Machine Learning / Data Analytics in Flow Assurance

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Machine Learning / Data Analytics in Flow Assurance

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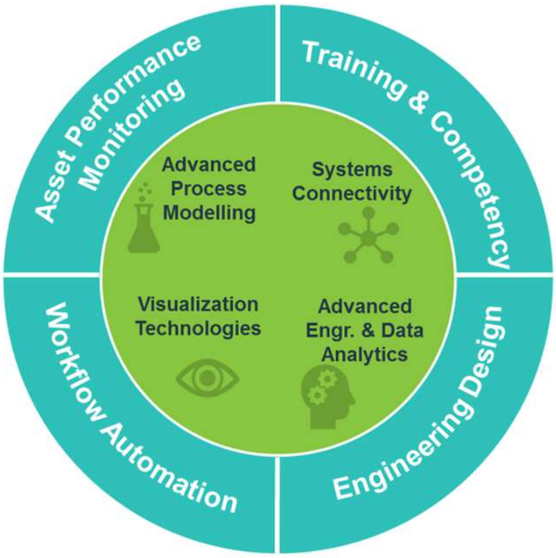
Introduction



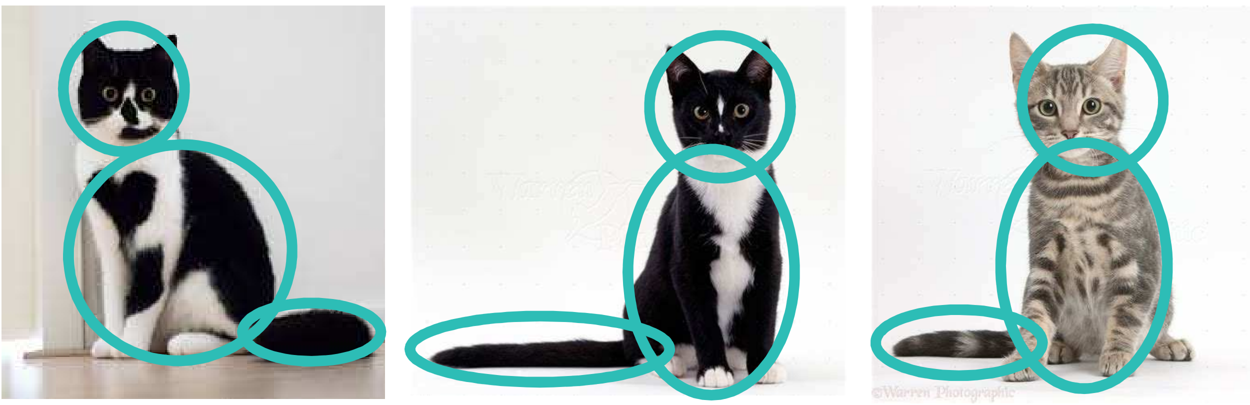
Agenda

Analytics & Machine Learning

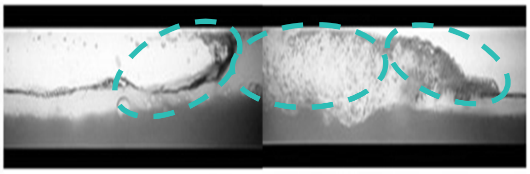
Analytics
Discover patterns in data

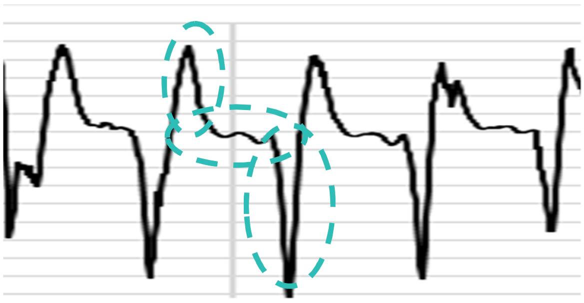
Machine Learning
Learn from patterns to identify relationships

Analytics and Machine Learning

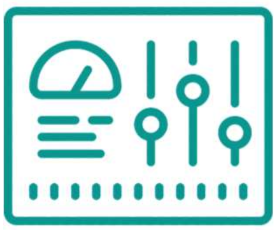


Artificial Intelligence





Flow Assurance Applications



Design Operate Maintain

Flow Assurance Applications

Design

- Automation of workflows
- Reduction in size of analysis
- Analogue information analysis

Operate

- Leak detection systems
- Slug detection and advisory
- Production management systems
- Operator performance tracking and KPIs

Maintain

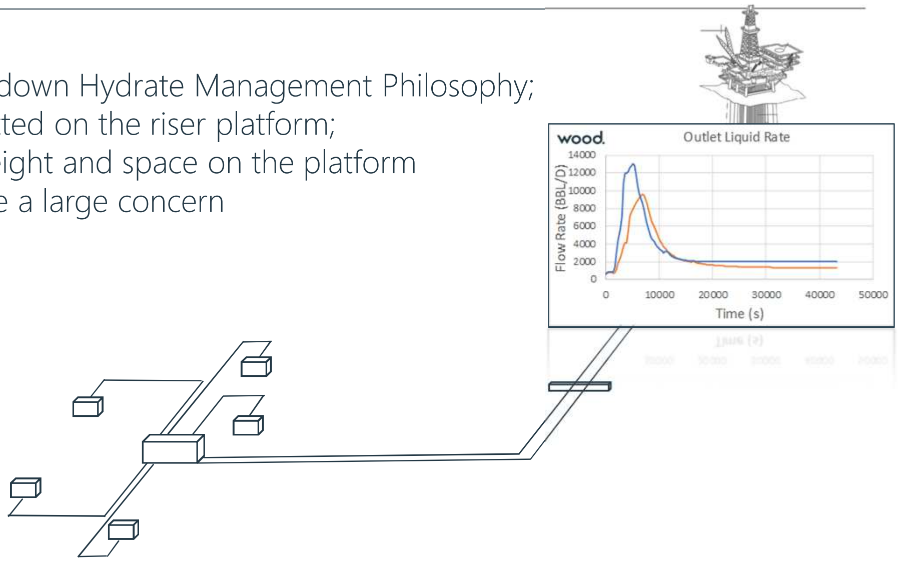
- Spares & maintenance optimization
- Maintenance of software for control and optimization based on real performance
- Root cause analysis

Case Study 1

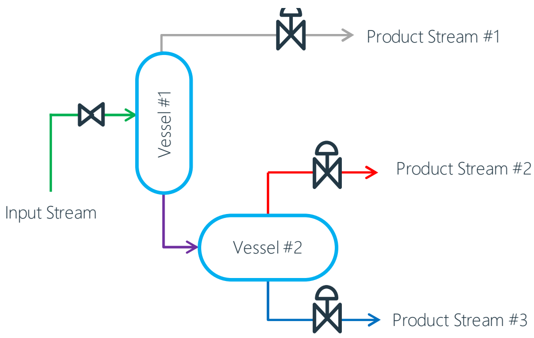
Design

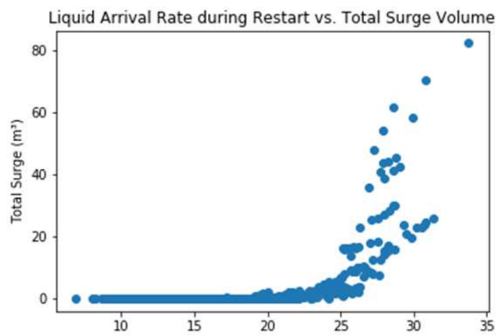
Case 1: The problem

- Insulate and Blowdown Hydrate Management Philosophy;
- Separation retrofitted on the riser platform;
- Limited power, weight and space on the platform
- Surge volumes are a large concern



Case 1: The problem





Complex analysis to size system

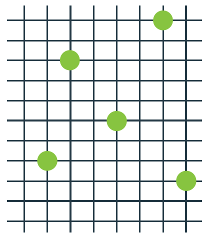
Non-linear system response

Multiple input parameters

Case 1: The problem

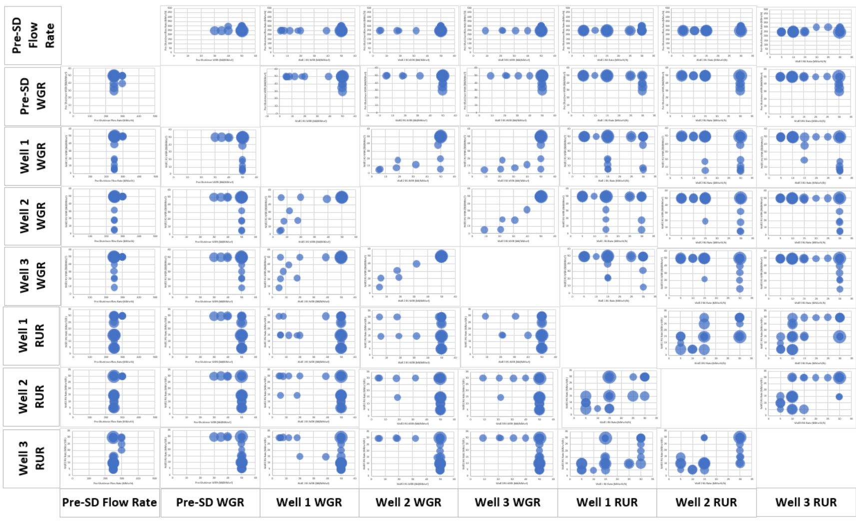
Input features

- Pre-shutdown water-gas ratio (i.e. 10 to 60 units)
- Pre-shutdown flow rates (i.e. 150 to 500 units)
- Restart well water-gas ratio (i.e. 10 to 60 units)
- Well bean-up rates (i.e. 5 to 35 units)



41,472 potential permutations
Cases were simulated in 1-D Dynamic Multiphase Flow Simulator
1 x simulation = 20 mins
41,472 x 10 mins = 290 days (!)

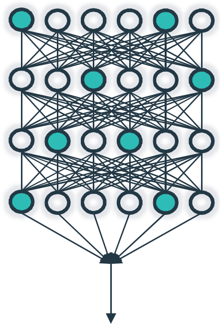
Case 1: Human analytics



Case 1: Machine learning objective & method

Simulation Results

NORMALIZED



Liquid Surge

- Sample data set
- Filter / Normalise data
- Split data set
- Select ML model
- Train ML model
- Check success metrics of trained model
- Run full data set

- Re-train model
- Select different model
- Increase sample data set

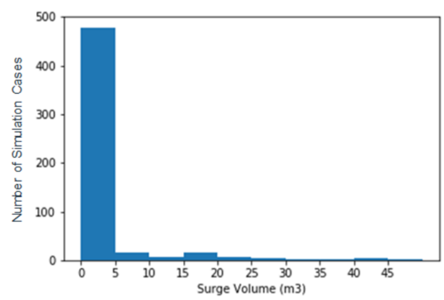
Case 1: First ML algorithm

- 500 simulations input sample;
- 80% to train model and 20% to test model;
- Neural Network Regression and Binary Classification (Surge / No Surge);

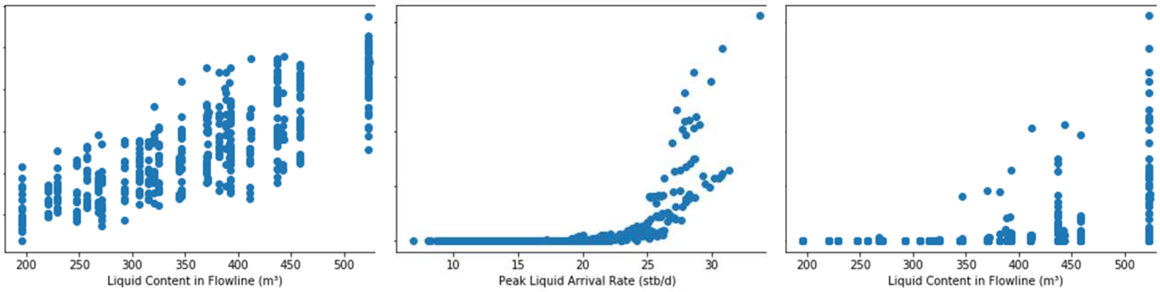
- R^2
  - Training Set > 0.9, Validation Set ~ 0.6;
- Accuracy:
  - Training Set > 90%, Validation Set ~ 70%;

- Model was overfitting (zero surge cases);

- An additional 200 cases were run with higher surge volumes to balance dataset.

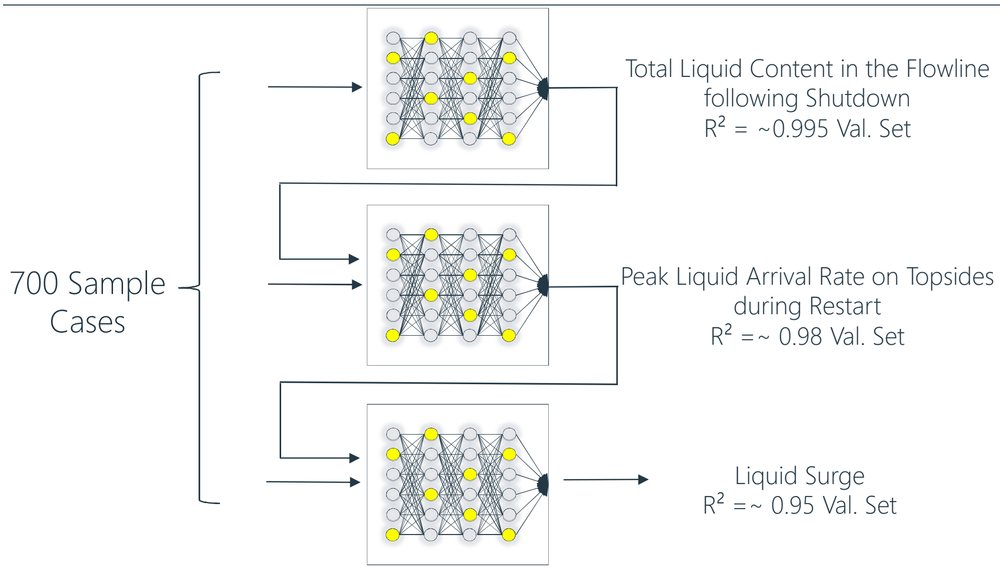


Case 1: Second ML algorithm



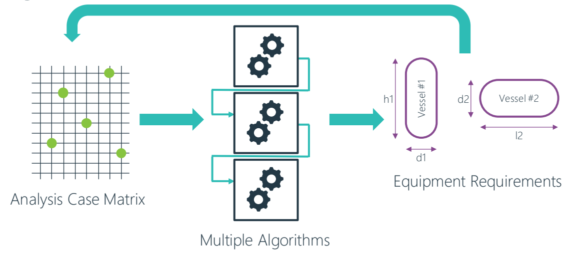
- Added 2 additional features:
  - Total Liquid Content in the Flowline following Shutdown;
  - Peak Liquid Arrival Rate during Restart.

Case 1: Second ML algorithm results



Case 1: Summary

- Efficient screening for equipment and operation
  - 1.5 weeks versus "40 weeks"
- Workflow of the future?



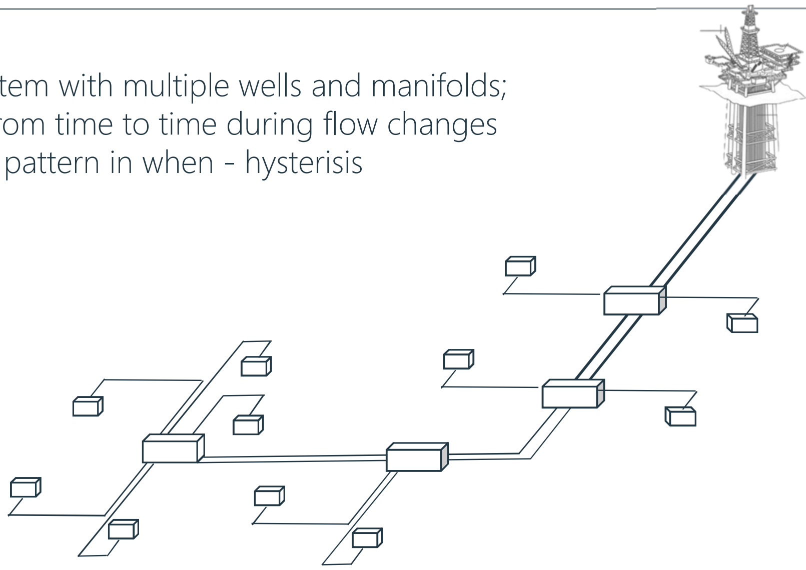
- Challenges: What is the right amount of input? What is right input data set? Which method of ML to use?

Case Study 2

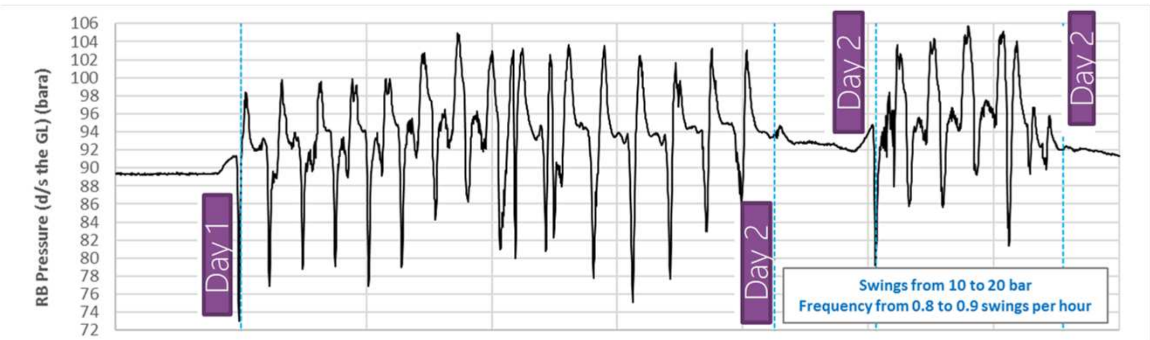
Operate

Case 2: The problem

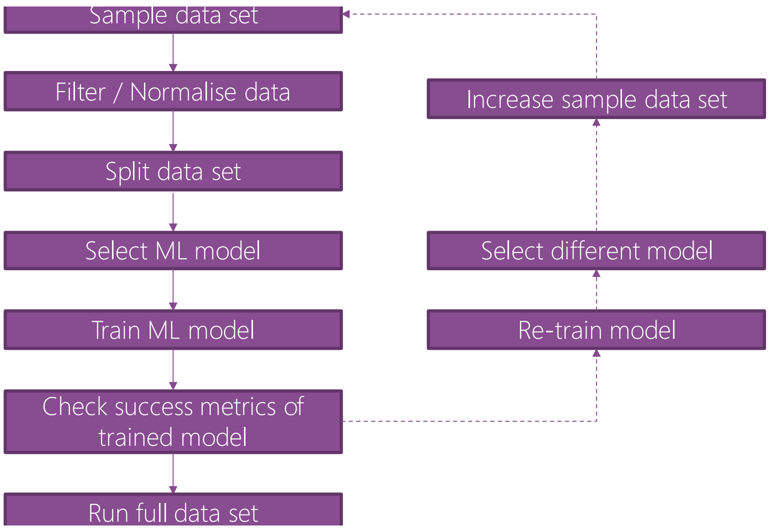
- Daisy-chained system with multiple wells and manifolds;
- Slugging occurs from time to time during flow changes
  - No apparent pattern in when - hysterisis



Case 2: The problem

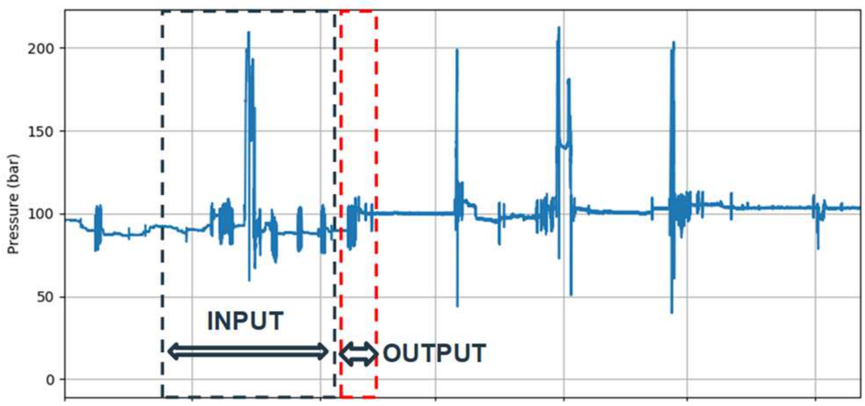


Case 2: Machine learning objective & method



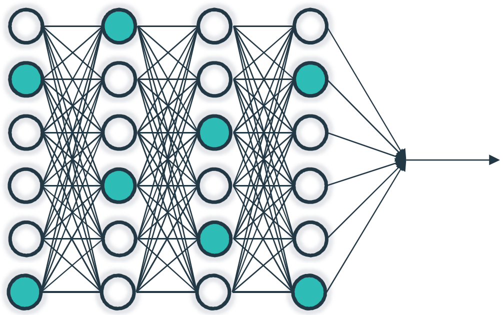
- Identify slugging events using riser base pressure.
- Filter the data to eliminate large pressure swings from transient events.
- Feed model with data from before slugging events to train
- Use model in predictive mode with field data

Case 2: Method



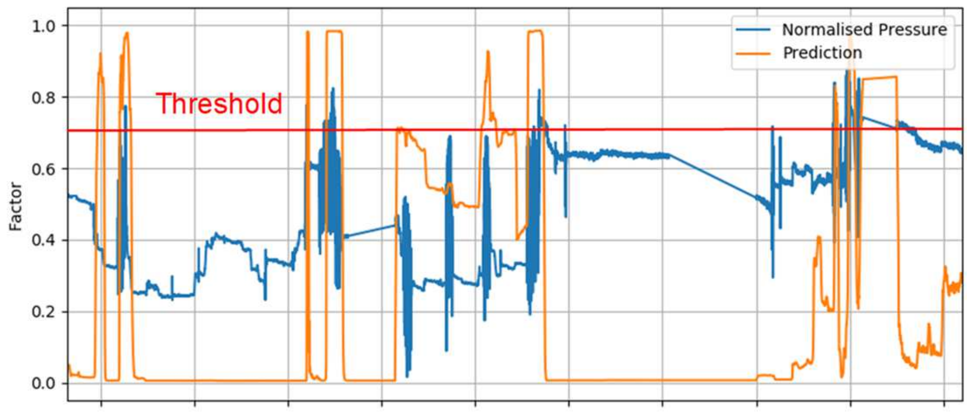
Case 2: Method

- 40 Features as input
    - P, T, V_{op}, etc.
- Few hours of operational data prior to time of interest

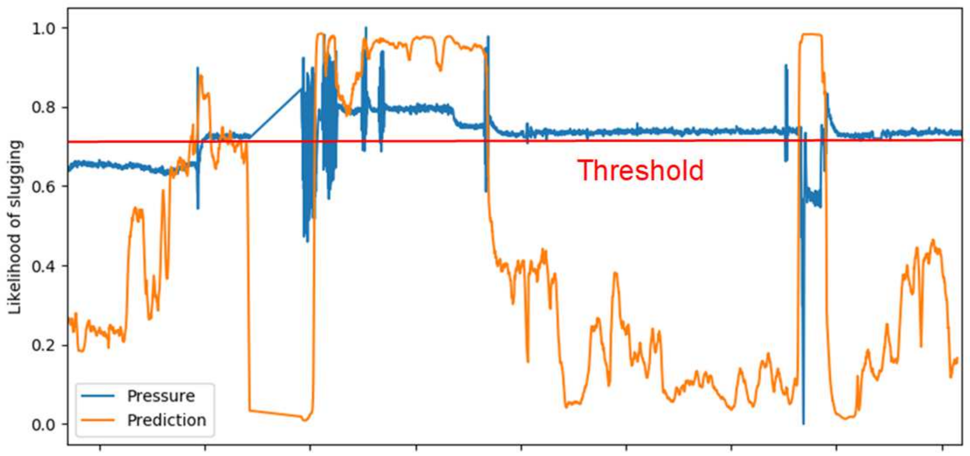


Likelihood of slugging

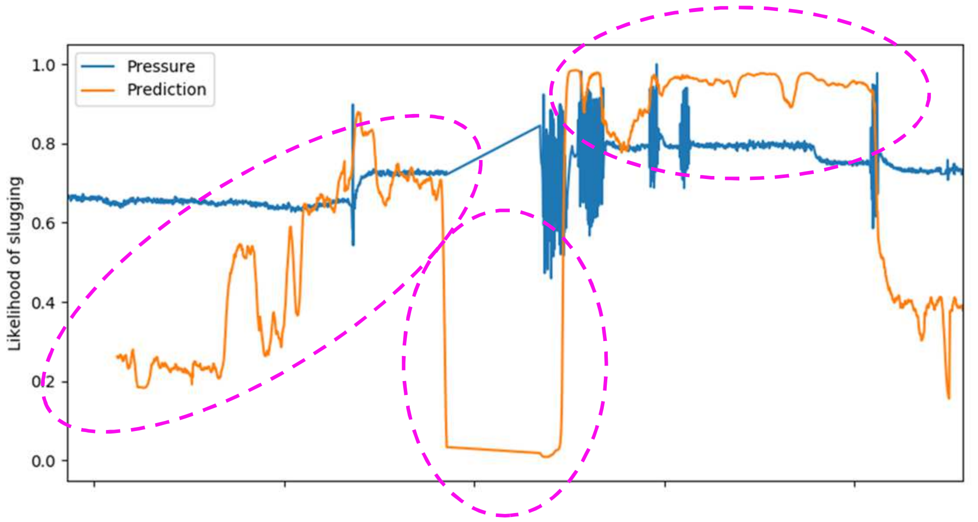
Case 2: Results (Training)



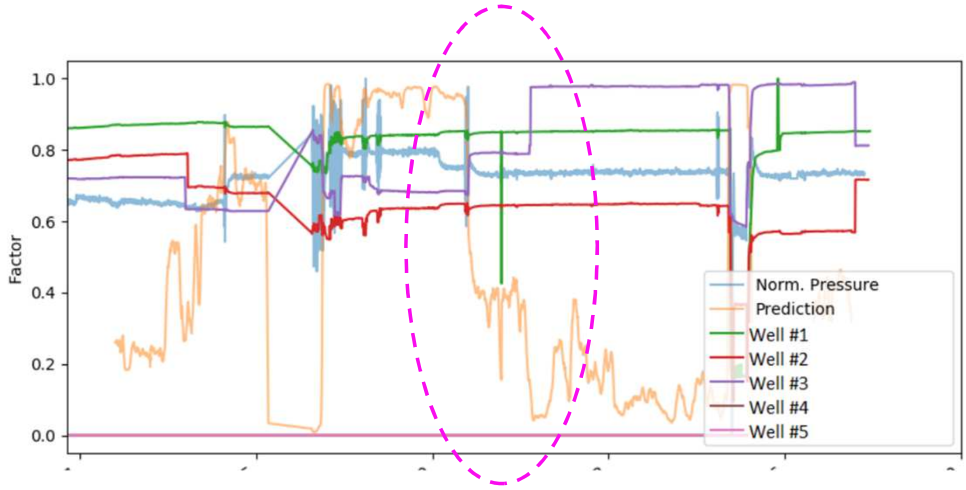
Case 2: Results (Test Set)



Case 2: Results (Test Set)



Case 2: Parameter dependence



29 A presentation by Wood.

Case 2: Summary

- Machine learning model has been built to provide an early warning system
  - More data……better performance!
- Can be used for brownfield systems for real-time advisory

- Challenge: Combine field data with physics based model and machine learning to provide not only early warning system, but control as well!

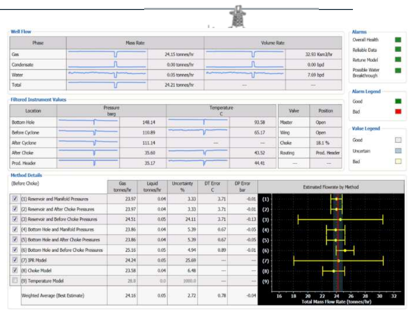
30 A presentation by Wood.

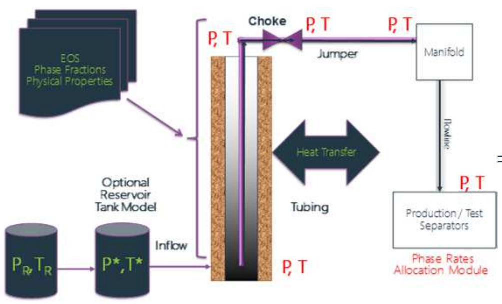
Case Study 3

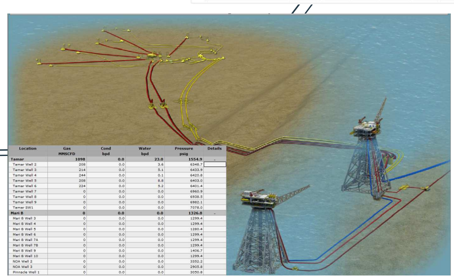
Maintain

Case 3: The problem

- Long-distance deepwater gas condensate system
- Multiphase meter at each well installed and failed within year 1
- Virtual meter is the primary means of allocating flows to wells
    - Virtual meter cum. accuracy > 98%
        - Challenge to improve cum. accuracy to above 99% and increased allocation accuracy
        - Quarterly (Periodic) tuning to ensure high-accuracy
            - Data-driven approach







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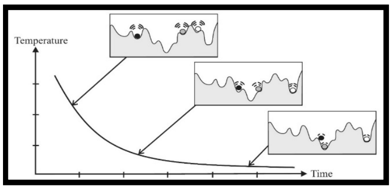
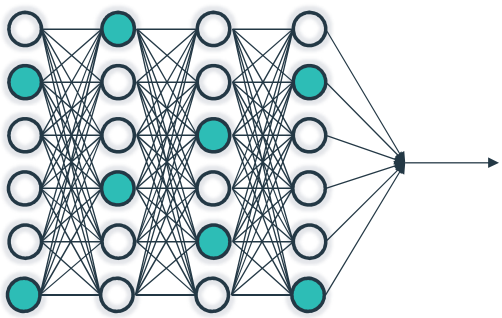
Case 3: Challenges

- Multi-parameter optimization problem
  - 35+ adjustable parameters
  - Time dependent
- Local minima issues
- Multiple solutions possible
- Bad field data, data drop-out, etc.
- Problem constrained by previous quarter estimates
- Human intervention needed when stuck
- Lots of data!



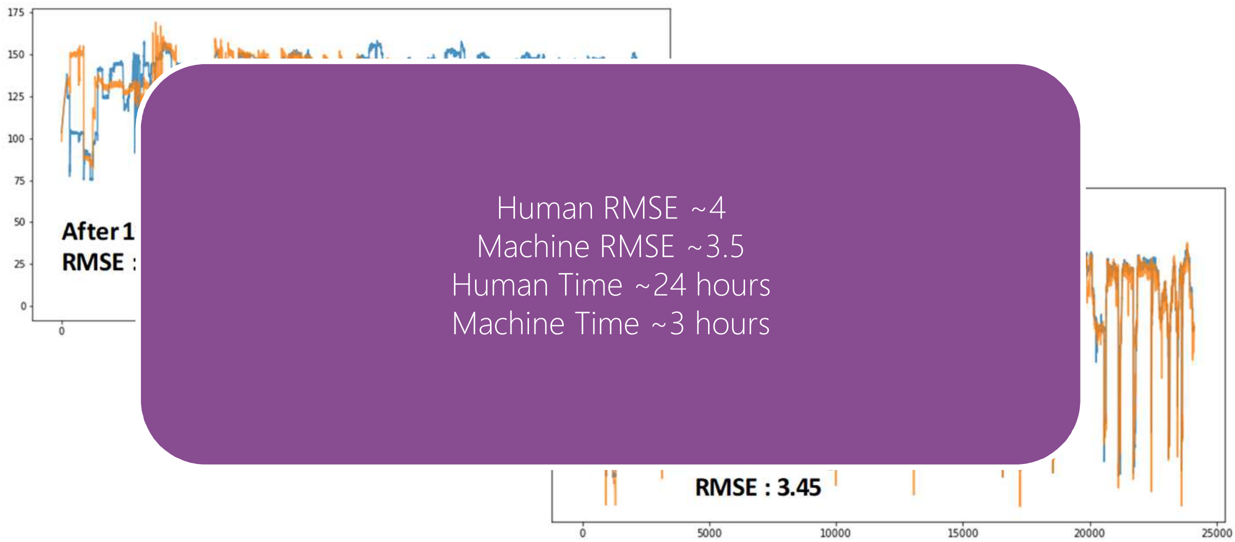
Case 3: Method

- P, Q (topsides), T, V_{op} as F(Time)
- 1 year+ data



- Well flow rates for each well
- Parameter for use in next quarter

Case 3: Results



Human RMSE ~4
Machine RMSE ~3.5
Human Time ~24 hours
Machine Time ~3 hours

35 A presentation by Wood.

Case 3: Summary

- Data analytics used to automate human workflows
- Analytics achieved or bettered human accuracy performance
- Analytics exceeded expectations on analysis time
- Virtual metering can now be scaled to 1000s of wells which was not humanly possible earlier

36 A presentation by Wood.

Future Application in Flow Assurance

The challenge

Can a generic machine learning model be developed that can calculate ramp-up surge volume from steady state information?

Take SPE123934 further……

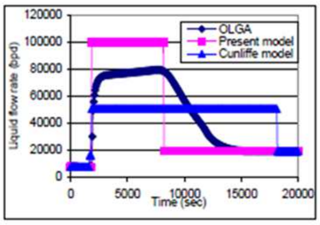


Figure 4-Liquid flow rates at at pipeline outlet

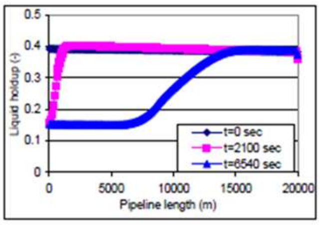
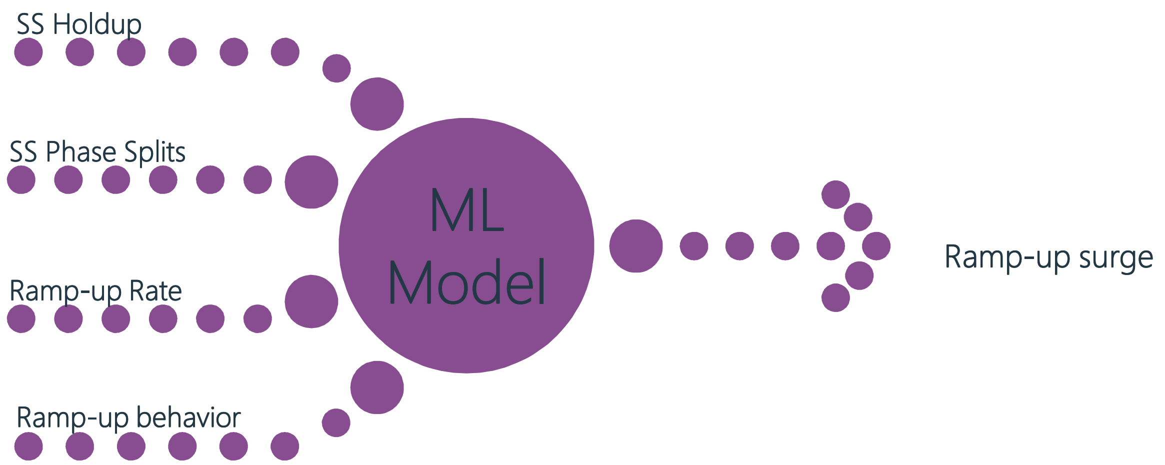
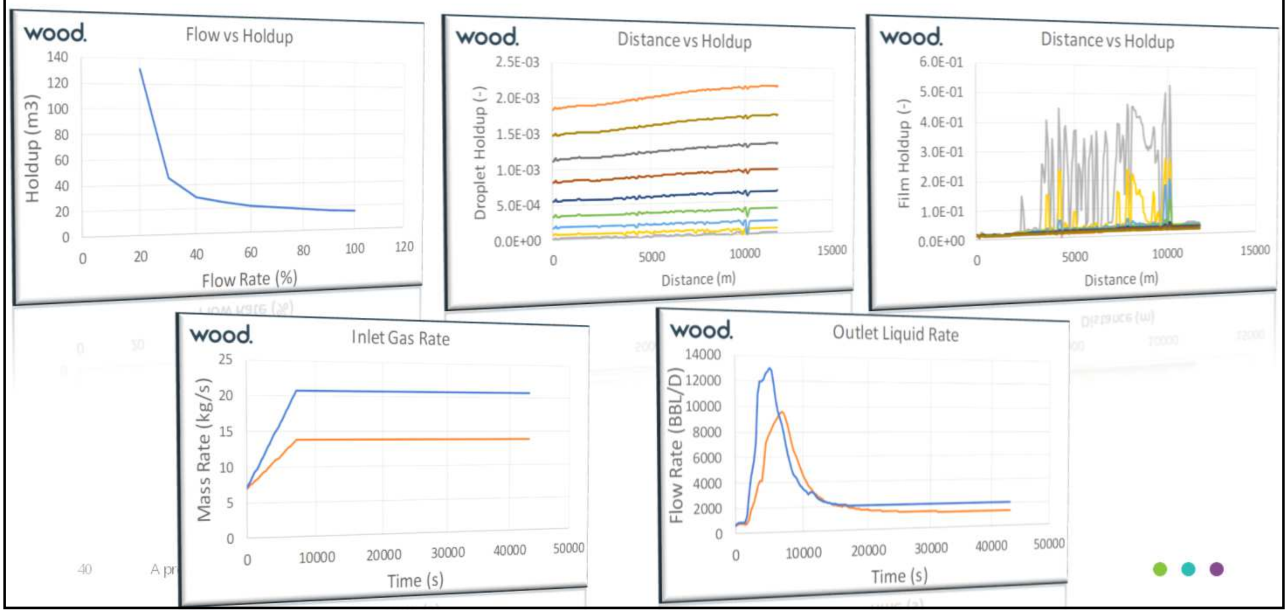


Figure 5-Liquid holdup profiles (OLGA)

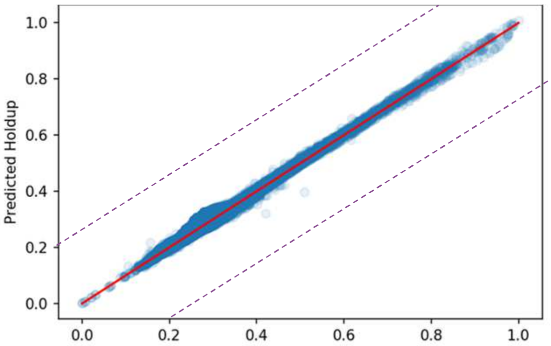
The idea



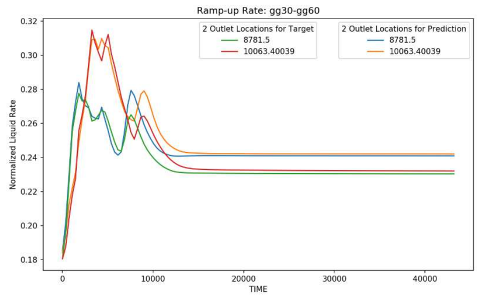
The inputs



The output



Transient Liquid Holdup prediction ML vs Simulation



Outlet Liquid Rate Prediction ML vs Ramp-up rate

Conclusions

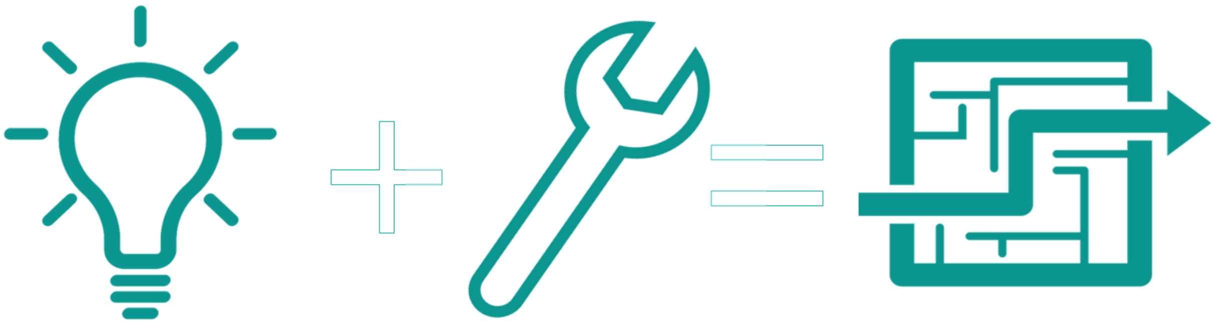
Conclusions

- Opportunity
  – Improve workflows
    - Efficiency gains
    - Build generic ML models for various operations; train and use for specific application
  – Find patterns in complex problems where physics is too hard
    - Slugging / root cause analysis
  – Utilise big data - we probably don't even know! But potential is huge to reshape both design and operations.

Conclusions

- Risks / Threats
  – Engineers need to be conversant with the use of data science results
  – Training / Governance
    - Not based on physics, trust becomes an issue.
    - It isn't always easy to introduce a new skill set to existing organisations.
    - Difficulties in QA/QC
  – Data scientists are in demand!
    - Finance, marketing, etc.
    - Experienced data scientists = Big **$$** in what is still a challenging market
  – Continued undervaluation of flow assurance skills in the market
    - It is not general engineering which is where it is categorized now
    - Innovations need $$s to become usable solutions

Conclusions



domain knowledge + machine learning = solutions to spend less & produce more!

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