Artificial Lift
R&D Council

A Brief (and incomplete) Review of ML/AI Applications in Artificial Lift

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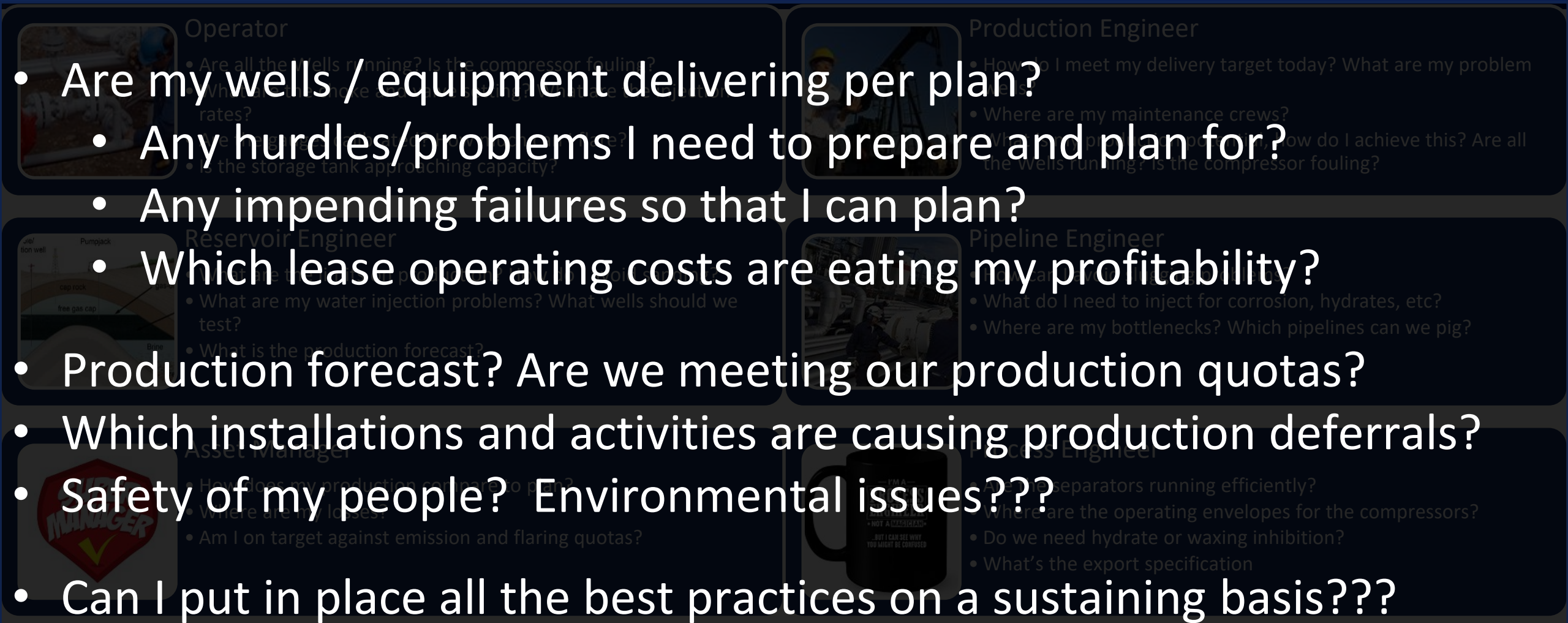
ALRDC Artificial Lift Workshop

February 28th – March 3, 2022

Presentation Outline

- Data Landscape in Artificial Lift
- A Few Examples
  - Anomaly Detection: Gas-Lift, ESP
  - Failure Prediction: ESP, SRP
  - Virtual Flow Metering: Plunger Lift
- Conclusion

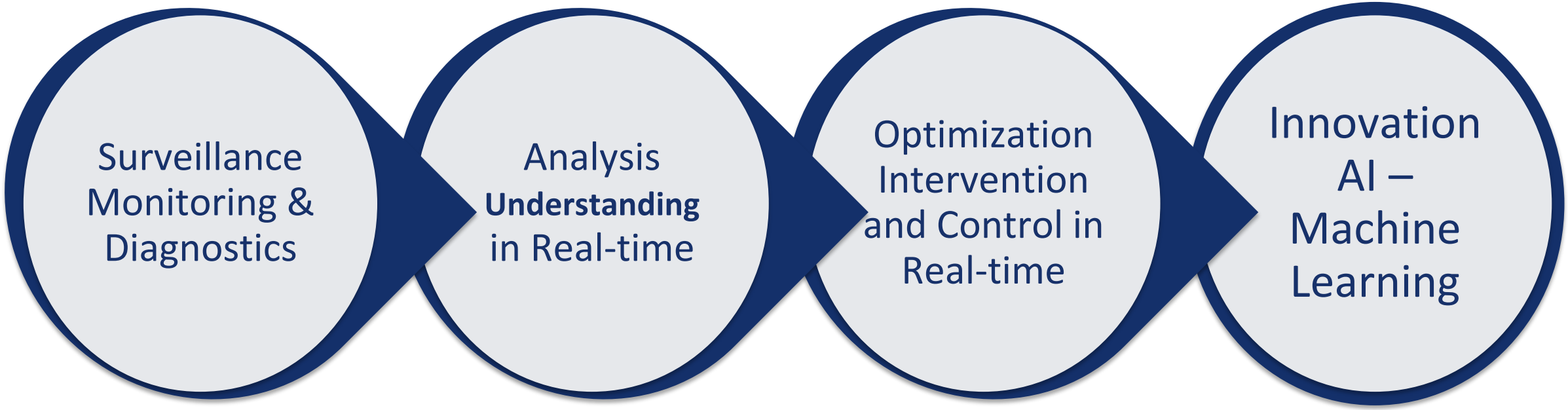
Problems facing operators:
Day-to-day operational questions



- Are my wells / equipment delivering per plan?
  - Any hurdles/problems I need to prepare and plan for?
  - Any impending failures so that I can plan?
  - Which lease operating costs are eating my profitability?
- Production forecast? Are we meeting our production quotas?
- Which installations and activities are causing production deferrals?
- Safety of my people? Environmental issues???
- Can I put in place all the best practices on a sustaining basis???

Source: Edwards T, SPE Webinar 09/2017, DO in Business, https://tinyurl.com/y4amup8z

Digital Oil Field Progression



- Sensors downhole, wellsite, & facilities - **SENSE**
- Connectivity to office – **COMMUNICATE, STORE**
- Dashboards - **ANALYZE**

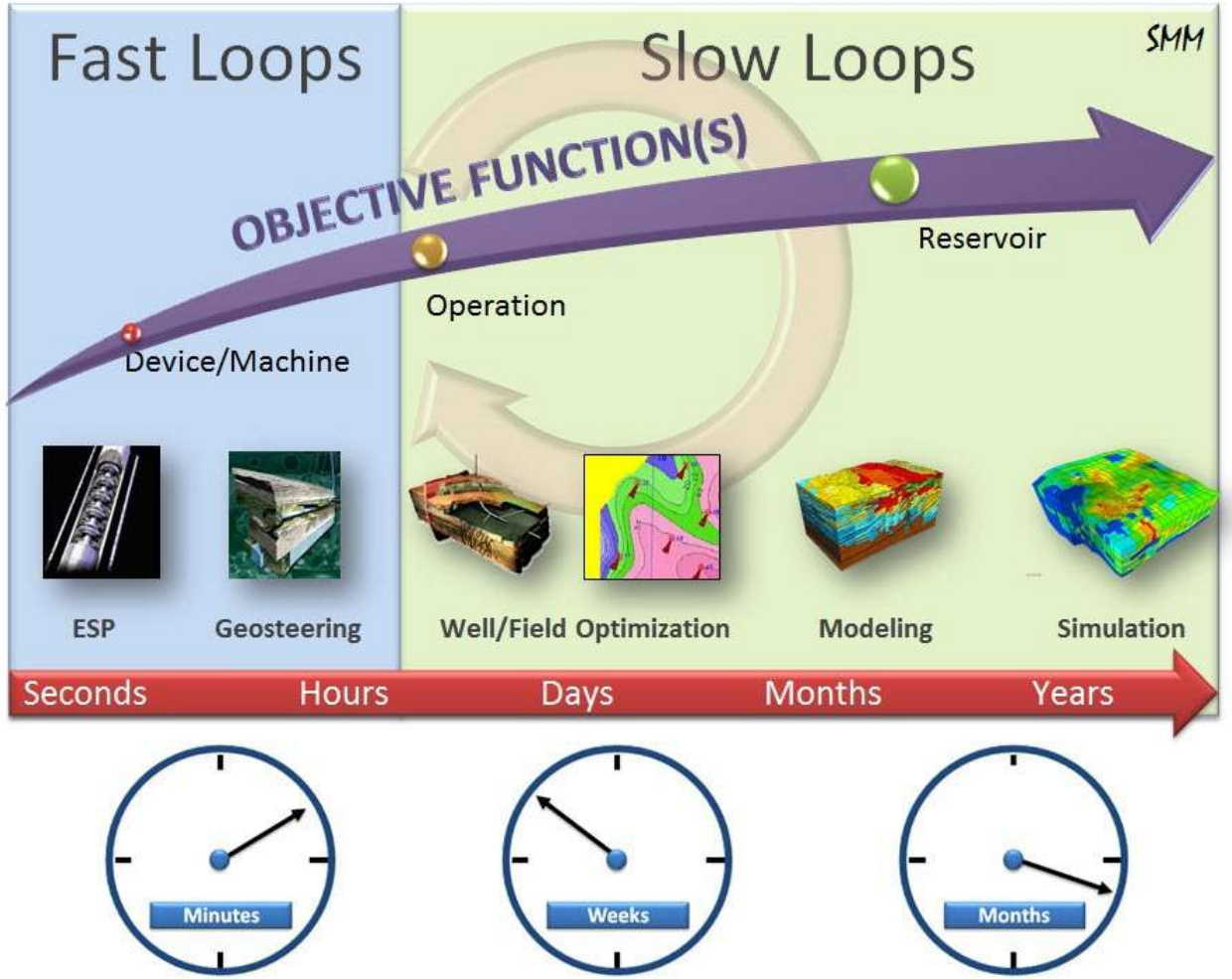
- Smart alarms
- Guided Workflows -- **DECIDE**
- Centralized control -- **ACT**

- Adjust production at wellsite or remotely
- Predictive and preventative maintenance-- **PRESCRIBE**
- Collaboration Room

- Autonomous Operations -Demanning
- Integrated Asset Management

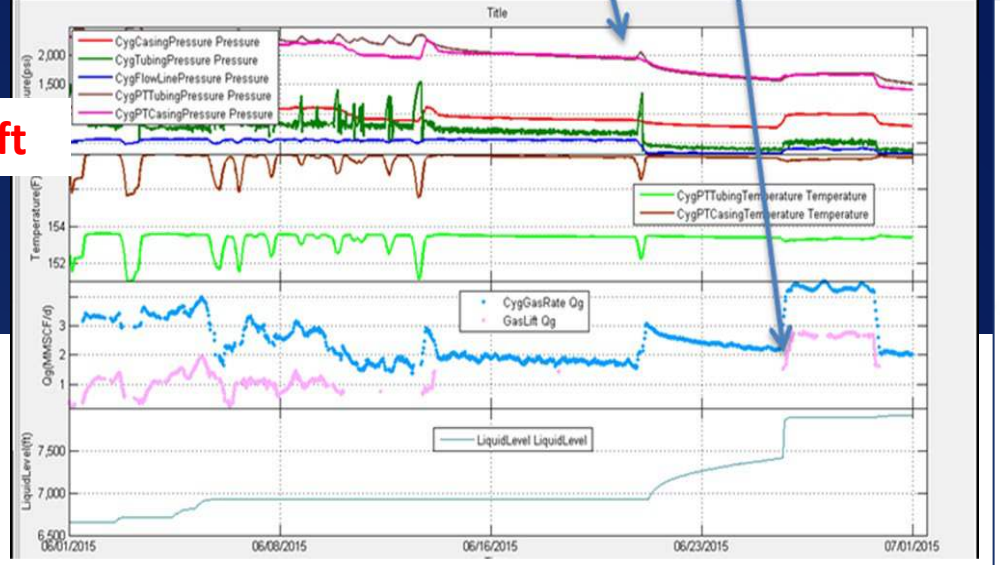
DATA LANDSCAPE

Cycle Times – Data Loops are fast for production

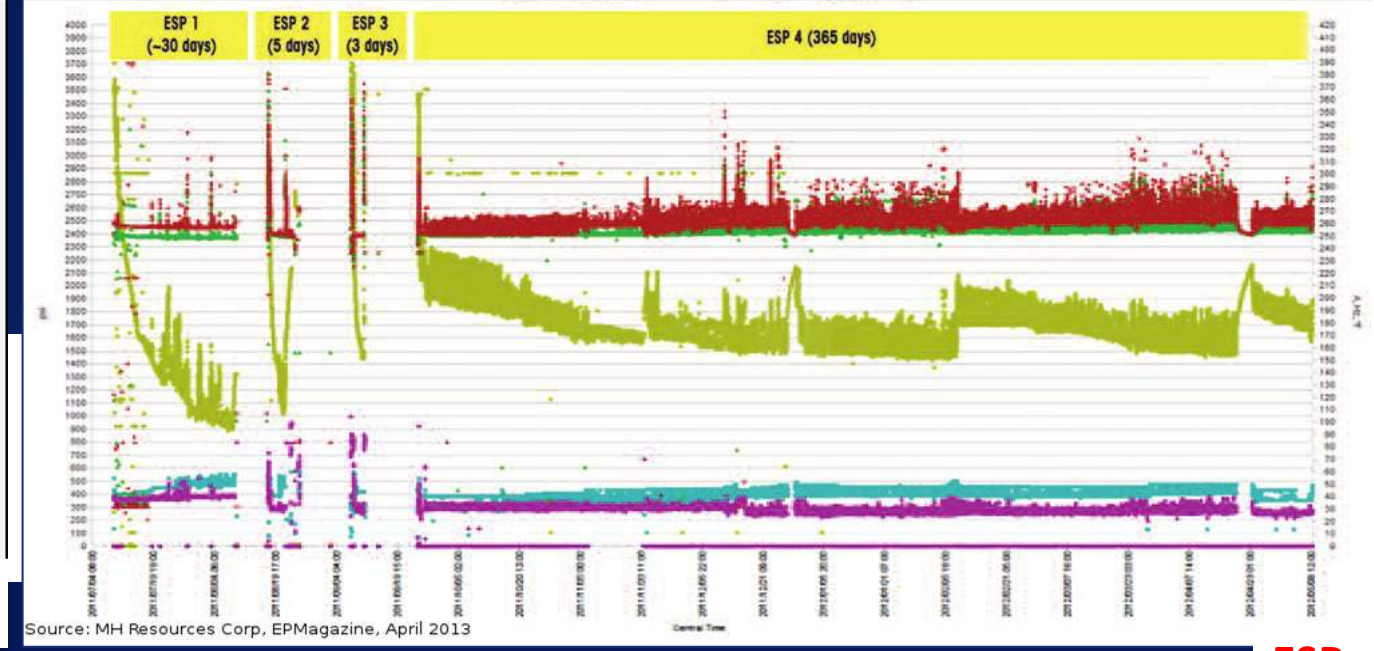


Source: Al-Mubarak, S M. "Real-time Reservoir Management from Data Acquisition through Implementation: Closed-Loop Approach." 2008 doi: https://doi.org/10.2118/111717-MS

Gas Lift



Source: SPE 180949, Gonzalez, Chokshi, *et al.* Lessons Learned in Permian Gas Lift Shale Well: Dynamic Production Analysis with Downhole Gauge

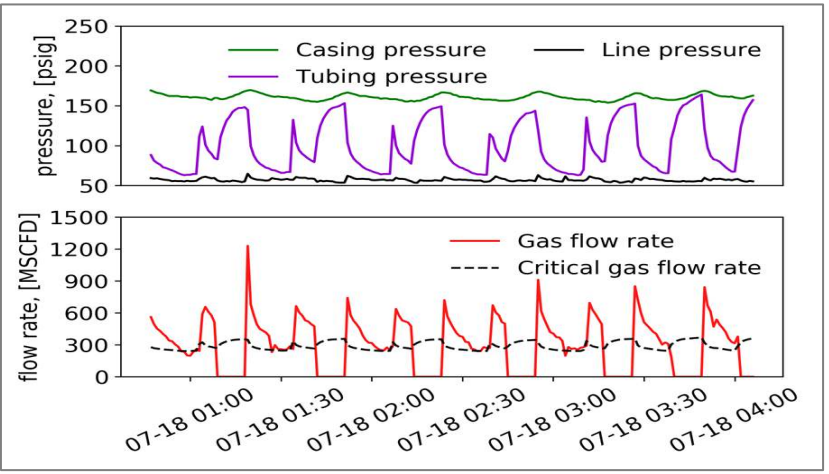


Source: MH Resources Corp, EPMagazine, April 2013

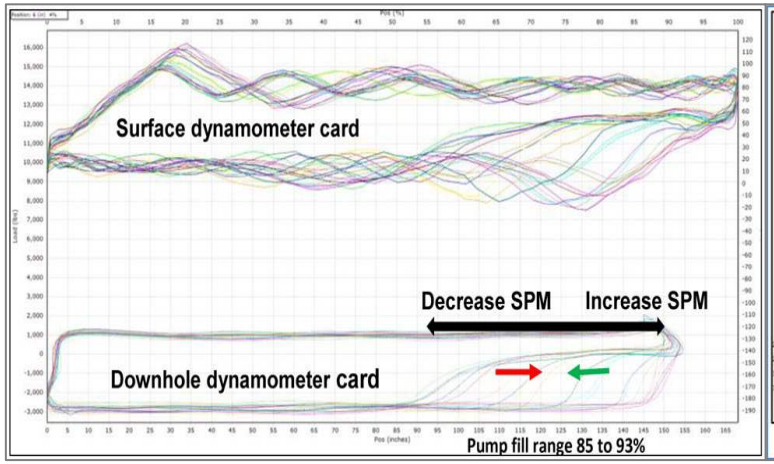
ESP

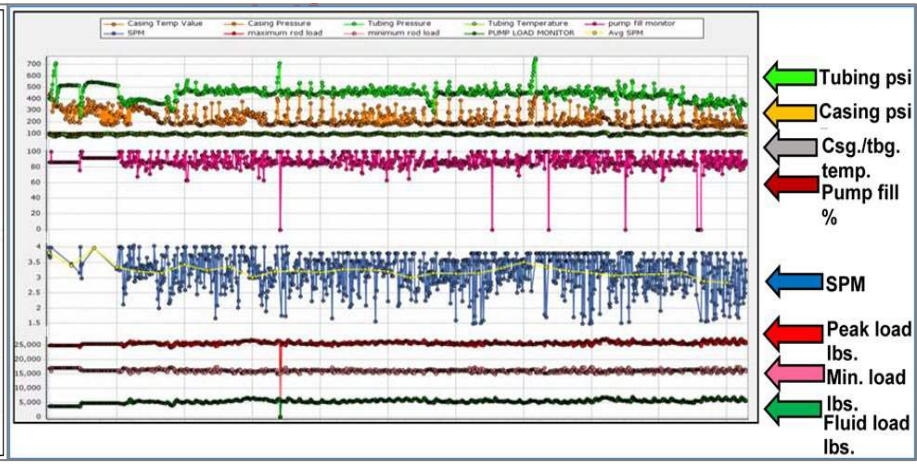
Types of Data – Time series Real-time – Point Measurements

Plunger Lift



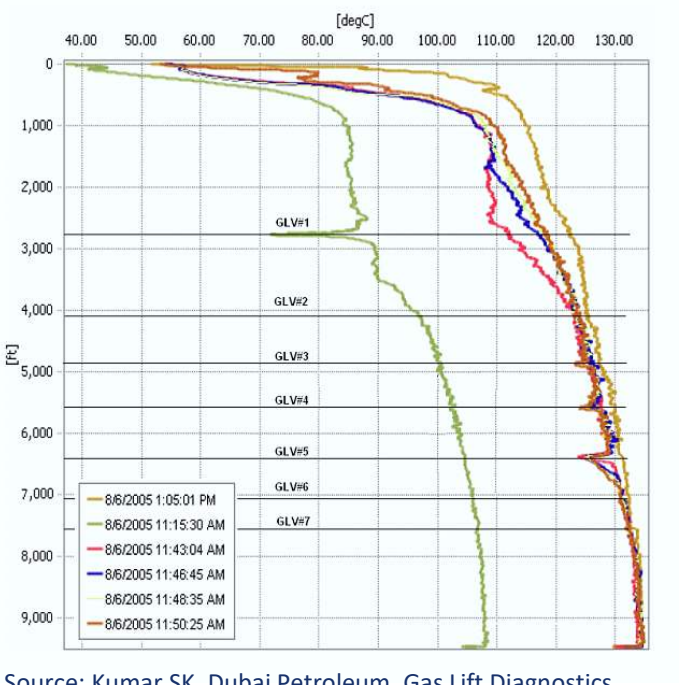
Source: Akhiiartdinov & Peyrera, Data Mining and Virtual Flow Metering in Plunger Lift Well, ALRDC GL Workshop, 2021



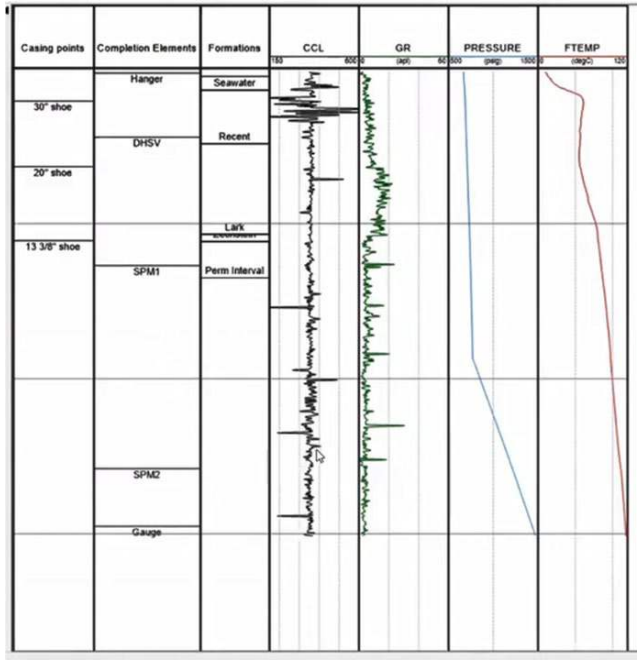


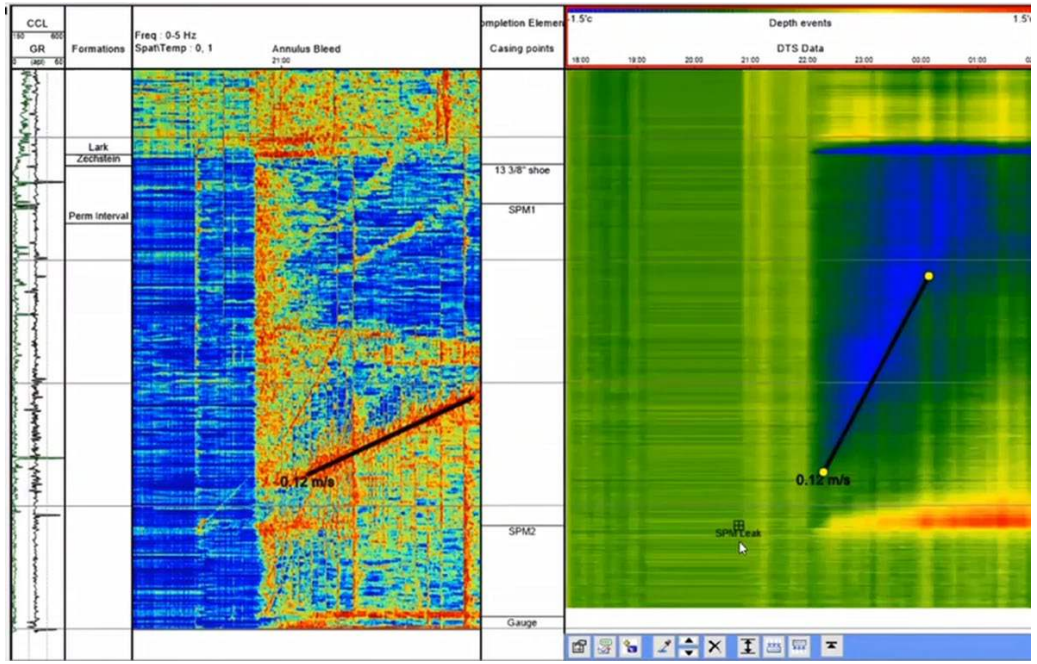
Source: SPE-181214, Clarke, F. and Malone, L.Sucker Rod Pumping in the Eagle Ford Shale Field Study.. 2016

Types of Data: Time series – Slickline DTS to diagnose badly slugging Gas-lift well in Dubai; DTS + DAS for Packer / GLV Leak in North Sea



Source: Kumar SK, Dubai Petroleum, Gas Lift Diagnostics Using Distributed Temperature Sensor (DTS) System on Slick line**, ALRDC 2007 Gas-lift Workshop**

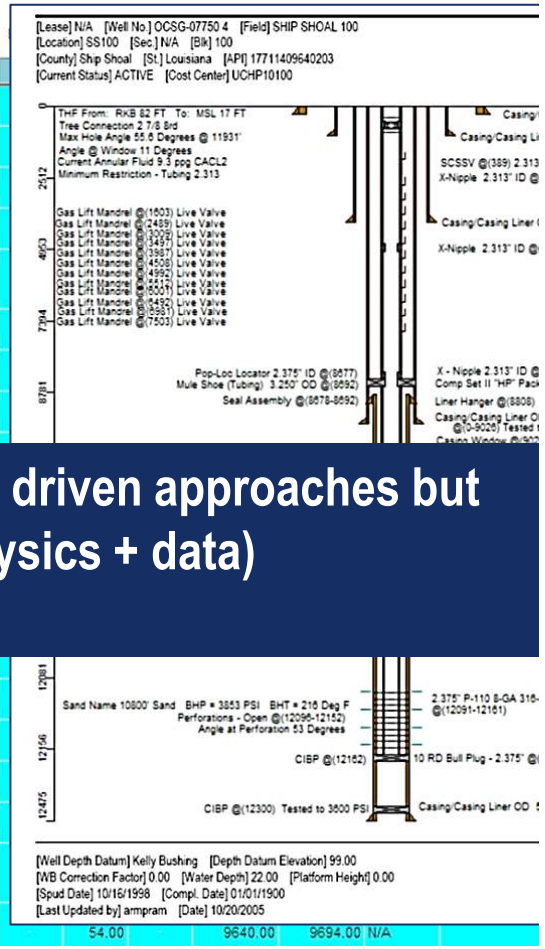




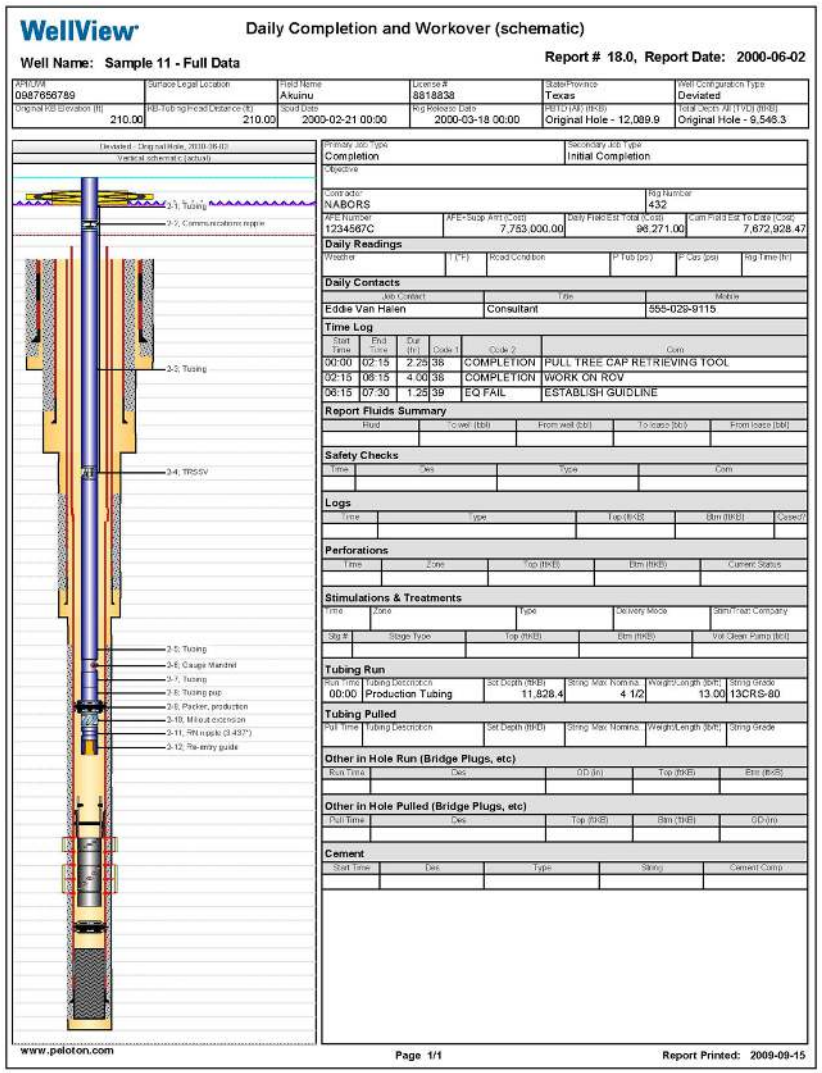
Source: Webster, M, Integration of DAS, DTS and conventional data, Sep 2020, https://www.youtube.com/watch?v=Rh4RwjhjFAA

Types of Data – Discrete events: Production Well Tests, Well completion, Reservoir, PVT, Equipment Changeovers, Workovers, Well / Surface Activities, ……

User	Dt/Tm		Grouping					
armpram	03/13/2006	Primary Wellbore	Production Casing		Liner Hanger	Liner Top	08/23/2005	1
armpram	03/13/2006	Sidetrack 1	Tubing String		Tubing - OD 3.500	3-1/2" 9.3# 13CR85 BTS-8 Tbg	01/15/2003	0
armpram	03/13/2006	Sidetrack 1	Tubing String		Tubing - OD 2.875	2-7/8" Blank	01/15/2003	0
armpram	03/13/2006	Sidetrack 1	Tubing String		Tubing - OD 2.875	2-7/8" Blank	01/15/2003	0
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Profile Nipple	Halliburton "X" Nipple 3.915" O.D. / 2.813" ID	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Subsurface Safety Valve	Halliburton "WellStar" Tbg Ret SV 4.750" O.D. / 2.813" I.D.	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Gas Lift Mandrel	Gas Lift Mandrel (3.500")	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Gas Lift Mandrel	Gas Lift Mandrel (3.500")	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Gas Lift Mandrel	Gas Lift Mandrel (3.500")	01/15/2003	1
armpram	03/13/20							
armpram	03/13/20							
armpram	03/13/20							
armpram	03/13/20							
armpram	03/13/20							
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Profile Nipple	Halliburton "X" Nipple 3.210" O.D. / 2.313" I.D.	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Profile Nipple	"X" Nipple 1.875" I.D.	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Tubing Jewelry		Profile Nipple	"X" Nipple 1.875" I.D.	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Conductor Casing		Casing/Casing Liner OD 20.000	20" 94# K55	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Intermediate Casing		Casing/Casing Liner OD 10.750	10-3/4" 40.5# K55/S80	01/15/2003	1
armpram	03/13/2006	Sidetrack 1	Production Casing		Wellbore Completion Detail (Perforations,	9000' Sand Perforations	03/07/2000	0



May not be required for some of the data driven approaches but these are a must for hybrid approach (physics + data)
Think digital twins



Data to Solve Artificial Lift Challenges with ML/AI

RRL	ESP	Gas-Lift	PCP	Plunger Lift	Production Data
Casing/Tubing/Line P, T PR Load, Displacement SPM Motor Amp, Voltage Stuffing Box level Fluid level Pumping Unit, Pump, Rods, Motor Specs	Casing/Tubing/Line P, T Pump Intake P, T Pump Discharge P, T Frequency/Speed Amp, Voltage Vibration I, V Imbalance I Leakage Fluid level Pump, Motor, VSD, Cable, Transformer, Power source Specs	Casing/Tubing/Line P, T Surface Gas Inj Rate Manifold Pressures Gradient Surveys Fluid Level GL valves' location specs, Inj Choke specs Valve performance	Casing/Tubing/Line P, T Speed/Frequency Pump Intake P, T Pump Discharge P, T Surface Flowrate Motor Amp, Voltage Motor Torque Fluid Level Pump, Motor, VSD, Power Source specs	Casing/Tubing/Line P, T Plunger arrival Gas Flow rate	Well Test, Choke Settings Well Config Reservoir PI/IPR Service Records Workover Records Teardown/DIFA Startup/shutdown data Facilities Status Injection (Corrosion, Surfactant)

Controller settings <u>Less Common:</u> Downhole gauge for GL, RRL, Plunger
<u>Rarely Available:</u> DTS, DAS, Multiphase Flow Meter Measurement

Implementation Caution : Field Realities

Data is not always what it seems: Need validation layer before analysis

Quality & Quantity Issues

- Key Measurements are missing; e.g., flow rate, pressure
- Measurements do not coordinate with each other;
  - upstream << downstream pressure
- Measurements do not correspond to a physical model;
  - Negative/Out of range Value, Flat-lined data, data clipping, outliers, discontinuities, repeated values.

Implementation Caution : Field Realities

Causes

- Older Field infrastructure
  - Analogue instrumentation conversion // need for new sensors
  - Communications Infrastructure: Line of site issues/ Radio/
  - Legacy Data formats.. Non-Digital Archives
- Lack of information for some time intervals:
  - loss of signal / data maintenance
- Malfunctioning measurement devices:
  - Calibration
- Human errors in captures:
  - Wrong records of equipment/ assets: wrong location / model

Incomplete Data & Bias in Models

- Incomplete data can lead to bias in AI
  - **Bias makes it challenging to develop AI that works for everyone.**

For example, if you were teaching AI to recognize shoes and only showed it imagery of sneakers, it wouldn't learn to recognize high heels, sandals or boots as shoes.

Source: "Making sense of artificial intelligence," https://atozofai.withgoogle.com/intl/en-GB/bias/

ML/AI Code is small part of the system

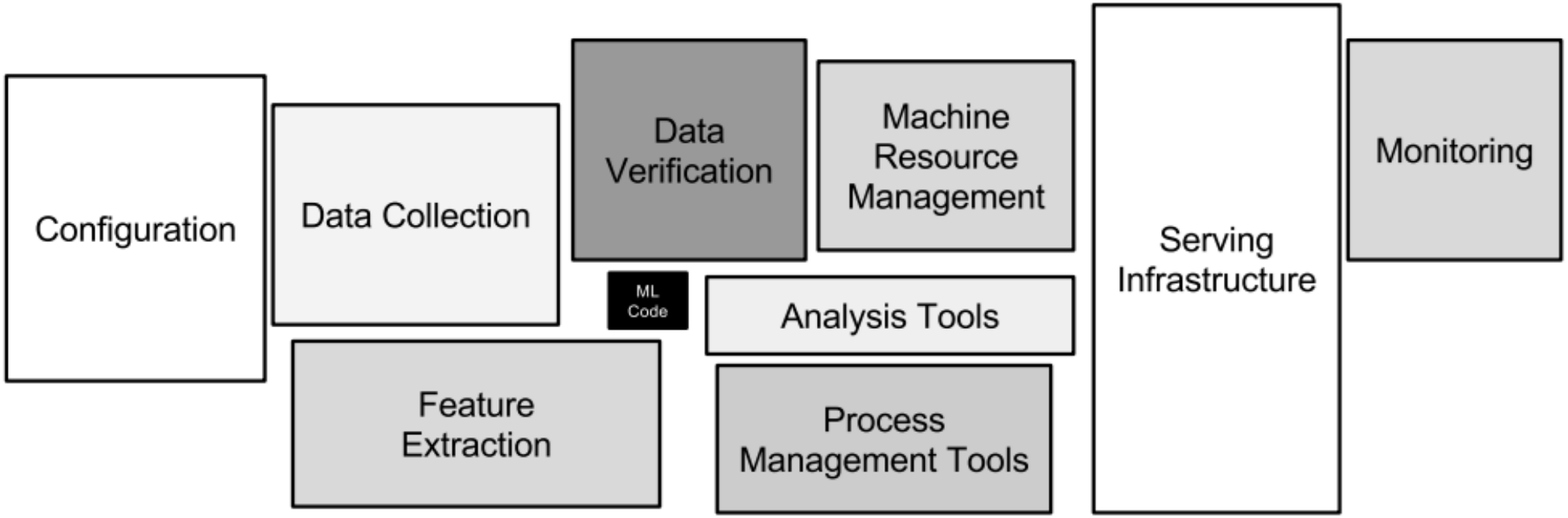


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

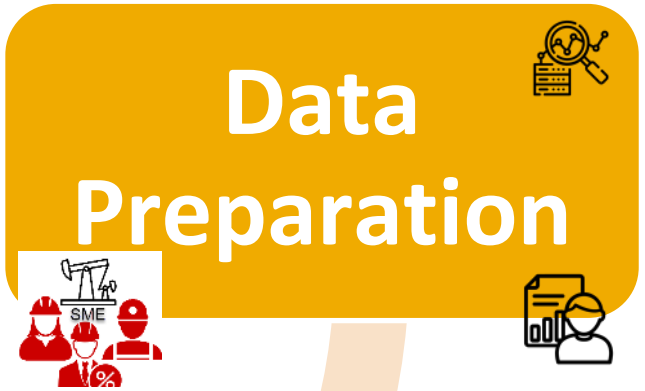
Hidden Technical Debt in Machine Learning Systems

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips
{dsculley,gholt,dgg,edavydov,toddphillips}@google.com
Google, Inc.

Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-François Crespo, Dan Dennison
{ebner,vchaudhary,mwyoung,jfcrespo,dennison}@google.com
Google, Inc.

ML/AI Cycle

80% of Work
80% of Frustration



- Acquisition
- Exploratory Analy
- Preprocessing
- Labeling
- Splitting

- Input Drift Tracking
- Performance Drift
- Online Evaluation

80% of Project Risk

- Feature Engineering
- Training
- Experimentation
- Evaluation
- Comparison

- Runtime Environment
- Scaling
- QA
- Logging/Alerting

Anomaly Detection

Failure Prediction

Virtual Flow Metering

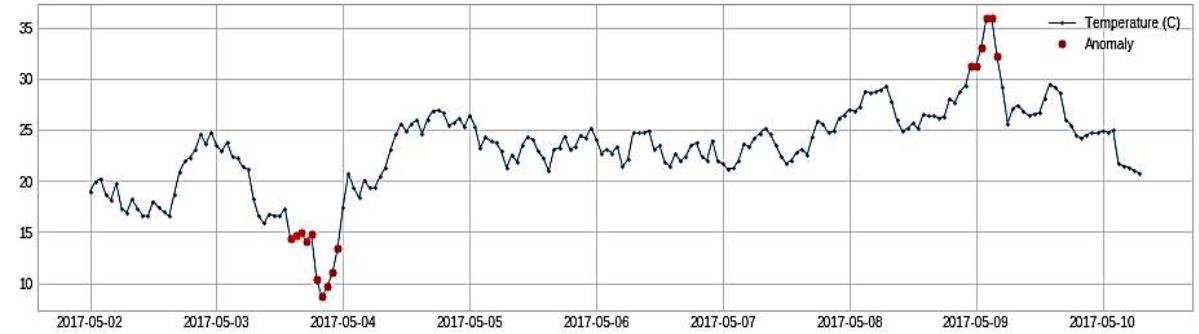
WHAT PROBLEMS ARE BEING ADDRESSED

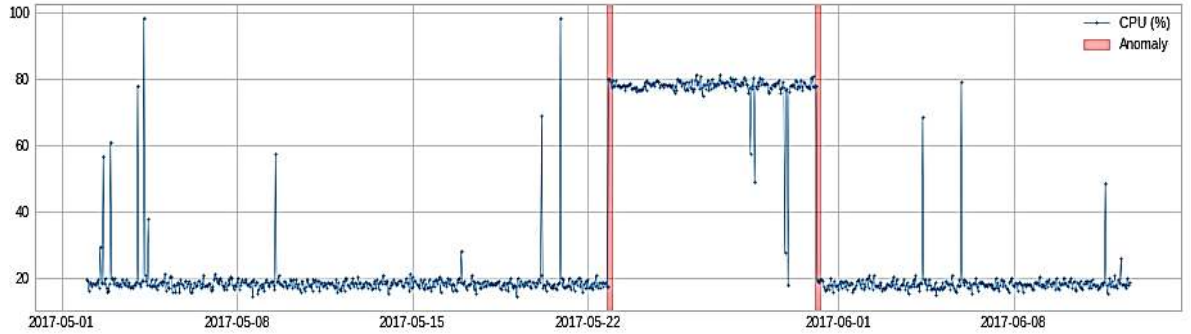
Anomaly Detection

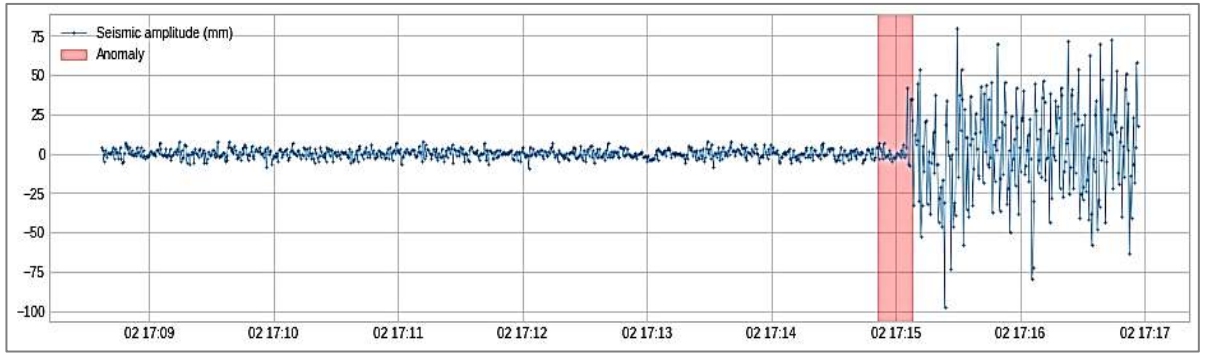
Objective:

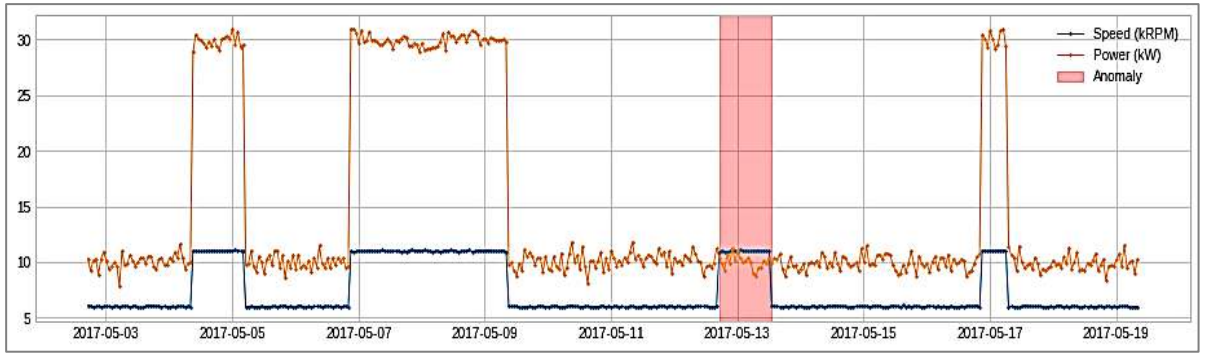
Discover deviation in data potentially signaling an event like process upset, imminent failure, defect.

Learn what “normal” data looks like then use data to detect abnormal instances



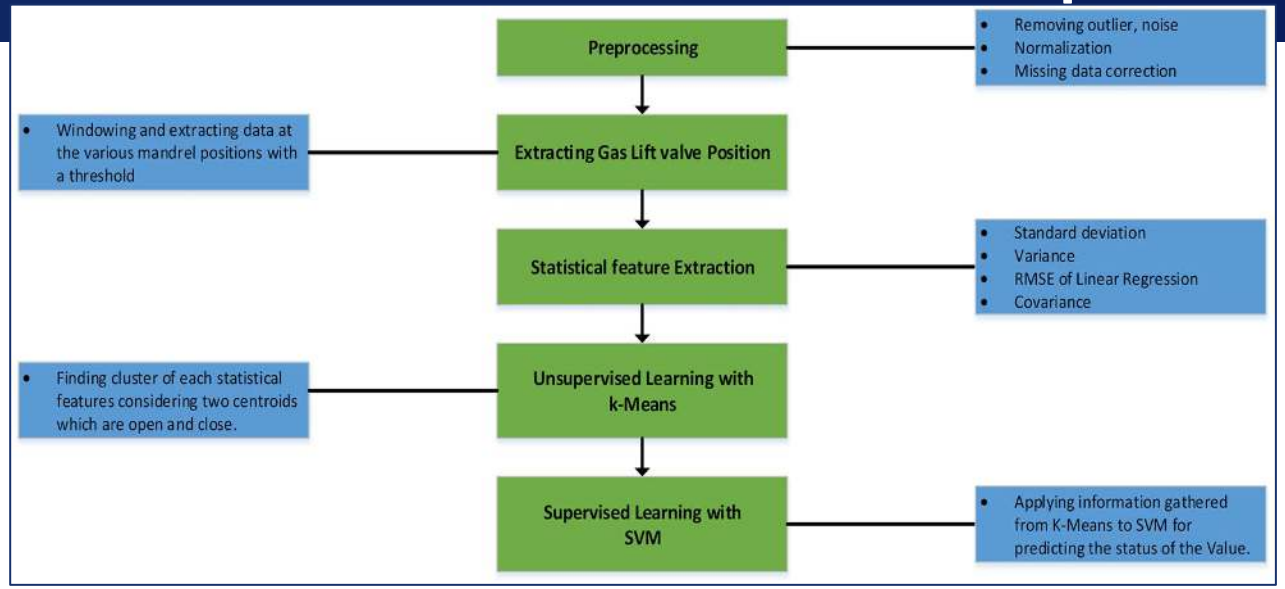


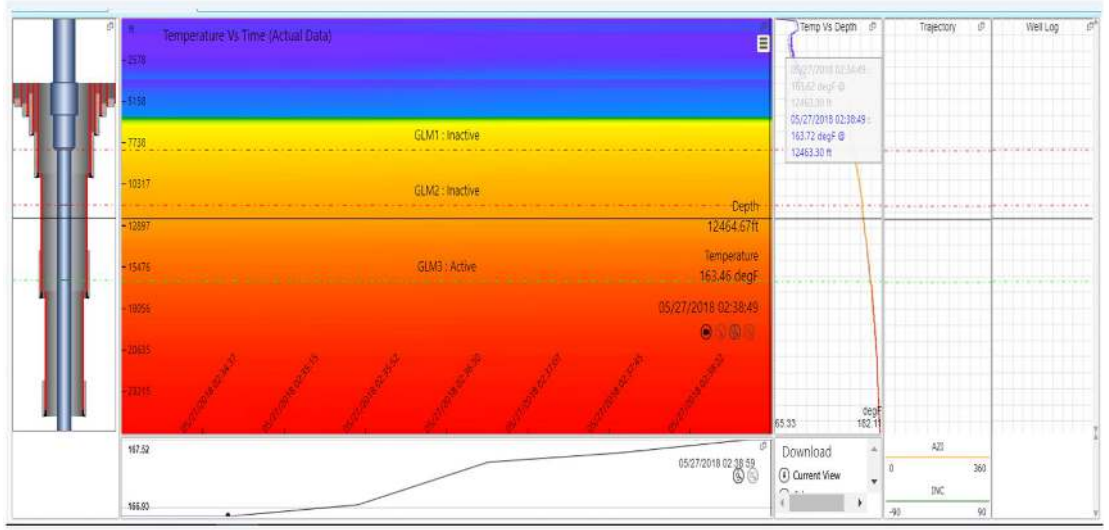


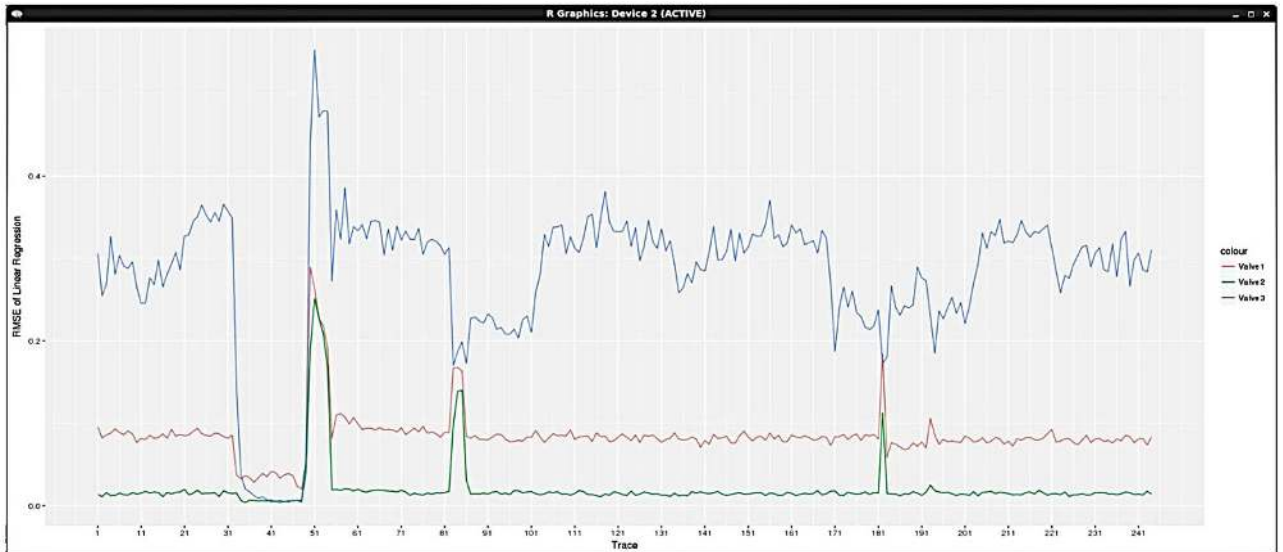


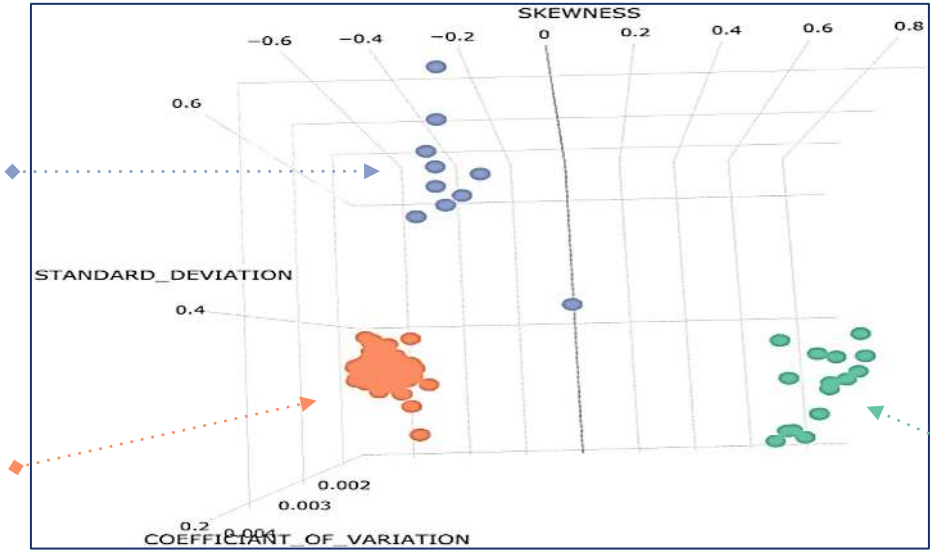
DTS Analytics for Anomaly Detection in Gas-Lift – GLV Open or Close??

Source: Bello *et al.* (2018) Integrating Downhole Temperature Sensing Datasets and Visual Analytics for Improved Gas Lift Well Surveillance, SPE 191626

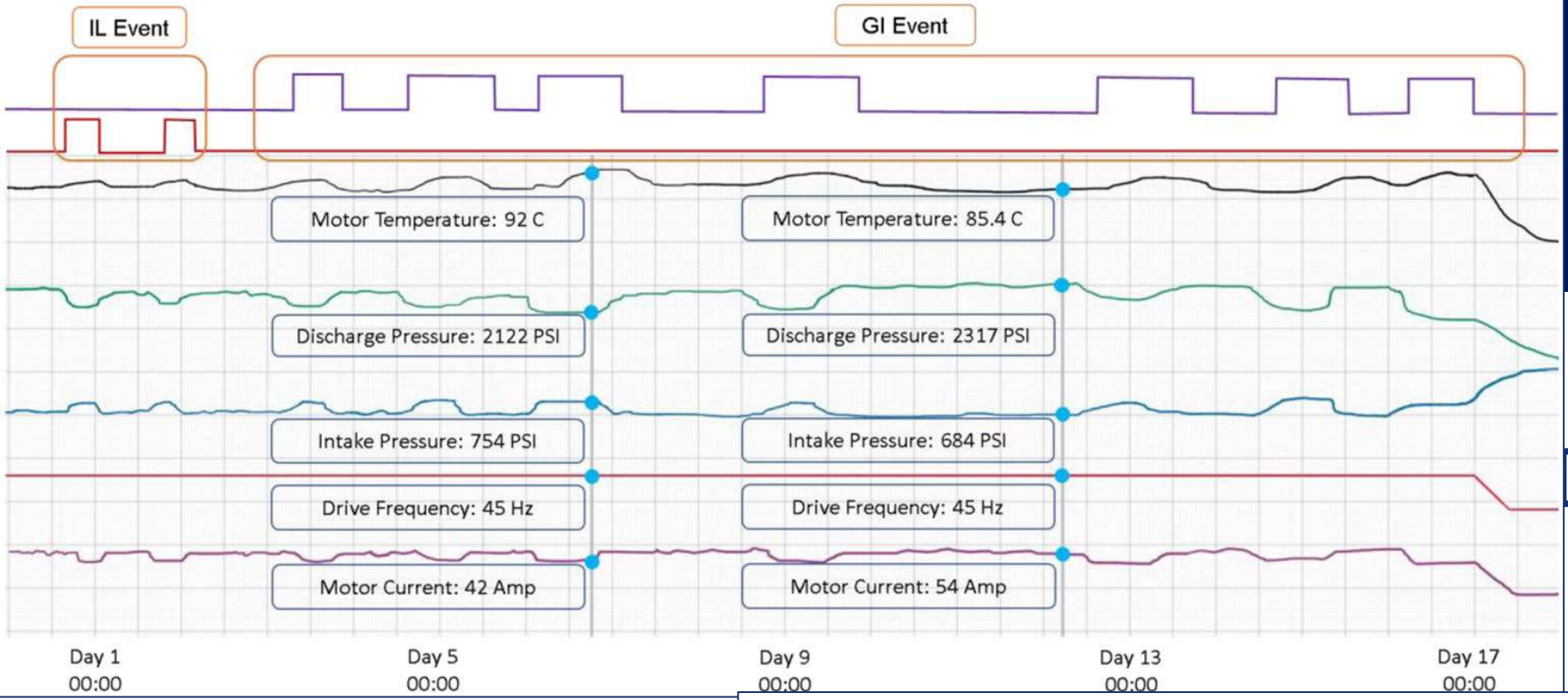


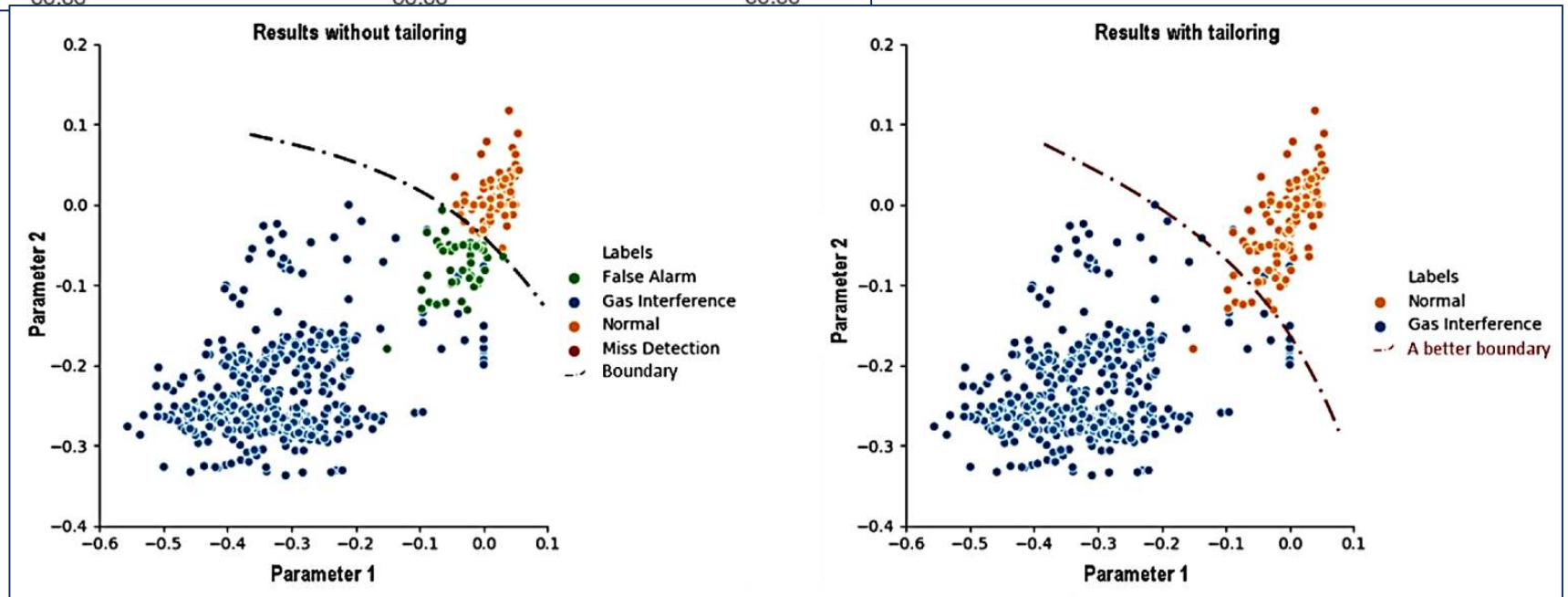






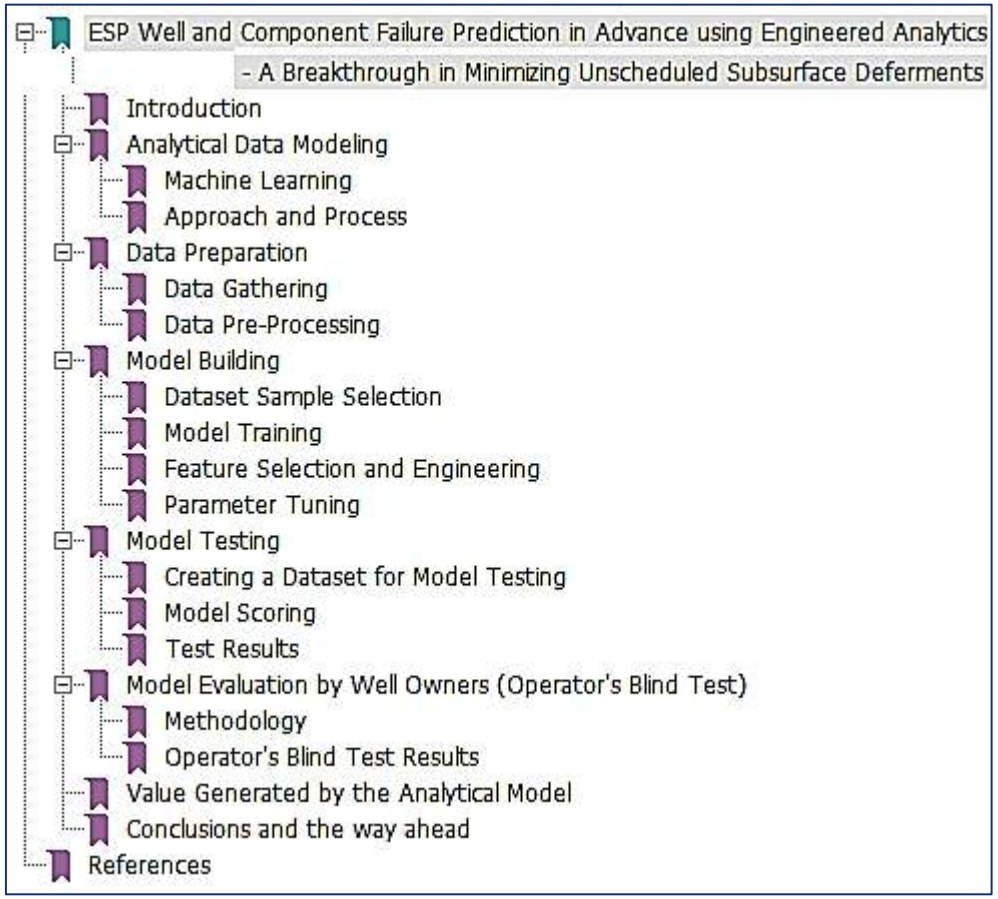
ESP Anomaly Detection Engine

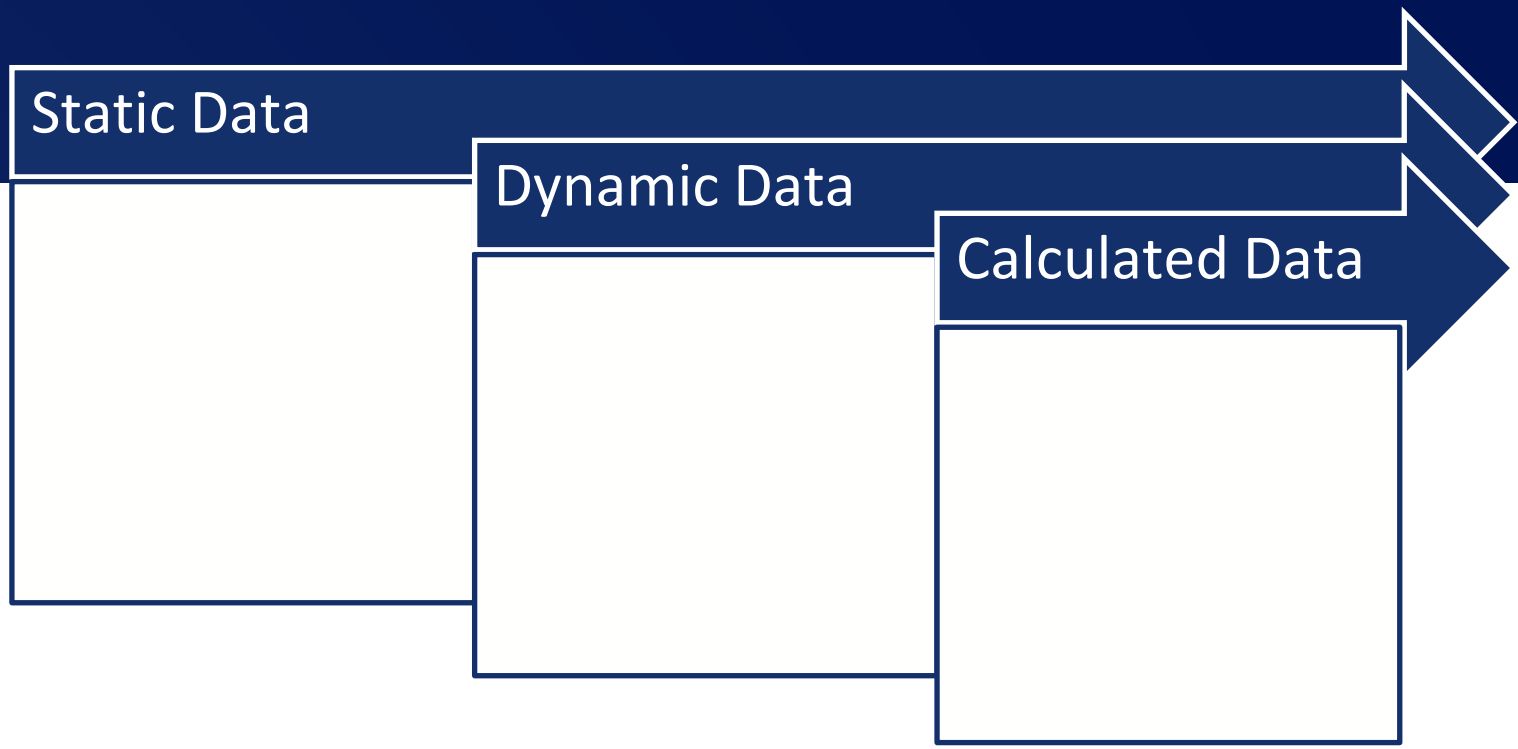




Source: Nguyen *et al.* (2020), Real-Time Automated Event Detection Framework for Electrical Submersible Pumps, SPE 203277

Failure Prediction Machine Learning approach for ESP



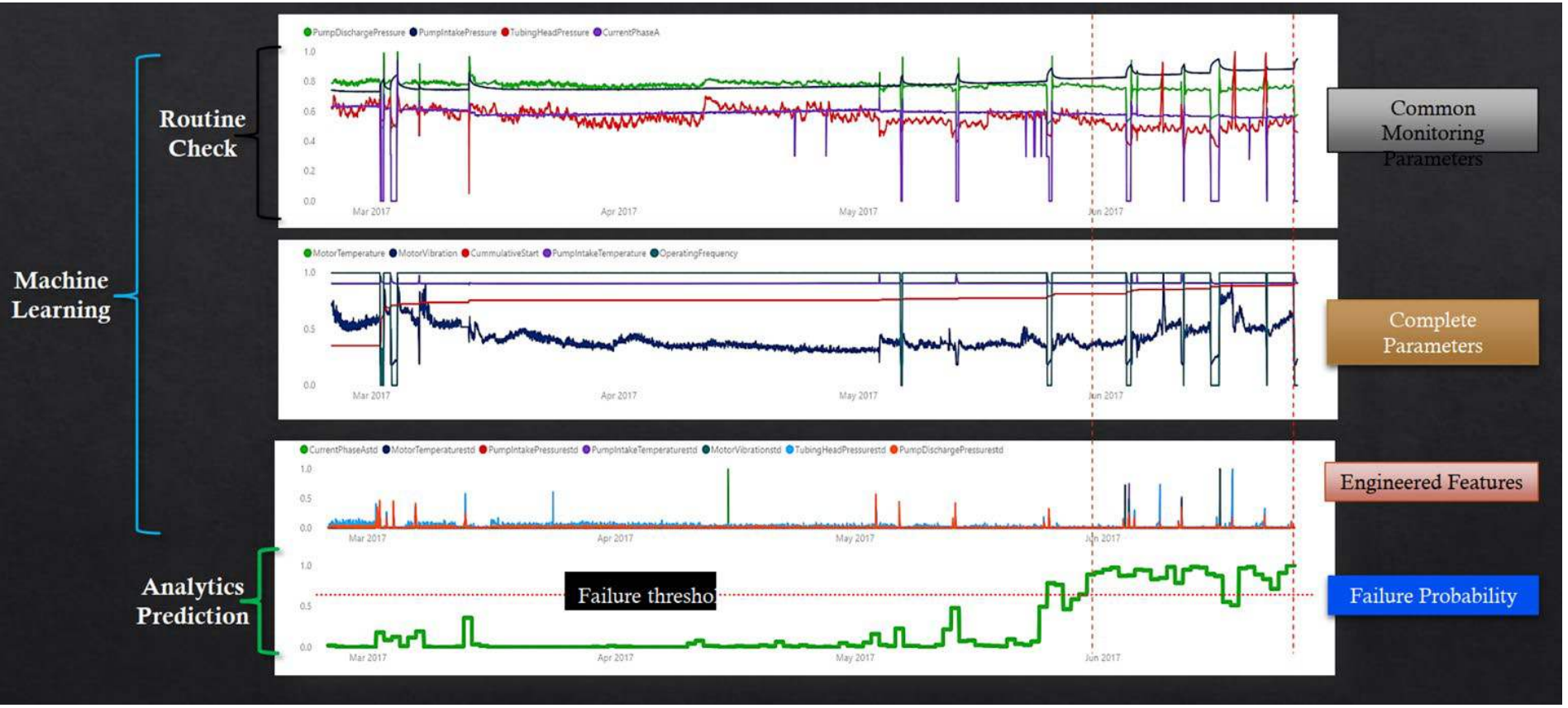


Supervised learning approach: Random Forest based classifier developed using above and engineered features like standard deviations, param differences across fixed time intervals, differential pressures, etc.

Well Level Failure and component level failure models developed.

Source: Marin *et al.* (2019) ESP Well and Component Failure Prediction in Advance using Engineered Analytics - A Breakthrough in Minimizing Unscheduled Subsurface Deferments, SPE-197806

Failure Prediction
Machine Learning approach for ESP



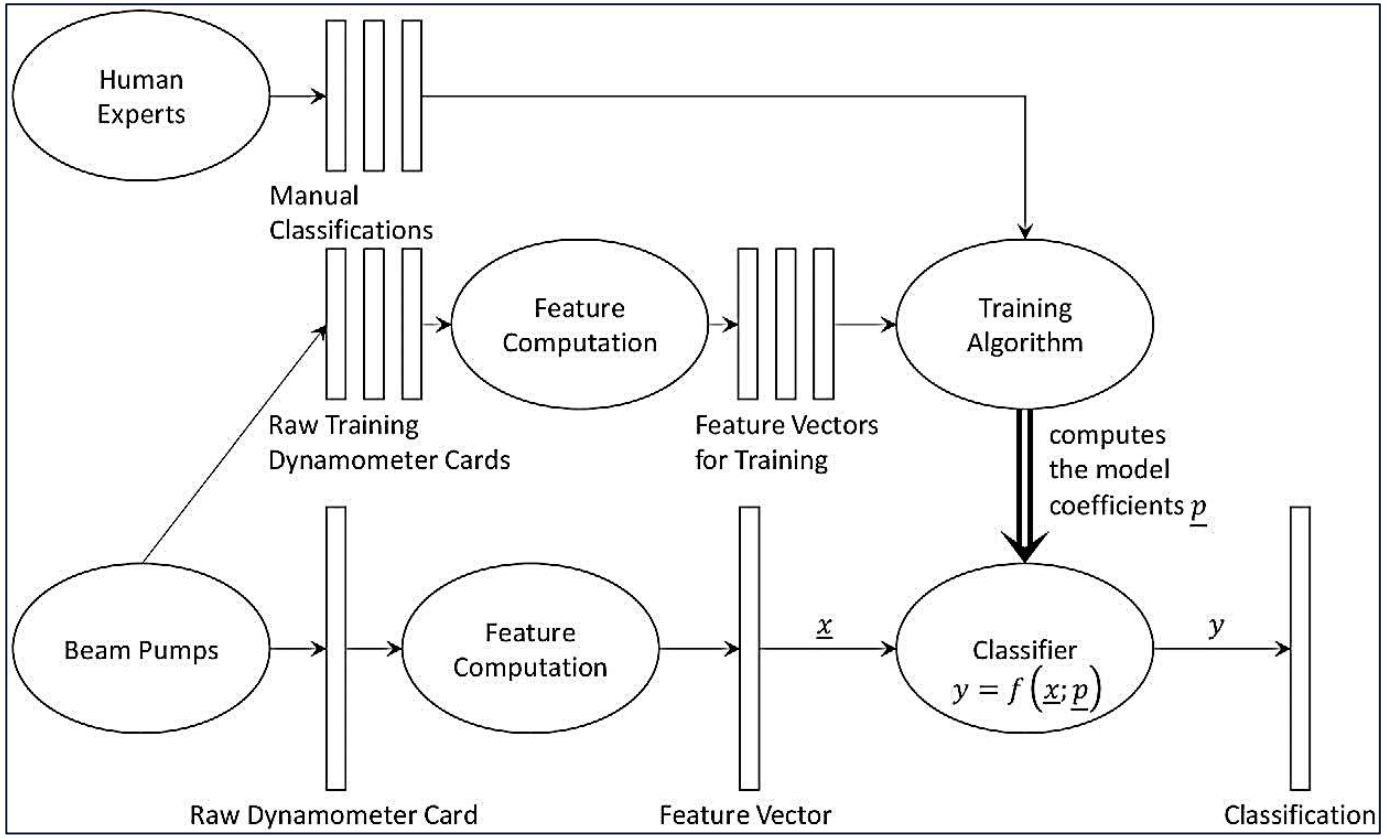
- Data driven models captured 58.62% of the well failures and 66.66% of the pump failures while keeping all false alarms negligible.
- The Blind Test confirmed that ESP Well Failure model scored a high precision of 89.47% and 75.86% accuracy, the ESP Pump (component) Failure model scored a very high precision of 92.31% and 88.11% accuracy.

Source: Marin *et al.* (2019) ESP Well and Component Failure Prediction in Advance using Engineered Analytics - A Breakthrough in Minimizing Unscheduled Subsurface Deferments, SPE-197806

Predictive Maintenance for Rod Pumps

Source: Bangert & Sharaf: SPE 195295 – "Predictive Maintenance for Rod Pumps", 2019

- **Procedure of generating and using classification model**
- **Formula taking card's features as input and produces a class number as output**



35292 cards from 299 beam pumps from Bahrain	
Normal	
Fluid Pound (Slight)	Inoperative Pump Hitting Down
Fluid Pound (Severe)	TV or Plunger Leak
Pump Hitting Down	SV, TV Leak or Gas Interference
Pump Hitting Up & Down	Inoperative Pump

Results:

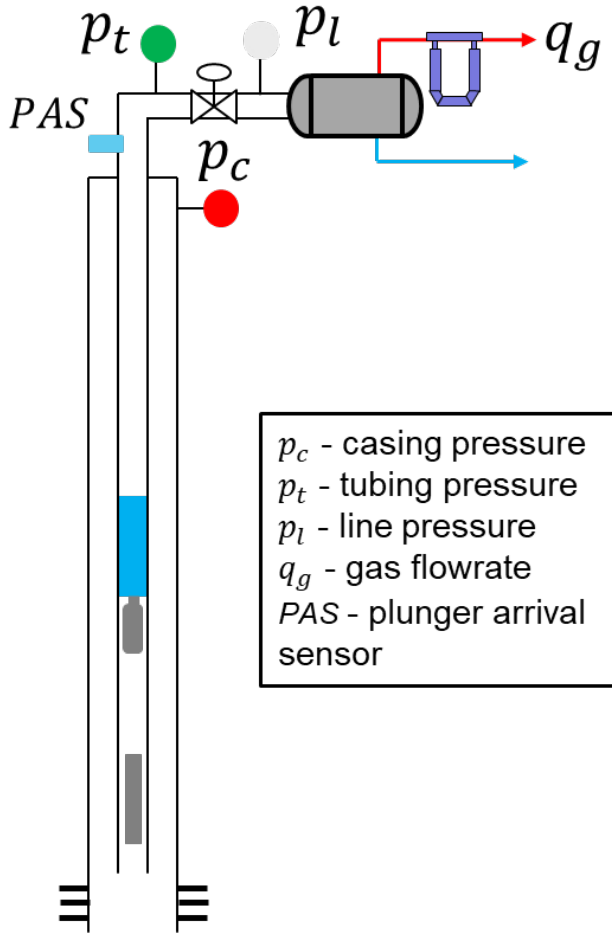
Using stochastic gradient-boosted decision tree model

Accuracy = 99.9% Evenly distributed errors

Virtual Flow Meter – Plunger Lift

Source: Akhiiratdinov *et al.* (2020) Data Analytics Application for Conventional Plunger Lift Modeling and Optimization, SPE 201144

- Using plunger arrival and pressures data, determine the gas flow rate to back-allocate the flow rates.
  - Challenging or computationally expensive using traditional physics-based model
- Approach:
  - ANN – 3 hidden layers, 10 nodes each layer
    - Brute force approach utilizing raw pressure and flow rate data in the ANN does not yield acceptable results
    - Physics-guided features – pressure differentials and flow rate transformations – provide better model performance.
- More training data helps evolve model into better prediction performance.



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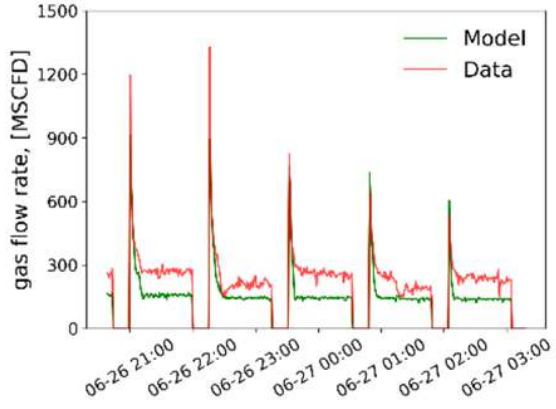
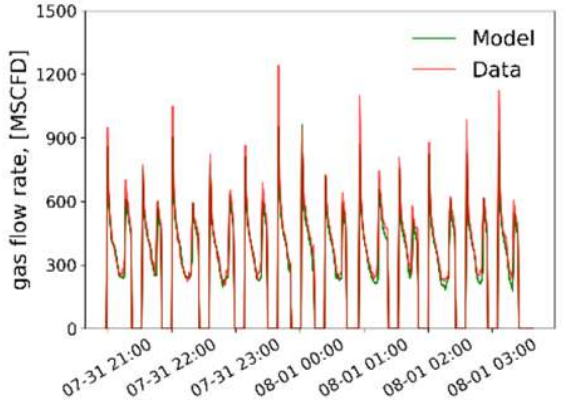
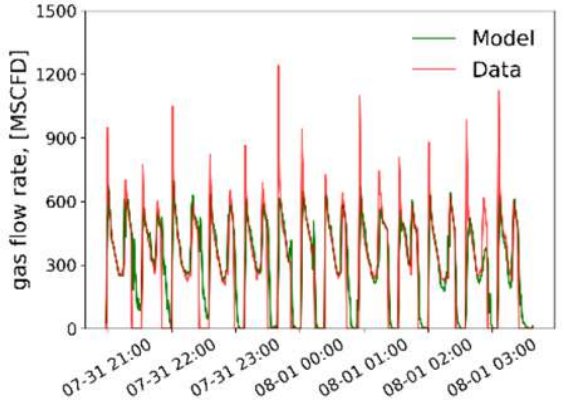


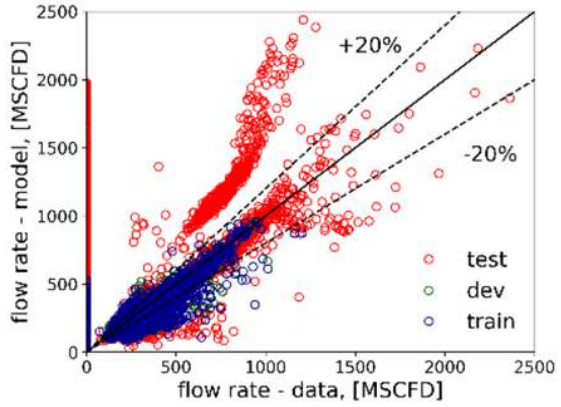
(a) Model predictions for 6 hours of the test set – 4 days training set.



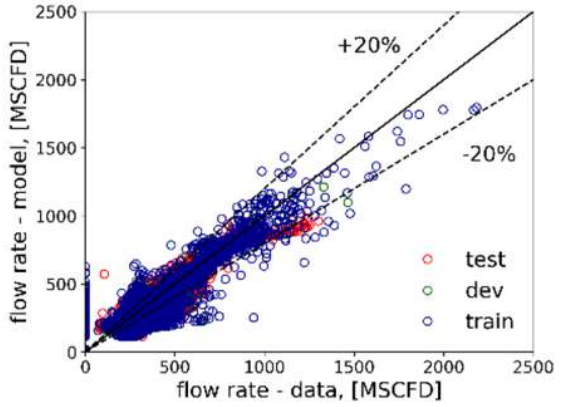
(b) Model predictions for 6 hours of the test set – 9 days training set.



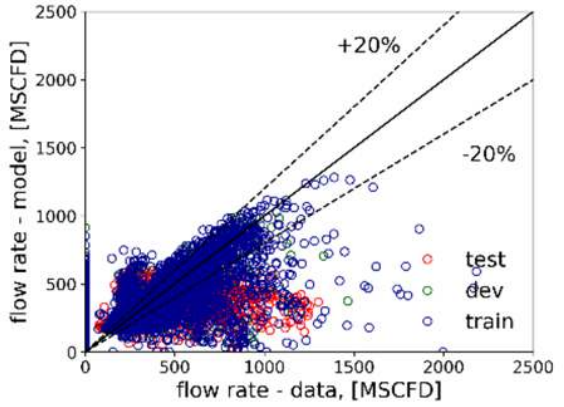
(c) Brute force model predictions for 6 hours of the test set – 9 days training set.



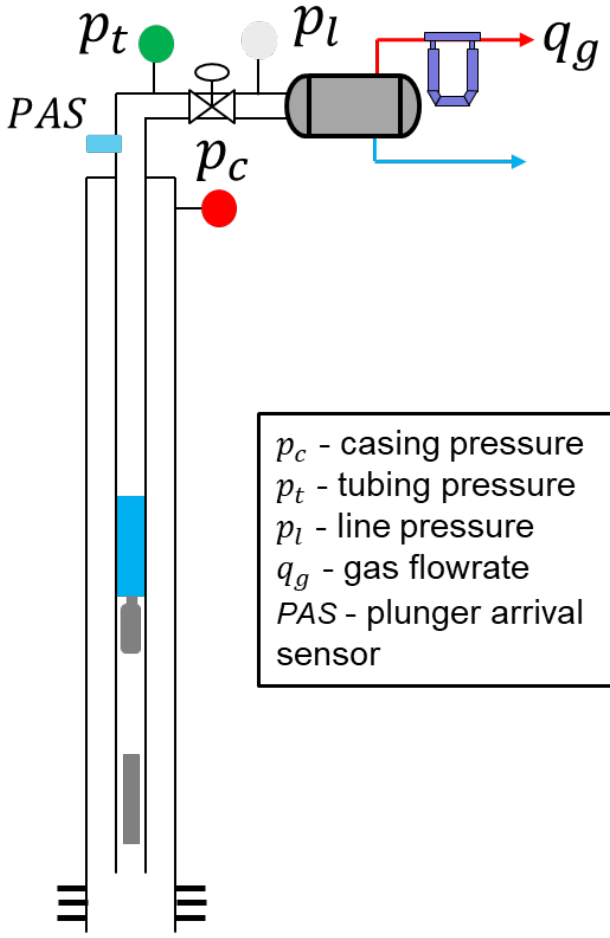
(d) Model parity plot for the full test set – 4 days training set.



(e) Model parity plot for the full test set – 9 days training set.



(f) Brute force model parity plot for the full test set – 9 days training set.



p_c - casing pressure
p_t - tubing pressure
p_l - line pressure
q_g - gas flowrate
PAS - plunger arrival sensor

Edge Device Application - SRP

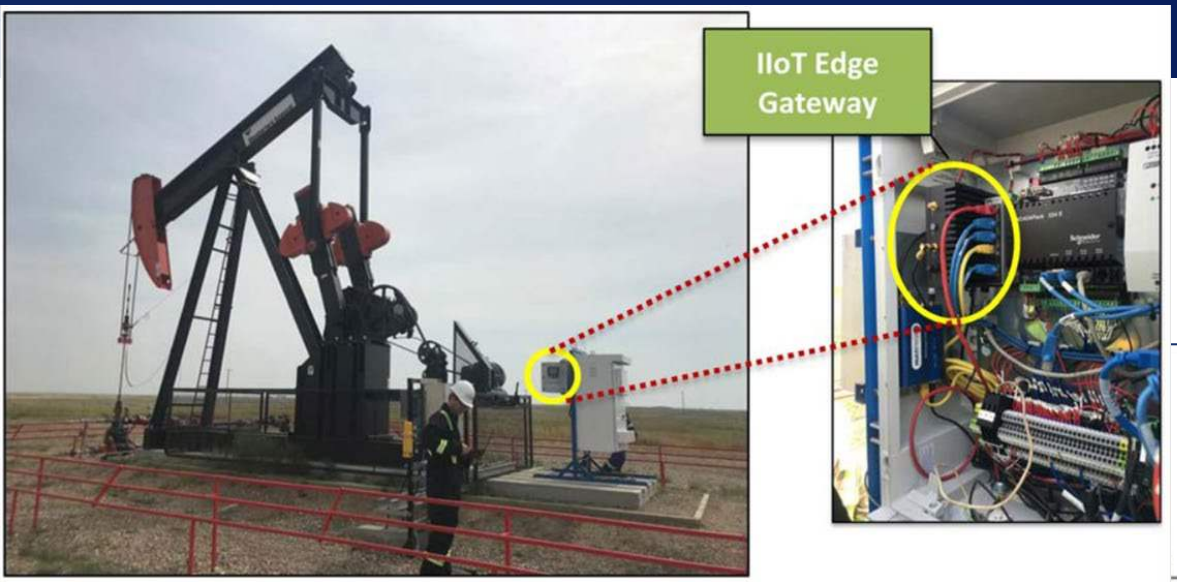


Figure 3—An IIoT Edge Gateway Installation for Rod Pump Analytics

Source: Saghir *et al.* (2020) Application of Augmented Intelligence and Edge Analytics In Upstream Production Operations: An Innovative Approach for Optimizing Artificial Lift Systems Performance, SPE 201516

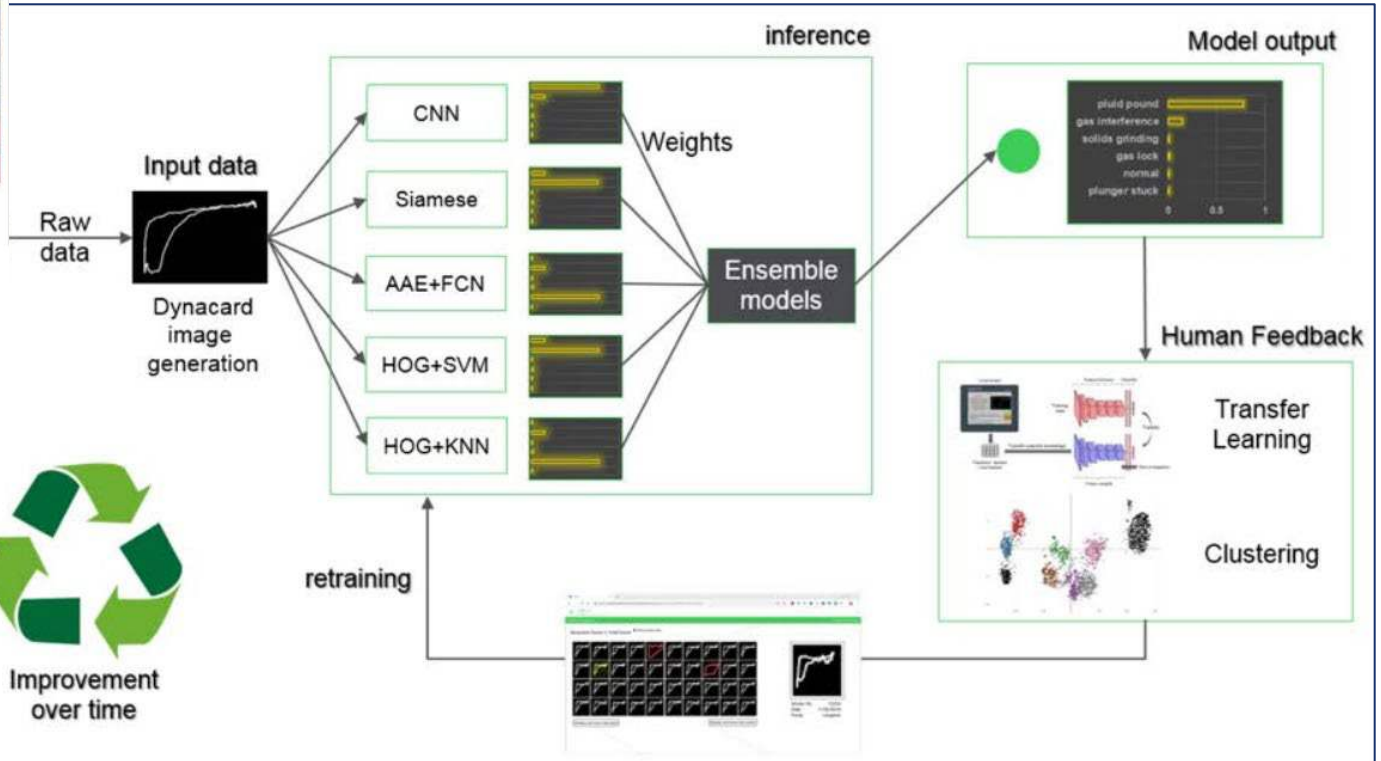


Figure 5—A simplified overview of the Augmented Intelligence Workflow

Conclusion

- Data driven approaches are increasingly being applied in the artificial lift domain
- Prevalent applications cover anomaly detection, failure prediction and virtual flow metering
- The use of ML helps save time, minimize effort, improve quality, increase yield, limit human error, increase accuracy and lower risk.

Takeaways

- While ML/AI approaches promise new pathways to solving our operational and design challenges, AL and the production community needs to actively pay attention to and participate in the data lifecycle from cleaning through modeling to production-deployment and retraining.

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