Production and Operation Optimization of Geo-Energy Systems with Artificial Intelligence

Pejman Shoeibi Omrani (Senior scientist, TNO)

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Webinars

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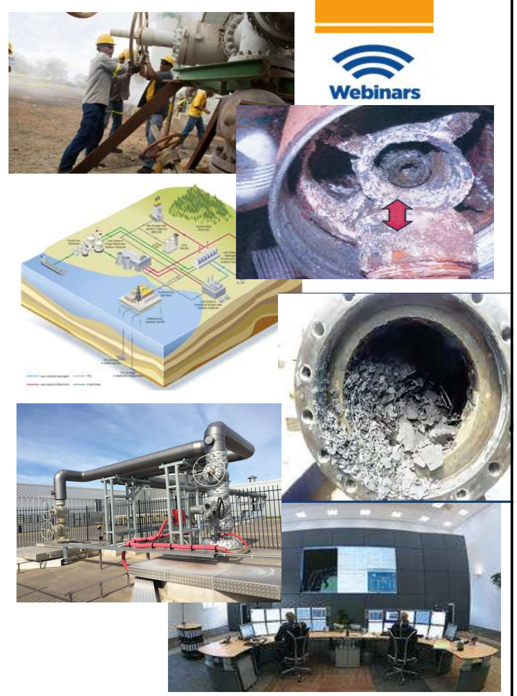
Background

Growing complexity in the operation of geo-energy systems

- Unstable production (mature, unconventional, horizontal wells)
- Complex reservoirs and processes
- Topside constraints and interactions
- Offshore & remote
- Climate drivers
- Increasing pressure on margins (produce more with less) and safety
- Climate drivers



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Background

"Conscious human information processing

is very limited (~60 bits/s),
requires full attention,
is serial,
is biased,

and we substantially forget what we learned."

(Tegmark, 2017)

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Why digitalization matters?

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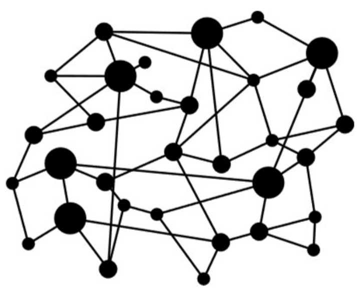
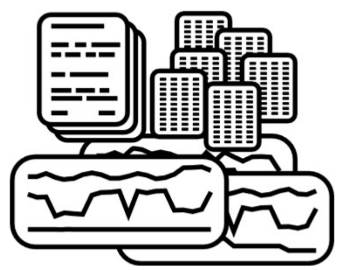
System complexity



Data quantity



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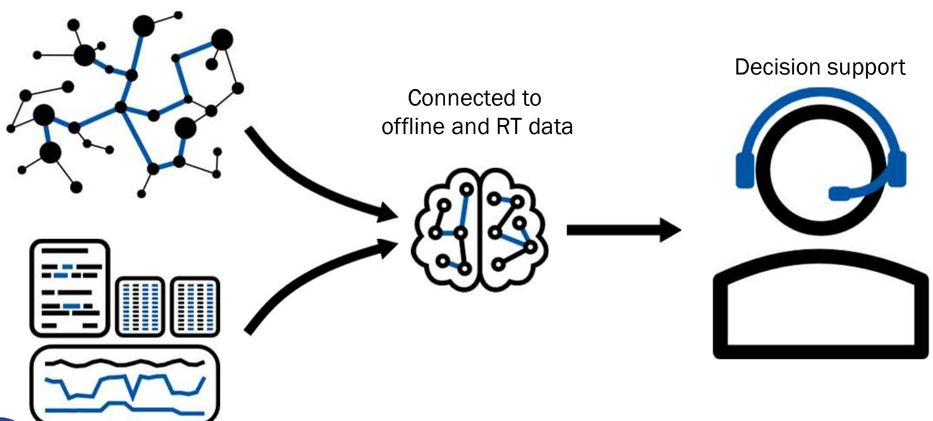
Why digitalization matters?



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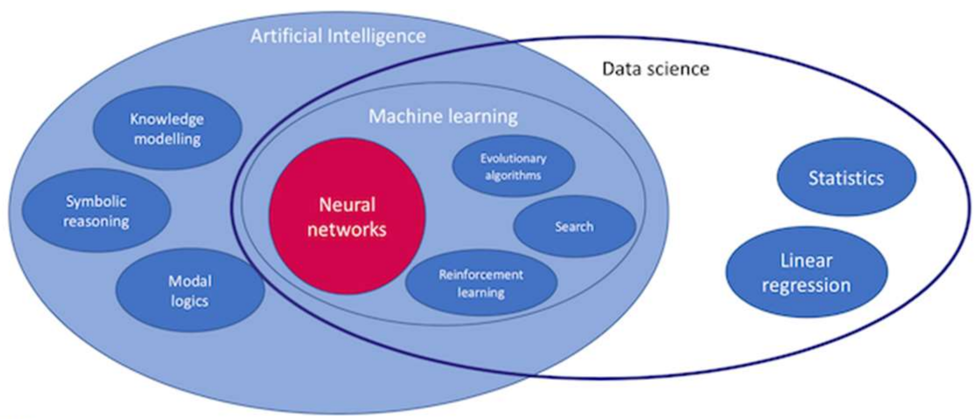
AI, DS, ML and DL



Courtesy of ICT institute

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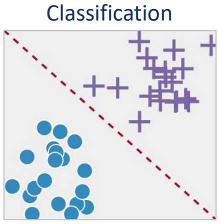
Machine learning

Machine learning originated in computer science

"Programming computers to perform tasks that human perform well but difficult to specify algorithmically"

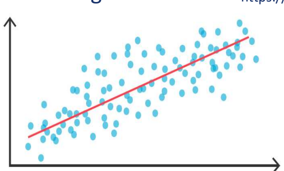
Classification



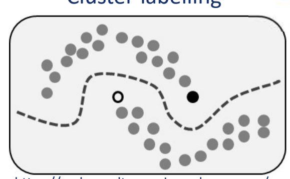
Clustering

https://www.kdnuggets.com/

Regression

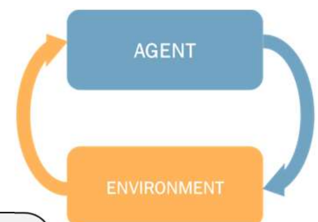


Cluster labelling



https://makarandtapaswi.wordpress.com/

Reinforcement learning



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ML is just like cooking

- You are the chef!
- To use appliances and ingredients to make the food
- To use algorithms and data to make the models

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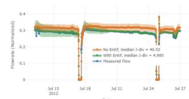
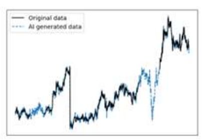
What do we work on?

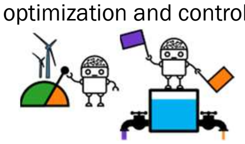
Real-time model updating



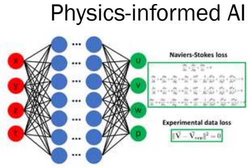
Generative AI



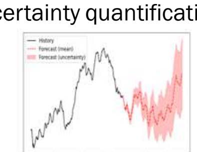
Agent-based optimization and control



Physics-informed AI

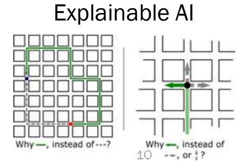


Forecasting and uncertainty quantification



Anomaly detection

Explainable AI



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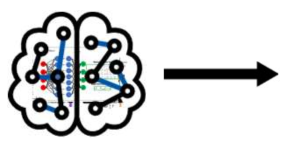
How do we implement it?



How do we implement it?

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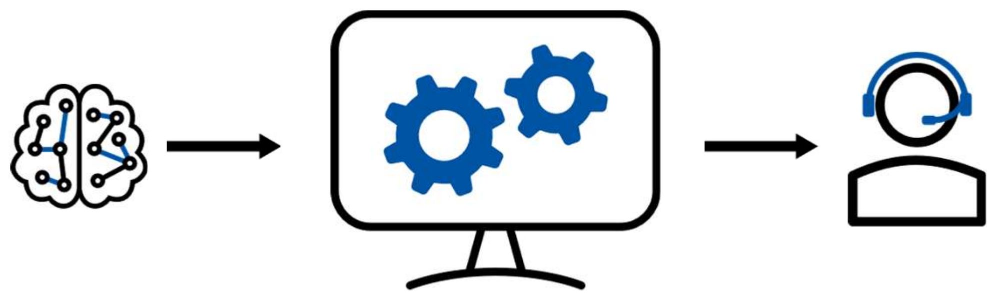
Applications and demos
Full stack end-to-end software
Digital twin; Real-time system deployment
Offline analysis and automated workflows



Applied to 20+ cases together in different sectors

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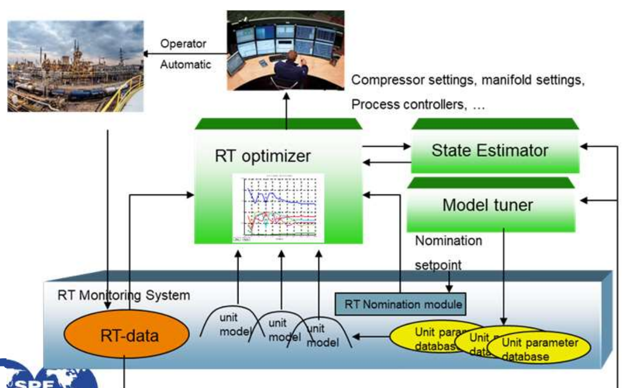
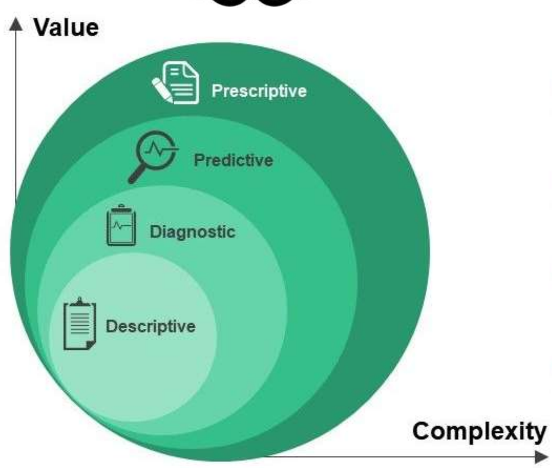
Levels of analytics





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DESCRIPTIVE ANALYTICS

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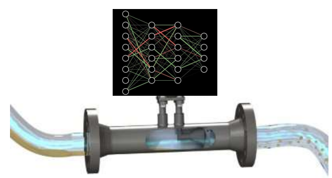
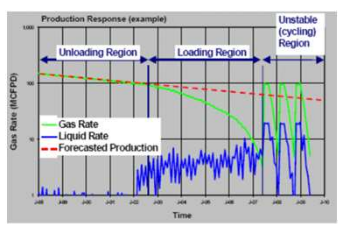
Virtual Flow Metering

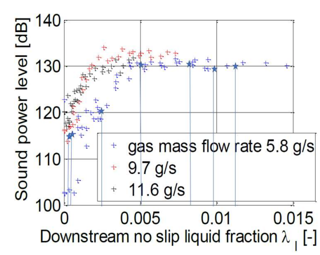
Can we measure small liquid rates (low Liquid Gas Ratio (LGR)) via virtual metering?

- **Boundary Conditions :**
  - Simple, (cheap) measurement techniques
  - Use of existing measurement data
  - Low liquid rates (gas wells with produced and condensed liquids)



- **Current approaches**
  - Well dynamics at well shut-in and start-up
  - Pressure drop and vibration over a U-bend
  - Pressure drop over a choke valve
  - Choke noise





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Virtual Flow Metering with Deep Learning

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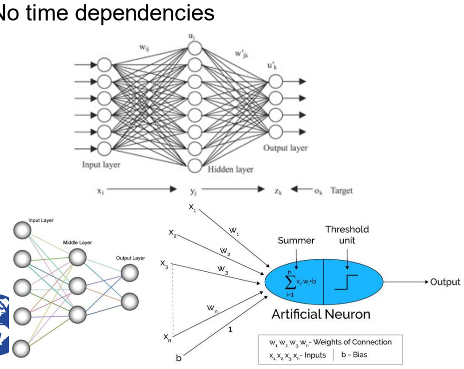
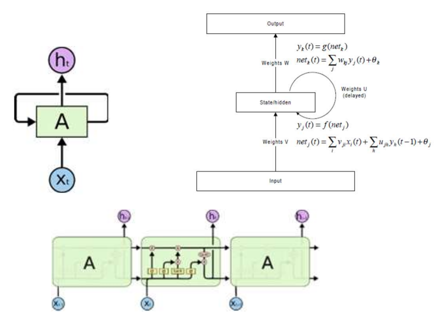
Can we develop a virtual multiphase flow meter based on machine learning?

- Feedforward (MLP) network
  - Functional mapping of inputs to outputs
  - No time dependencies



- Recurrent neural network
  - Suited for capturing time dependencies
  - Receiving feedbacks from states in previous timestep



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Virtual Flow Metering with Deep Learning

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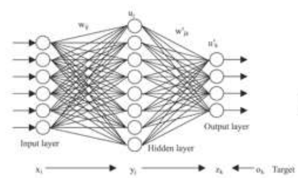
Which neural network shall we use ?

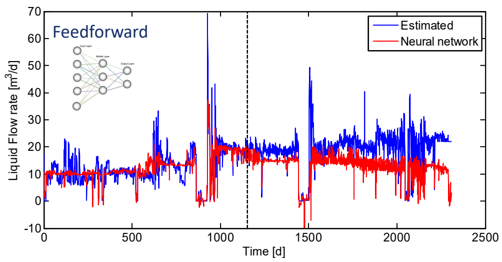
Dynamic RNN was better at capturing the physics compared to the feedforward network using field data

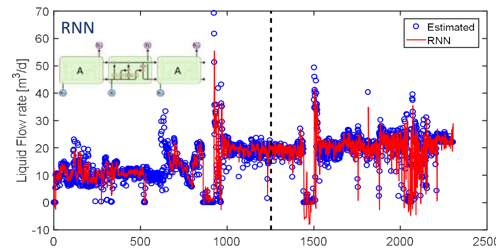
- Inputs:
- Pressures
- Temperatures,
- Choke opening



Output:
(multiphase) rates

Test on field data





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Shoeibi Omrani et al., SPE-192819-MS

Trained for a single well and has good prediction for that well !

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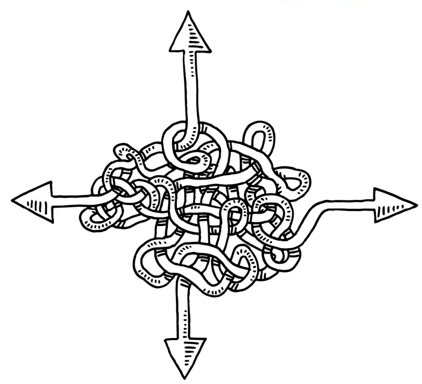
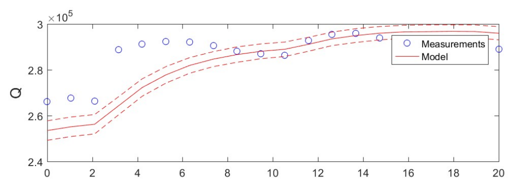
What about uncertainties?

- Two types of uncertainties : data + model parameters
- Training on data:
  - Uncertainties in data ➔ uncertainties in model parameters
- How much the prediction accuracy is affected by uncertainties in data?
  - Prediction horizon: increase in prediction uncertainties
- How the uncertainties in predictions could be accounted for ?





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Impact of probabilities on predictions

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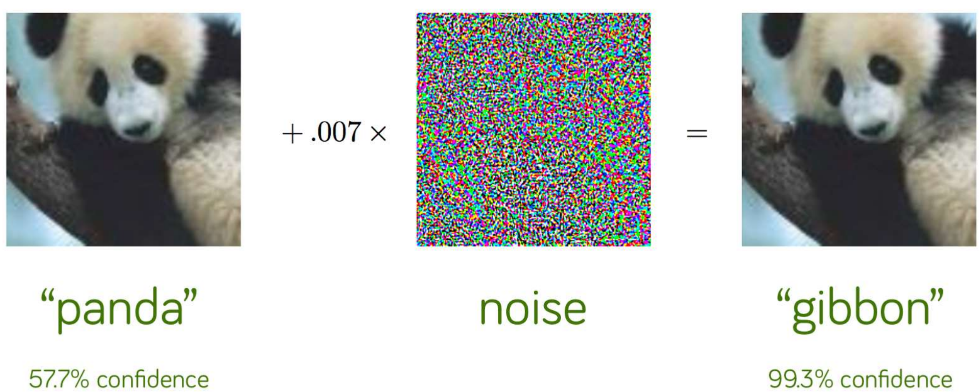

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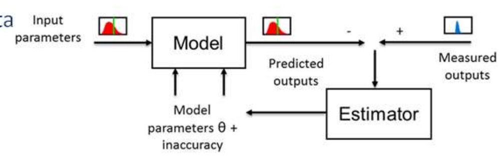
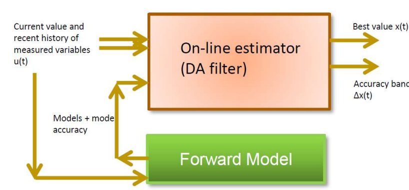
AI-assisted real-time model updating

Workflow:

- **Model derivation and training (hopefully, once in a life time!):**
  - ***Forward model training***: Trained LSTM network on historical data and test the prediction accuracy
  - ***Uncertainty characterization:*** Characterize the uncertainties in sensor data and model parameters



- **Prediction and updating (every time-step when new data is available):**
  - ***Prediction:*** Employ the forward model to predict the next time steps (e.g. gas production in the next 20 hours)
  - ***Ensemble based history matching :*** Ensemble Kalman filter for model parameters (in this case weights of neural networks) and their uncertainties with new available data



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AI-assisted real-time model updating

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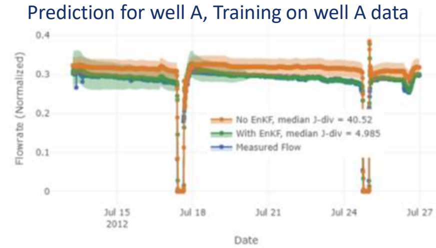
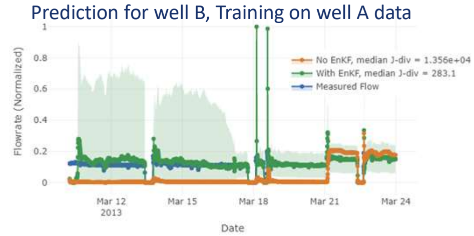
- Developed a model for estimation of gas production utilizing deep learning algorithms (LSTM)
- Auto-tuning a single deep neural network with history matching

- **Result :**
  - Cheap and accurate models for production predictions including the uncertainties using machine learning
  - Using a trained model on one well in the prediction/calibration workflow for another well
    - Better prediction accuracy
    - Uncertainties are decreasing over time
  - No need for expensive (re)training of neural networks (1000 times faster)

Prediction for well A, Training on well A data



Prediction for well B, Training on well A data



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Loh et al., arXiv:1802.05141

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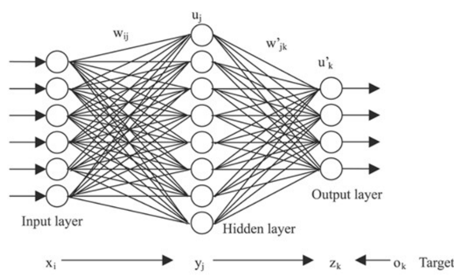
WHAT IS HAPPENING IN THE BLACK-BOX ?



CAN WE OPEN UP THE NEURAL NETWORK ?

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Explainable AI : Decoding the Results

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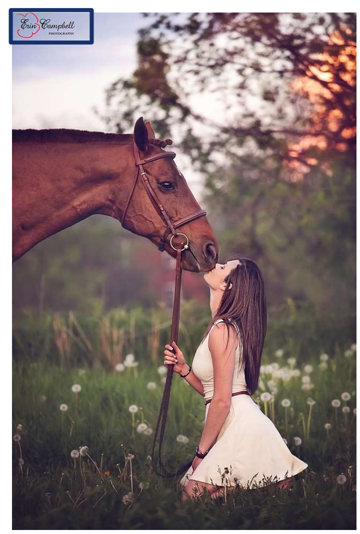
- **Challenge:** Can we understand/explain what happens in the hidden layers to help decision makers ?
- **Method:** Developed state-of-the-art algorithms to "decode" the inner workings of DL algorithms
- **Results**: Increased confidence expressed by decision makers to make data-driven decisions; lead to ERP Applied AI 2018 onwards



Predictive Policing with AI

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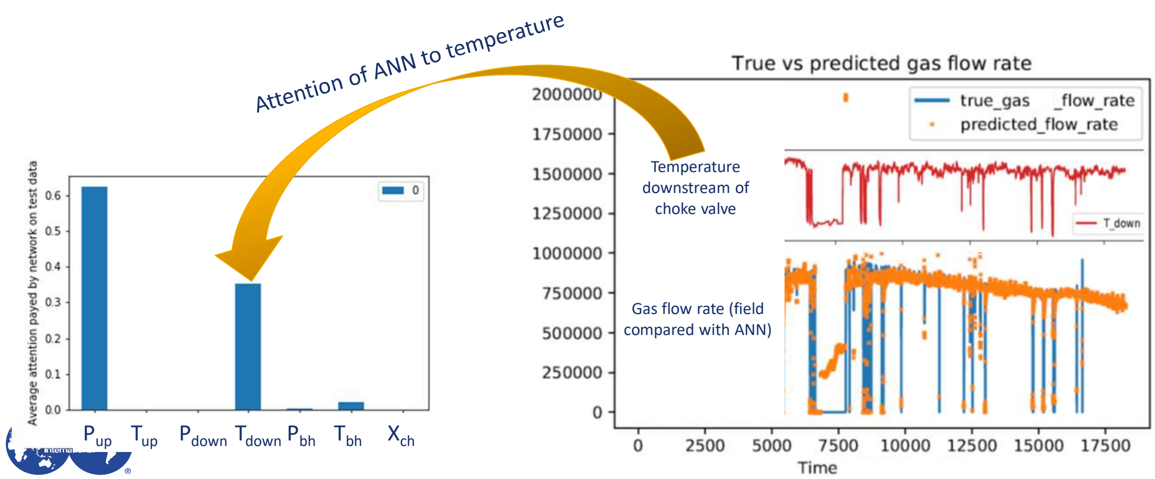
XAI for Virtual Flow Metering



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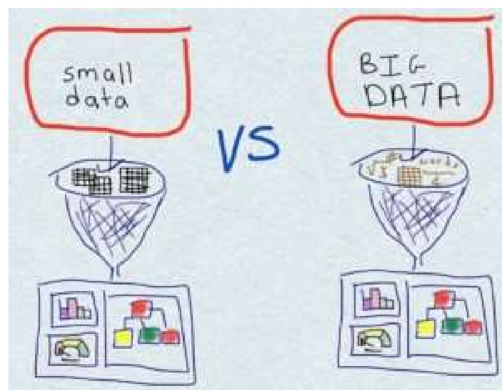
How to use in practice?

- We are dealing with small data problem
  - Lack of big data or variability in the data
  - How to generalize the models?
  - How to ensure the extrapolation error is minimized?



- Each model is good for the system which training data is available, but how about other similar systems?

Possible solution

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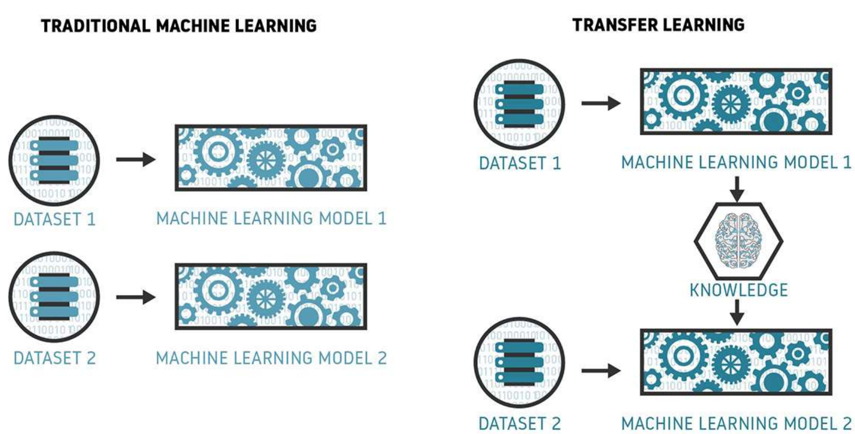

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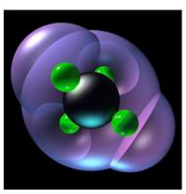
Transfer Learning

Challenge:

- From natural gas to Hydrogen
- Pulsation dampers in a reciprocating compressor system is critical from a pulsation or vibration risk mitigation perspective.
- An inadequate damper design may lead to high vibration levels and, eventually, to failures of the field piping and/or the compressor
- An optimum damper size estimate is challenging (or impossible) for new gas compositions (H2 admixing, biogas, …).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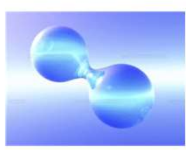

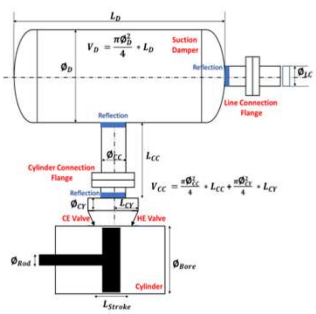

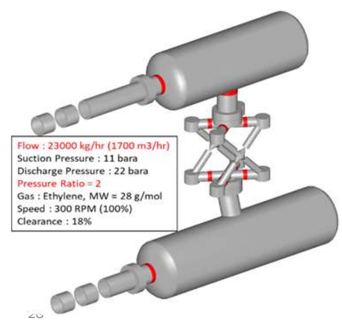

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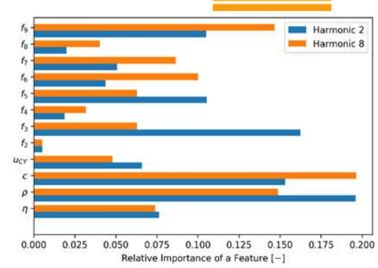
Transfer Learning

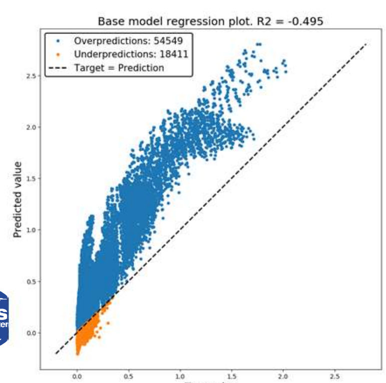


Method:

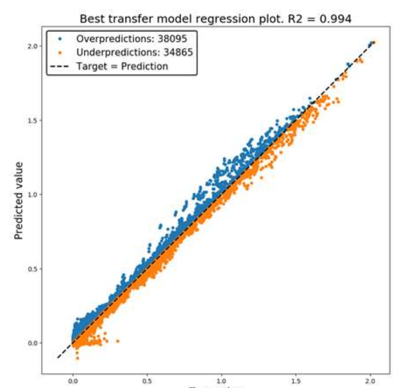
- Transfer learning coupled with simulated data
- Explainable AI using LIME to determine the most significant features

Results:

- Accurate and explainable model to predict API levels



Transfer Learning



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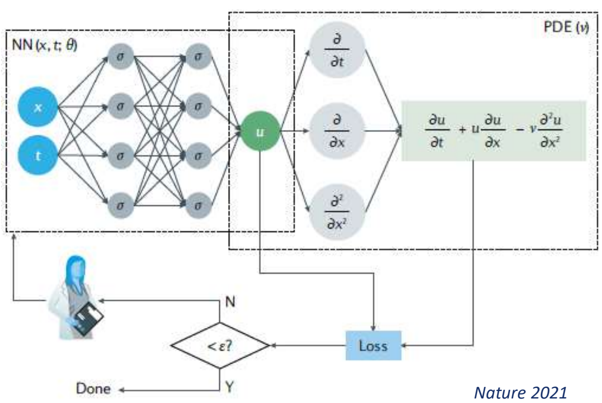
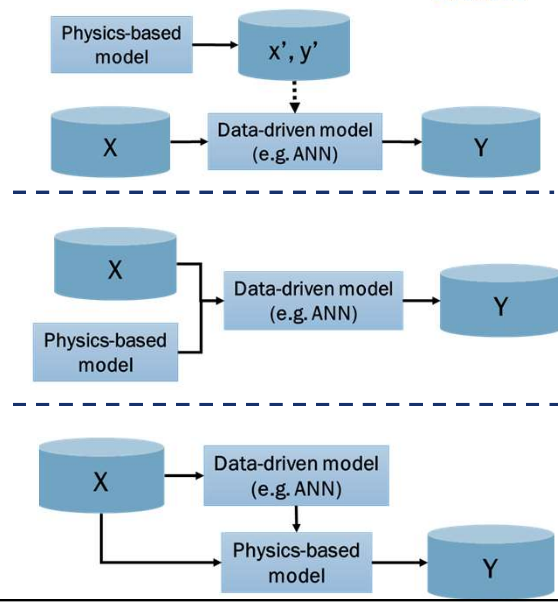
Physics-informed and physics-induced ML



Nature 2021



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DIAGNOSTICS ANALYTICS

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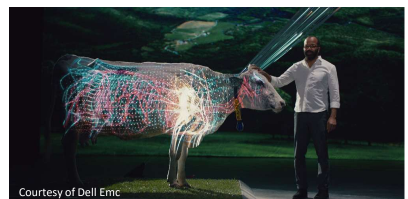
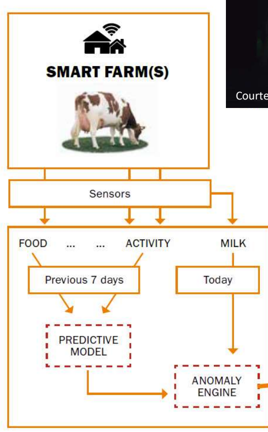
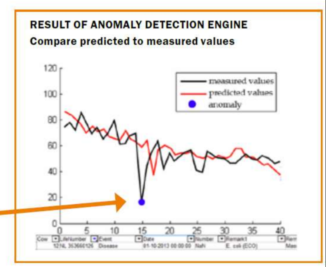
Inspiration: Digital cow!

- **Challenge:** Can we reliably predict the milk production for next couple of days for every cow ?
- **Method:**
  - Machine (Deep) learning technologies
  - Anomaly detection data analytics
- **Results**:
  - Reliable prediction of milk production 2 days in advance based on 7 days of data
  - Useful as an anomaly detector, cow with low productivity linked to health issues detected.

What can oil & gas learn from using machine learning to automatically detect anomalies?


Courtesy of Dell Emc





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Event detection for predictive maintenance

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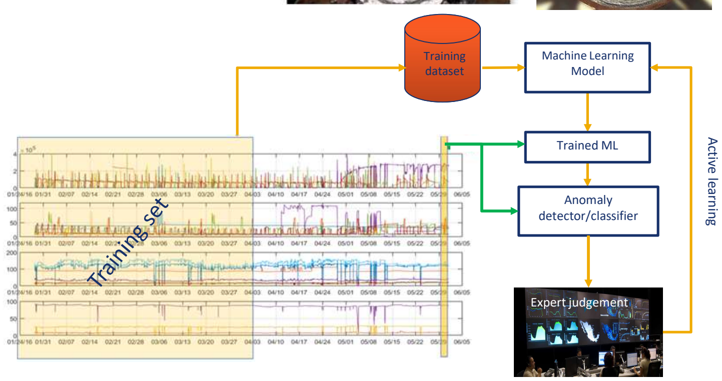
- **Challenge:**
  - Mature assets production suffers from off-normal events
    - Production losses
    - Equipment/surface facilities performance degradation
- **(Expected) Results:**
    - Faster operational alarm
    - Saving operational cost
    - Smoother operational knowledge transfer



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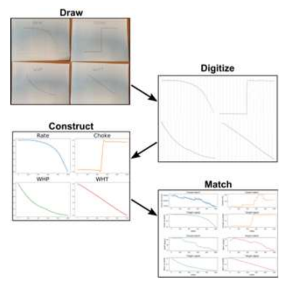
Automated event detection

Challenge
- Halite precipitation and liquid loading in mature gas fields
- Fast and reliable detection of mature production patterns

Approach
- Image-based Pattern Recognition & Match Detection
- Event definition by experts or from data (rule-based and patterns)
- Handling noisy data, Offline and real-time

Results
- Pilot in several gas wells in the North Sea
- Detected 8 new scaling events in less than a minute on 2 years of data!



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PREDICTIVE AND PRESCRIPTIVE ANALYTICS

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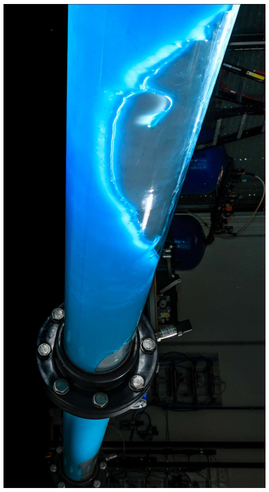
Slugging control and mitigation

- In many cases, oil, gas, or geothermal wells suffer from unstable production caused by multiphase flows (due to slug flow)
- These conditions can make control of such systems challenging
  - Reduce slugging vs. maintaining production
  - Dynamic system and changing overtime
  - Multi-objective, multi-constraint; desired production, scheduled maintenance, minimum changes in the control settings, …
- As such, finding operating settings that maximize production while minimizing slugging effects is a difficult process
- In this work, we investigated reinforcement learning as a novel method for optimal control of oil well production



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Introduction – Reinforcement learning

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- Based on the concept of “learning by doing”
  - By trying out different control actions and evaluating how these affect a system, an agent tries to find which actions lead to desired outcomes
- It has been used extensively in gaming and robotics
  - Seeing more and more use in many other fields

Advantages	Disadvantages
Adaptability to dynamic/stochastic systems	Takes a lot of iterations to converge
Can find novel “unbiased” strategies	Many parameters/settings to tweak
Can take long-term rewards into account	Still requires human input to shape problems
Doesn’t require a model of the system	

AlphaGo vs Lee Sedol

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Case description – Overview

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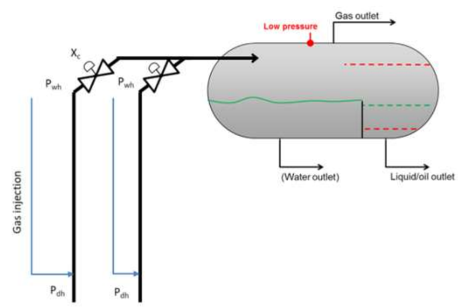
- Oil wells producing a mixture of oil, gas, and water under slugging conditions
- Production and slugging is controlled by valve opening and gas lift rate and pressure
- Wells have distinct responses to control variables
- Goal was to find optimum control settings to **maximize oil production**, but **minimize slugging** effects and **emission**



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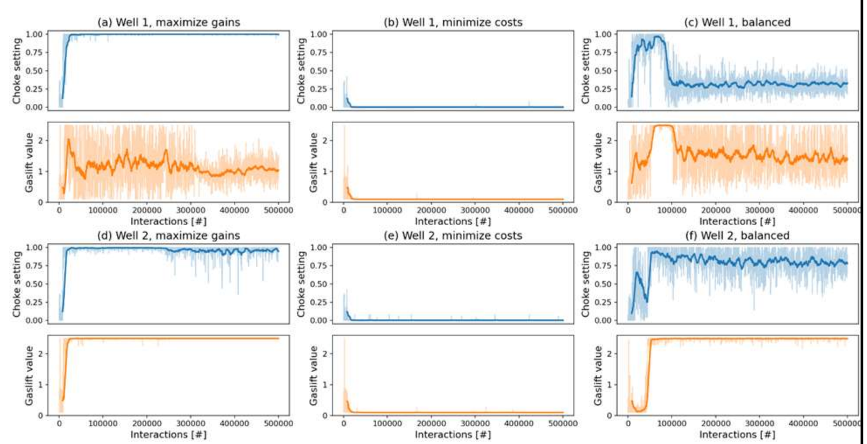
Results – Control actions over time

- Control variable values per episode shown
- Minimizing slugging/costs "trivial"
- Agent keeps exploring throughout
  - Most notable in the case of maximizing gains
  - Perhaps it keeps exploring too much

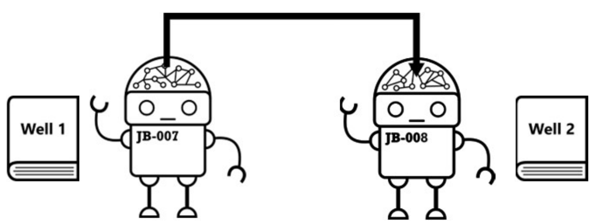


Policy transfer

- Training "from scratch" can take a long time
  - This is because the model takes time to learn the behavior of the system

- Both wells share underlying physics, so can we "transfer" the trained agent from one well to the other?

- Yes we can!



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Results – Policy transfer

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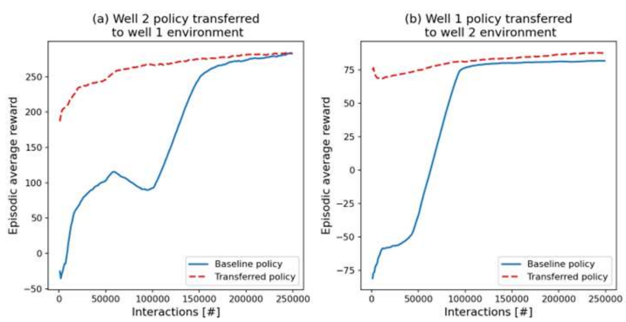
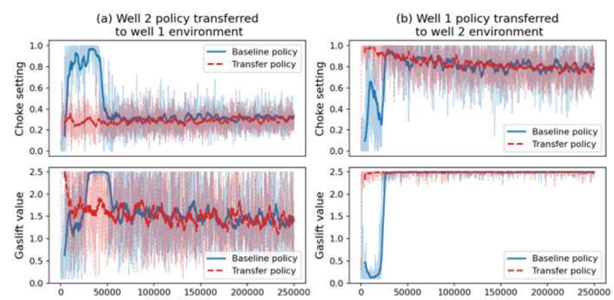
- By starting with a pre-trained agent, we can reduce training time up to 63%
  - Still achieving the same final policy and reward
  - **17% increase** in the revenue due to production increase
  - **6% decrease** in the slugging (based on WHP standard deviation)





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Poort et al., SPE-210277-MS

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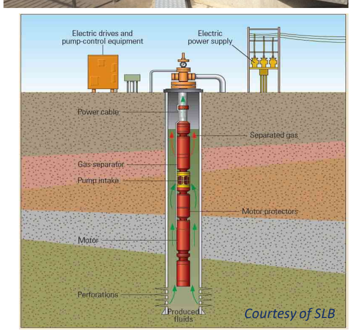
Artificial lift in geothermal systems

ESP is the most common artificial lift system in geothermal plants

The current geothermal ESPs have several shortcomings;

- Relatively **short lifetime**
- Available ESP designs are optimized for oil wells leading to **frequent failures**
- ESP operational envelope should accommodate with production variations (P, rates, clogging,…)
- Lack of **proactive monitoring** of system performance during the operation
- High **costs** associated with **ESP inspection** and **replacement**



Courtesy of SLB

Minimum design adaption of ESP from the petroleum sector to geothermal

Suboptimum operation of the ESP caused

Shoeibi Omrani, et al., SPE-204524-MS

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A geothermal case study

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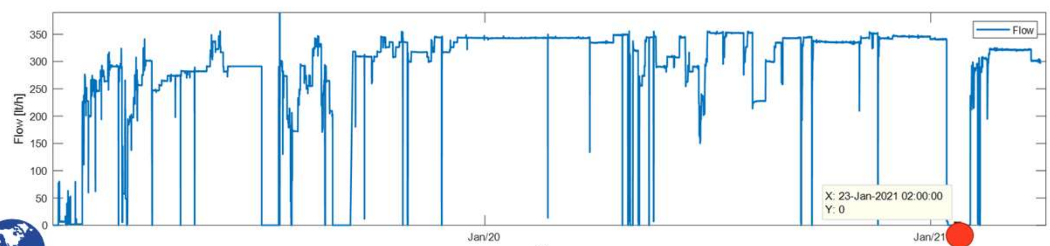
- A geothermal doublet for direct use (heating)
- Producer well was equipped with ESP
- ESP failure was observed

- Reservoir pressure ~ 200 bar
- Reservoir temperature ~ 80 C
- Brine specific gravity = 1.086
- Bubble pressure ~ 30 bar
- GLR = 0.5 nm^3/m^3
- Pump depth ~ 720 m



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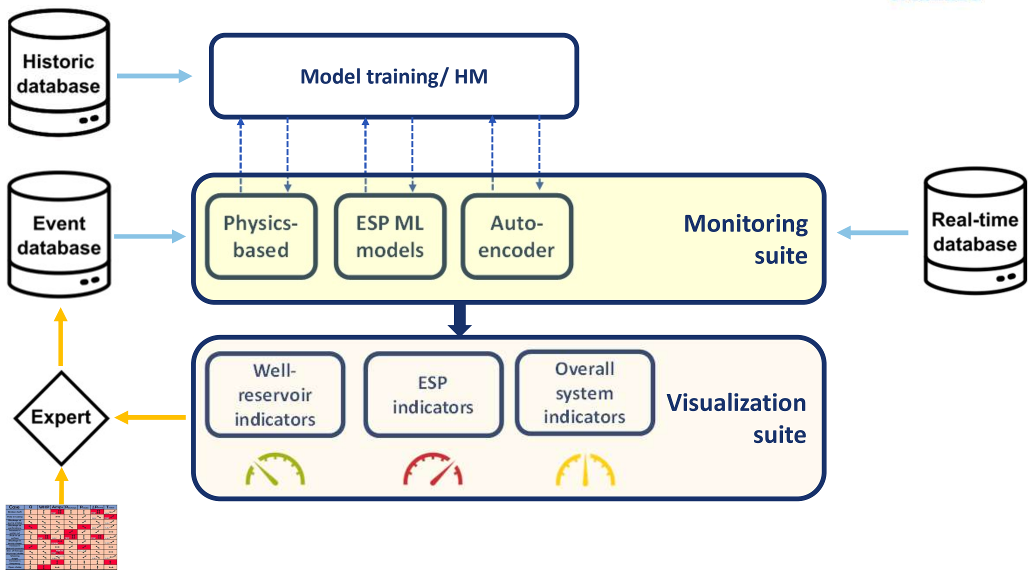
Workflow


Historic database
Model training/ HM
Event database
Physics-based
ESP ML models
Auto-encoder
Monitoring suite
Real-time database
Expert
Well-reservoir indicators
ESP indicators
Overall system indicators
Visualization suite

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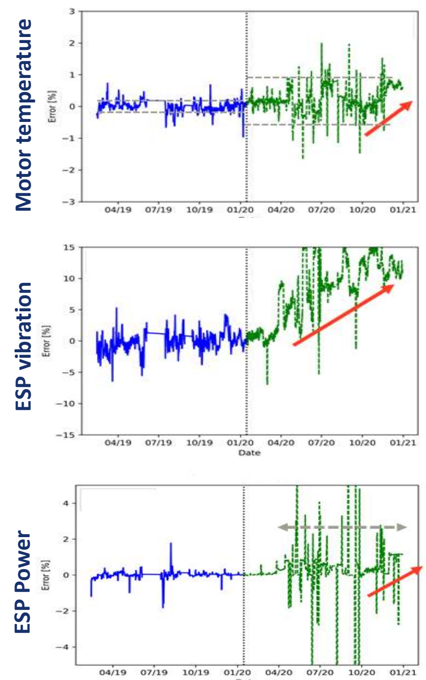
Geothermal ESP failures

- A group of trained machine learning models to monitor ESP parameters
  - Motor temperature
  - ESP vibration
  - ESP power (current, voltage and power)
  - ESP head

- The first indication of off-normal performance prior to the failure
  - 6 months for vibration (15% increase)
  - 3 months for motor temperature
  - 6 months for higher fluctuations in ESP power



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Geothermal ESP failures

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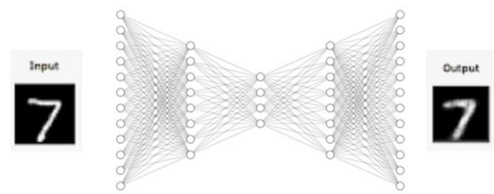
- Overall system performance by deep learning

- ***AutoEncoder*** is a neural network that aims to replicate the input quantities. Key aspect is a hidden layer smaller than the number of features so only important features of the variables are learned



- ***Anomaly detection***: when the error between the measured quantities and the model output is larger than a certain threshold

- AE was applied successfully in the past on data from process and petroleum sector.

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Geothermal ESP failures

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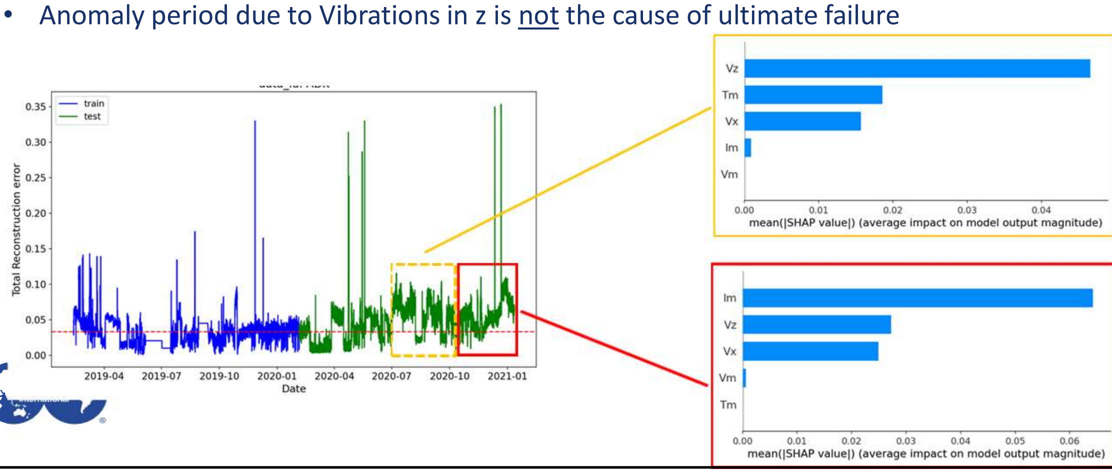
- Variables used: Vibrations-x, Vibrations-z, Temp Motor, Current, Voltage
- Reconstruction error increases close to ESP failure
- Explainable AI was applied to provide description of the feature importance
- Anomaly period due to Vibrations in z is <u>not</u> the cause of ultimate failure



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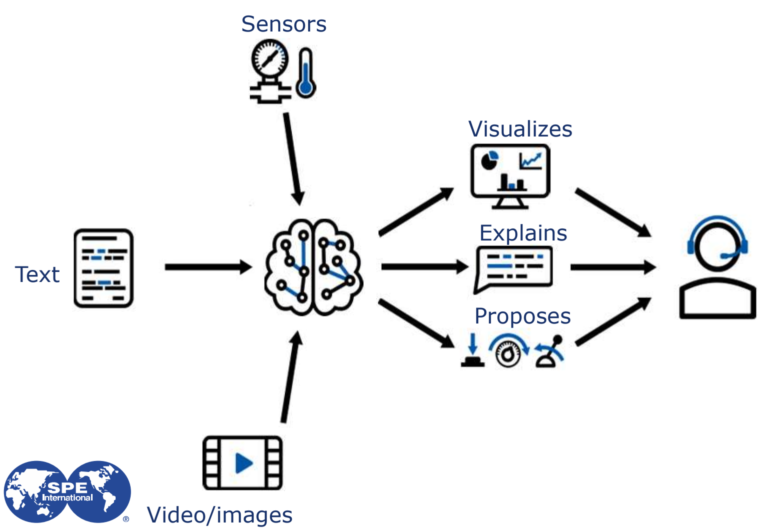
Our vision



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Take Home Message

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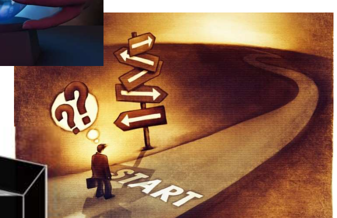

- Lots of potentials in using data-driven methods for ensuring prediction accuracy and speed
- Don’t forget about uncertainties in the data and its impact on training and prediction
- Unravel and explain the black-box ML models
- Utilize domain knowledge to solve the right question in a right way

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