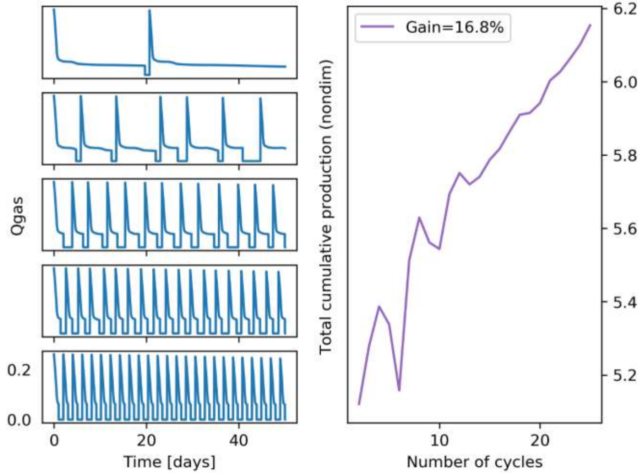


ONE MORE THING…NEXT STEPS

- 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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