Webinars

# Welcome!

The program will begin soon.

You will not hear audio until we begin.

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# Data Exploration and Analytics for Artificial Lift and Production Engineers

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Victoria Pons PhD, WellWorx

June 25, 2021

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WELLWORX

fathom
a deeper insight

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# Agenda

- Digital Transformation Enablers
- Is an Intelligent System right for you?
  - SME vs. Data Scientist
- A Few Examples
  - Data Analytics – traditional application
  - Anomaly Detection: Gas-Lift, ESP
  - Failure Prediction: SRP, ESP
  - Pattern Recognition: SRP
  - Virtual Flow Metering: ESP, Plunger Lift
- Conclusion

# Digital Transformation is Accelerating… Enabler Digital Oilfield…

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## 2010 Presentations

- "up to 25% savings in OPEX, up to 8% higher production rates, 2-4% lower project costs, and as much as 6% improved resource recovery within the first full year of deployment…" [1]
- BP-Valhalla, Field of the Future® : Production increase > 1.5 MM BOE/year [2]
- Shell: "10% ***sustained*** improvement in production, 5-10% increase in recovery, 20% reduction in OPEX, and 75% reduction in workflow cycle times in core processes." [3]

Sources:
1. IHS-CERA, Chevron's Next magazine, Issue 5: http://bit.ly/29rFpgR
2. BP's Field of the Future, http://on.bp.com/29EwtHp
3. Deloitte, Unearthing the potential of digital oilfield technology, http://bit.ly/29waG44

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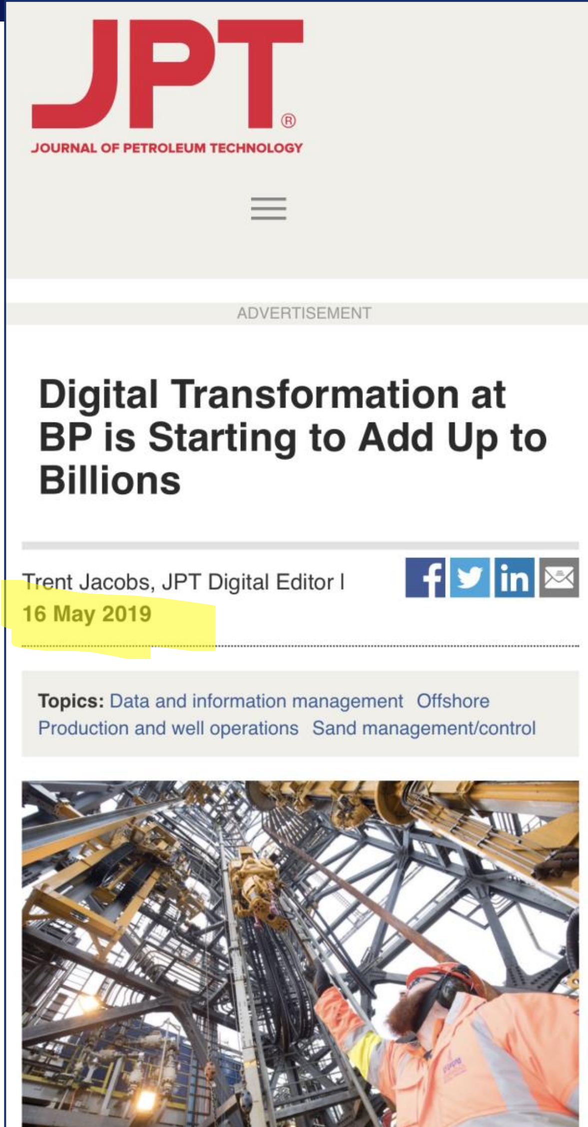


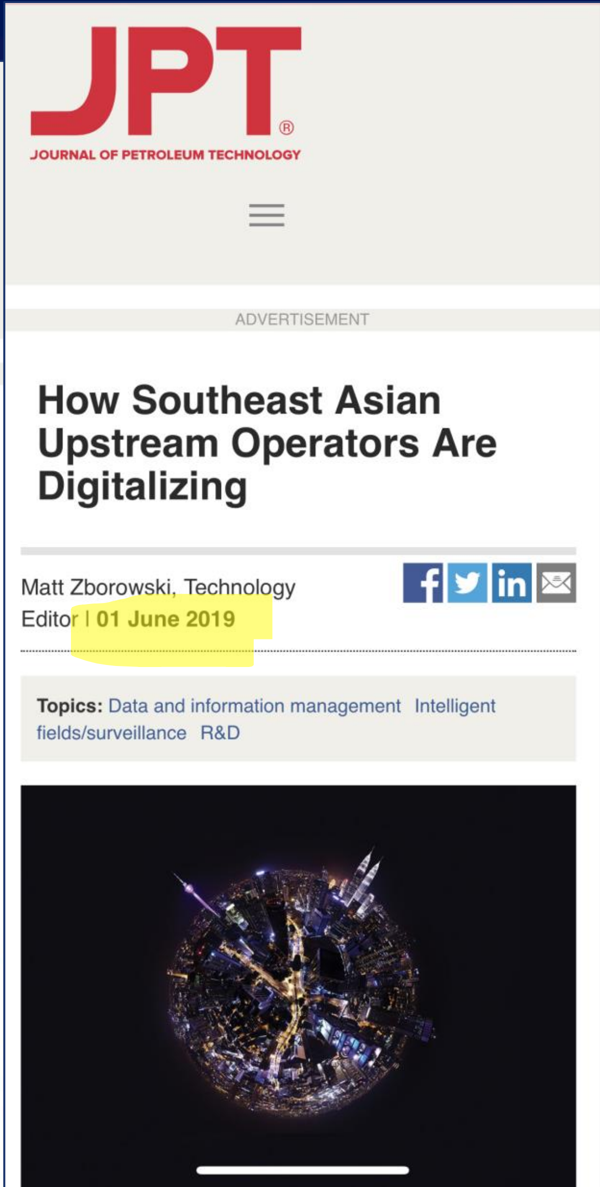

# Digital Oil Field Progression

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## Surveillance Monitoring & Diagnostics

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

## Analysis **Understanding** in Real-time

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

## Optimization Intervention and Control in Real-time

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

## Innovation AI – Machine Learning

- Autonomous Operations - Demanning
- Integrated Asset Management

# Is an Intelligent System right for you?

- If you can solve your problem without an intelligent system maybe you should
- Problems for ML/AI:
  - Big problems: require a lot of effort to solve
  - Open-ended problems: problems that continue to grow over time
  - Time-changing problems: where the right answer changes over time
    - needs ability to detect that changes and to adapt quickly enough to be meaningful
  - Hard problems: problems that push the boundaries to what we think is possible

# SME vs. Data Scientist



**SME:**
- Learned in domain
- Domain expertise
- Knows how the tools work
- What data is available?
- Which data matters?
- Is the data good?
- Voice of the customer

**Data Scientist:**
- Learned in data science
- Data science expertise
- What models are available?
- How processes work?
- How good is the model?

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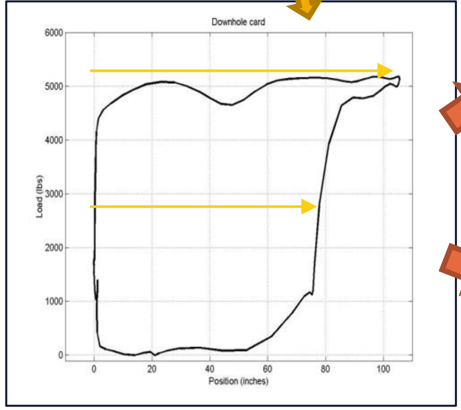
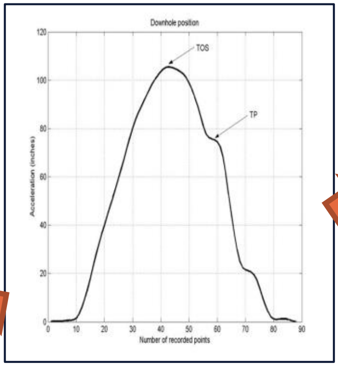
# Data Analytics – Traditional Application

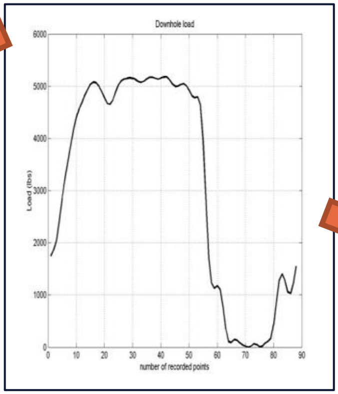
## Pump Fillage Calculation

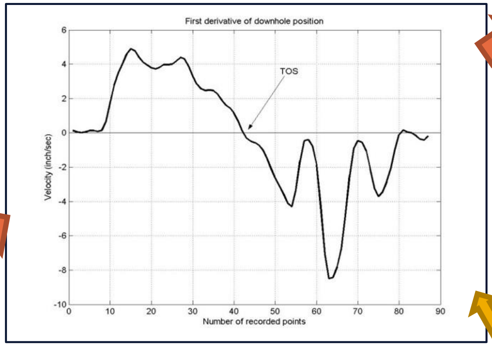
1) What data is available to solve the problem?

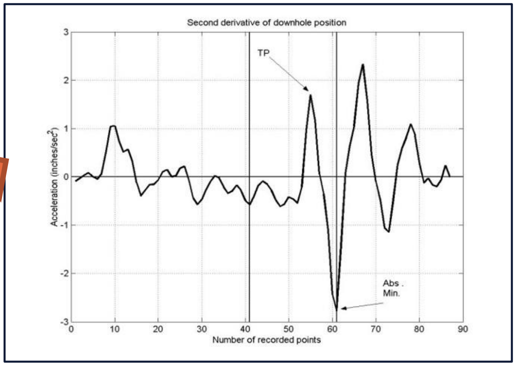



$$\textit{Pump fillage} = \frac{\textit{Net stroke}}{\textit{Gross stroke}}$$

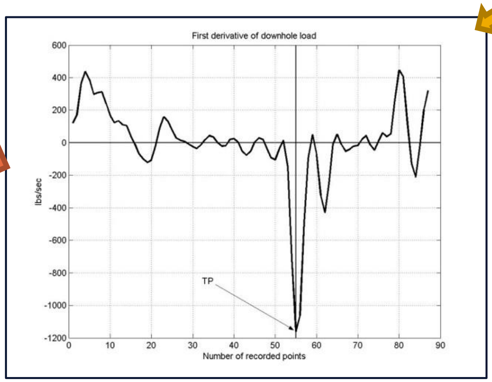


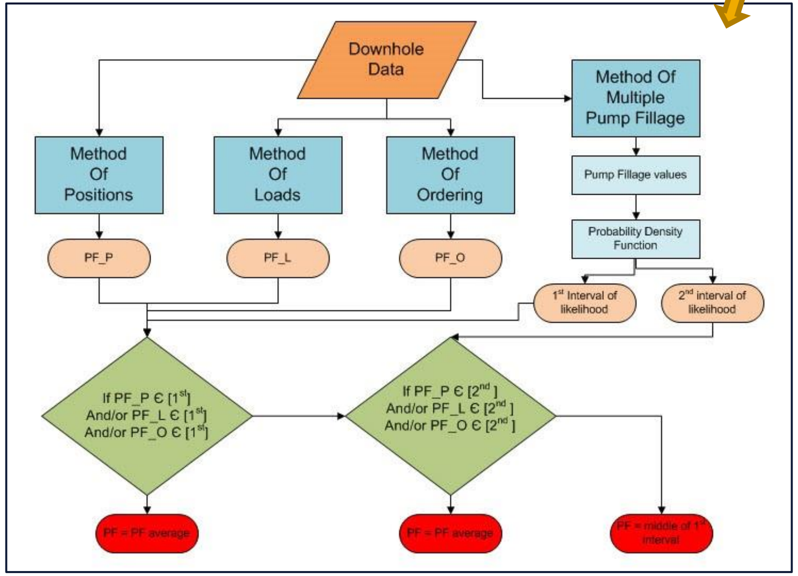




2) Can data be transformed to extract more diagnosing tool and additional data?




3) Methods are tied together into a process functioning on mathematics, statistics and rules.




V. Ehimeakhe, "Calculating Pump Fillage for Well Control using Transfer Point Location", SPE 136595

# ML/AI Cycle

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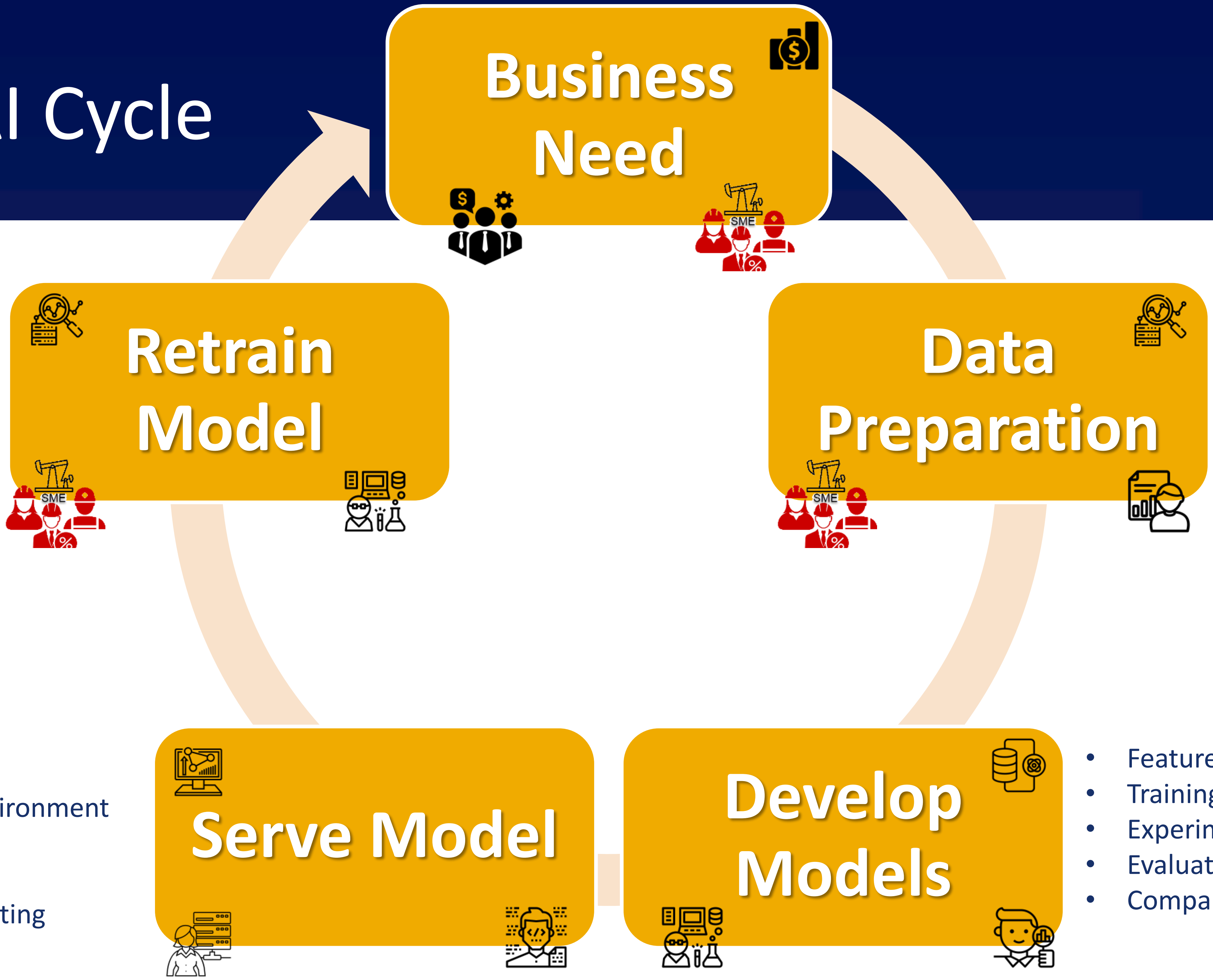


- Acquisition
- Exploratory Analysis
- Preprocessing
- Splitting

- Feature Engineering
- Training
- Experimentation
- Evaluation
- Comparison

- Runtime Environment
- Scaling
- QA
- Logging/Alerting

- Input Drift Tracking
- Performance Drift
- Online Evaluation

# Typical ML/DL Workflow

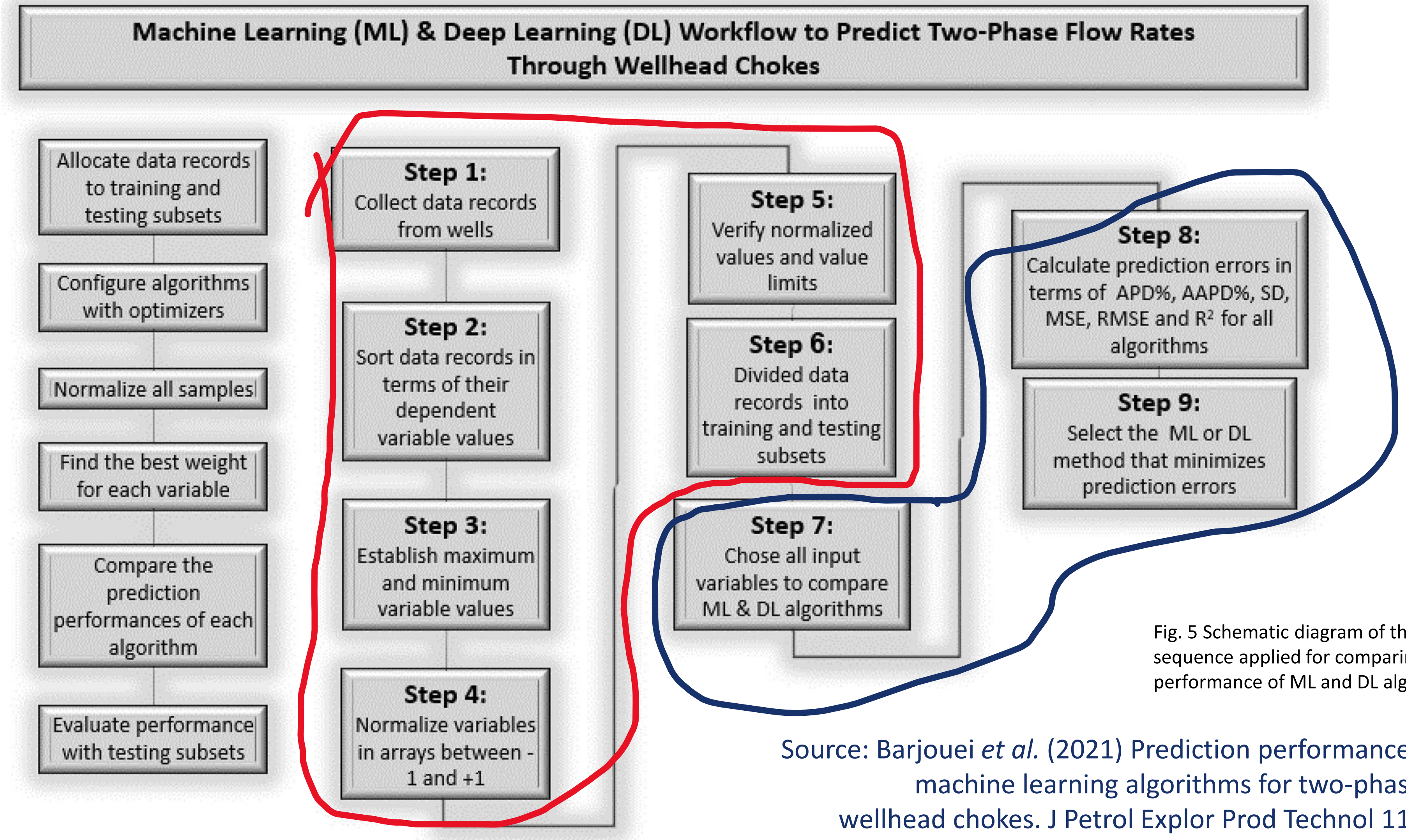


Fig. 5 Schematic diagram of the workflow sequence applied for comparing the prediction performance of ML and DL algorithms

Source: Barjouei *et al.* (2021) Prediction performance advantages of deep machine learning algorithms for two-phase flow rates through wellhead chokes. J Petrol Explor Prod Technol 11, 1233–1261 (2021).

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Anomaly Detection

Failure Prediction

Virtual Flow Metering

# WHAT PROBLEMS ARE BEING ADDRESSED

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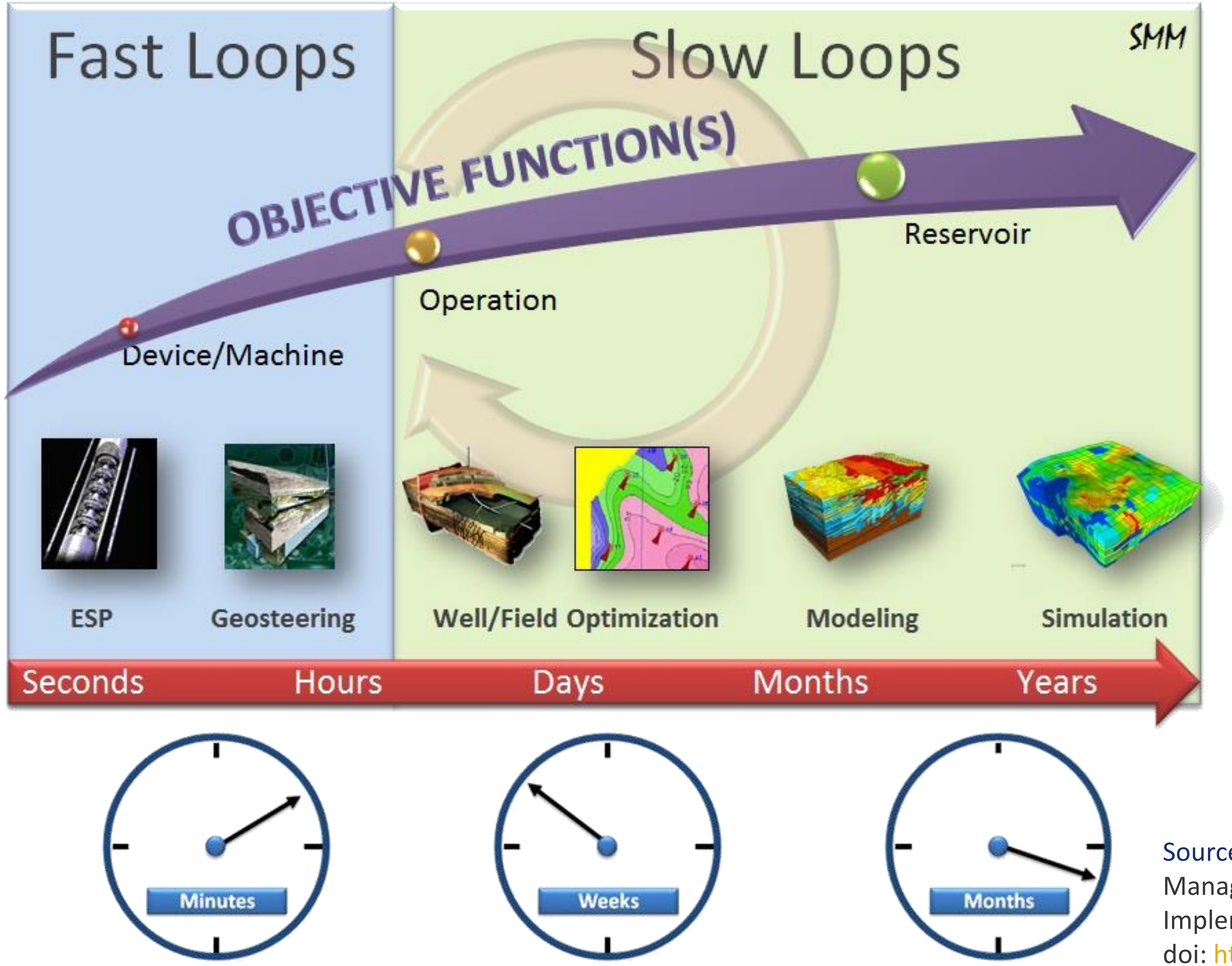
# Cycle Times – Data Loops are fast for production




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

# Anomaly Detection

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**Objective:**

Discover error or discrepancy in data signaling an event (ex: imminent failure, defect)

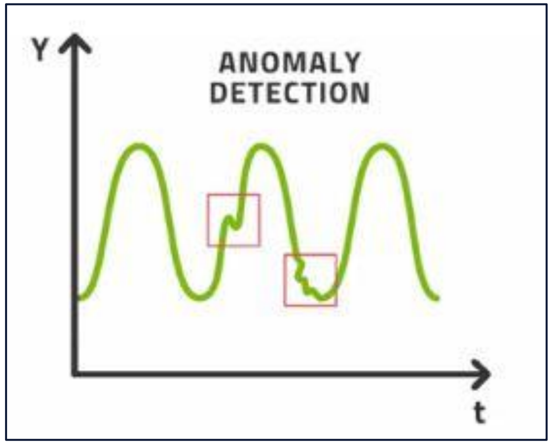
Learn what “normal” data looks like then use data to detect abnormal instances

**Traditional Data Analytics:**

- Analyze magnitude, period and signature of data event
- Use trends, calculus (derivatives), curve interpolation (Fourier)

**Machine Learning Models:**

- Unsupervised learning techniques (ex. Clustering, Gaussian mixtures)

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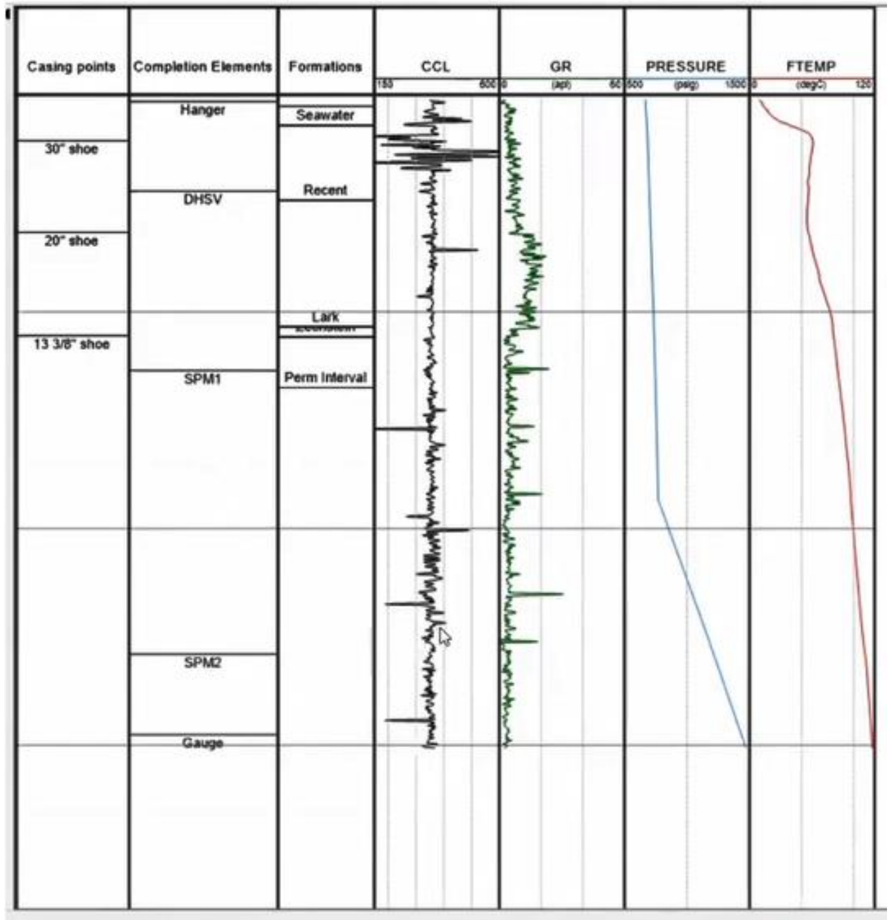
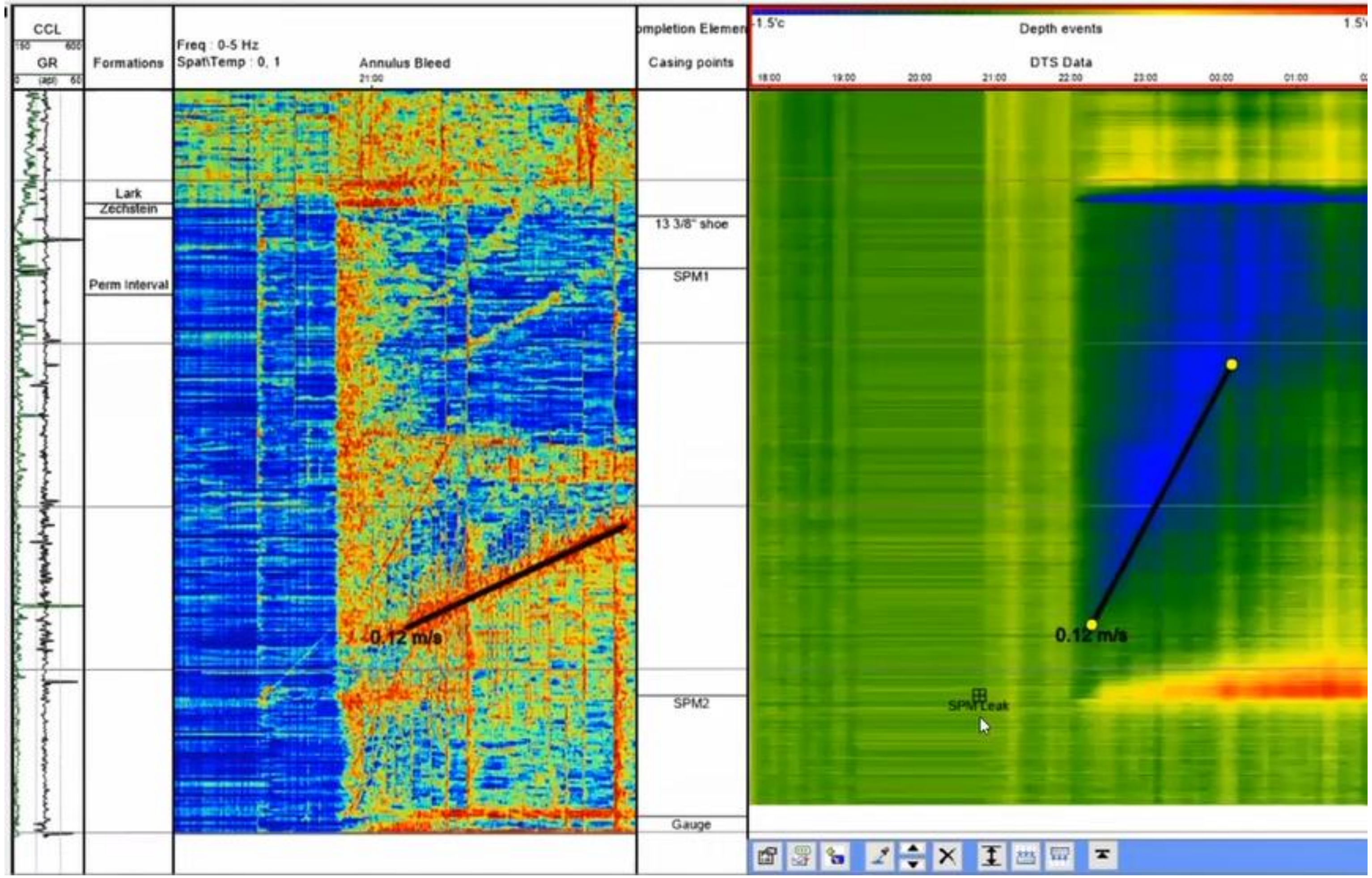
# Diagnostics by Integration of DAS, DTS & Conventional Data for a North Sea Well

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

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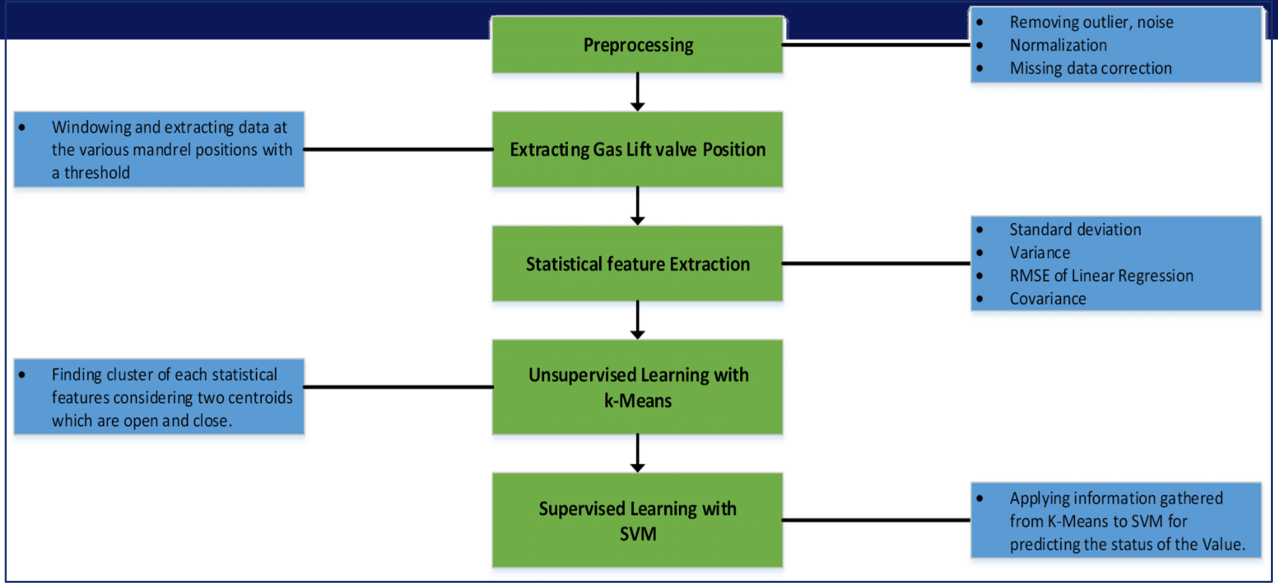
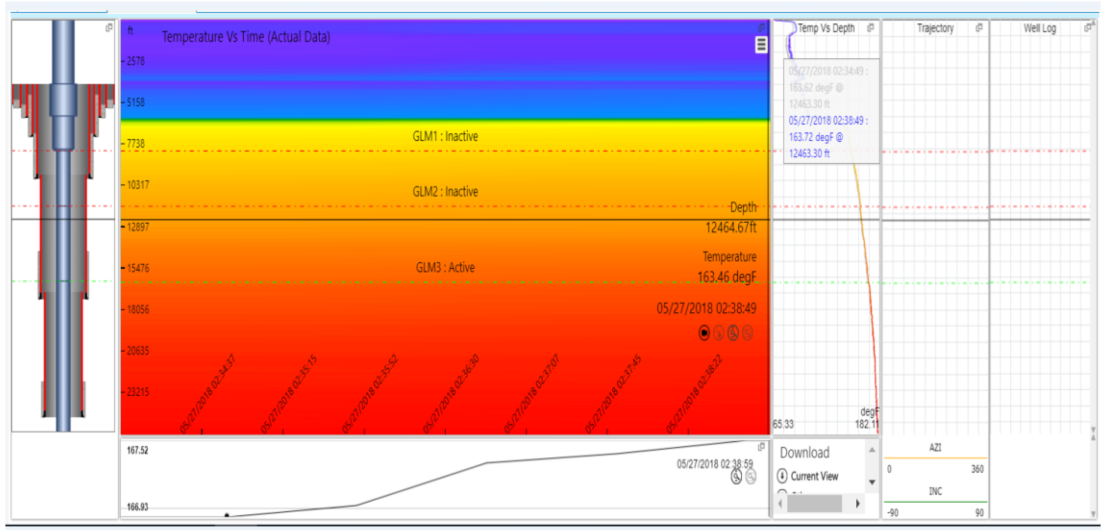
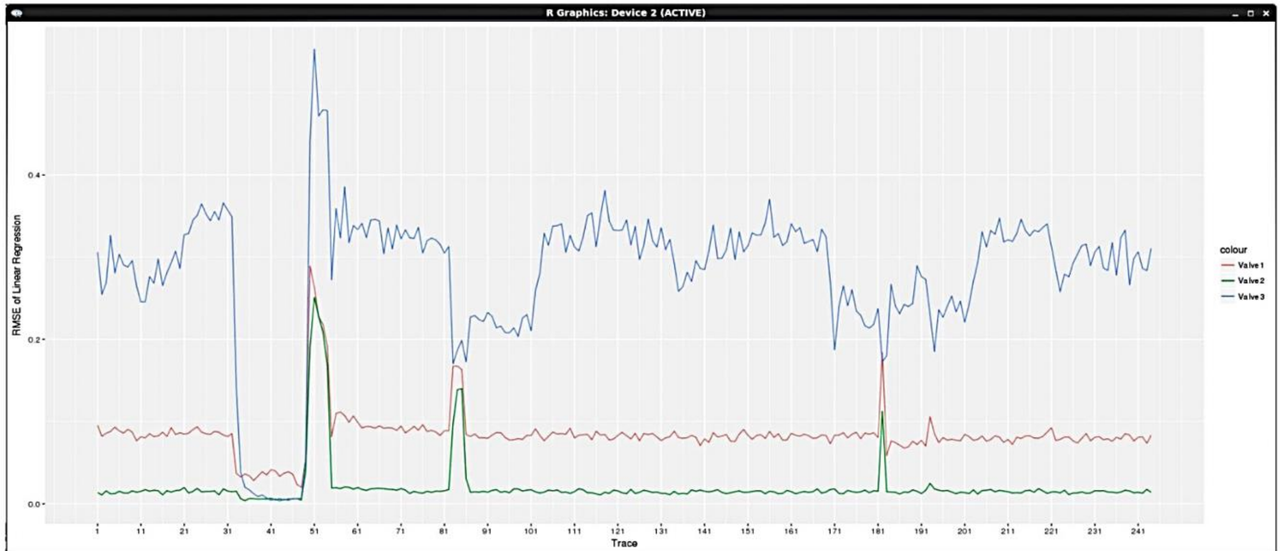
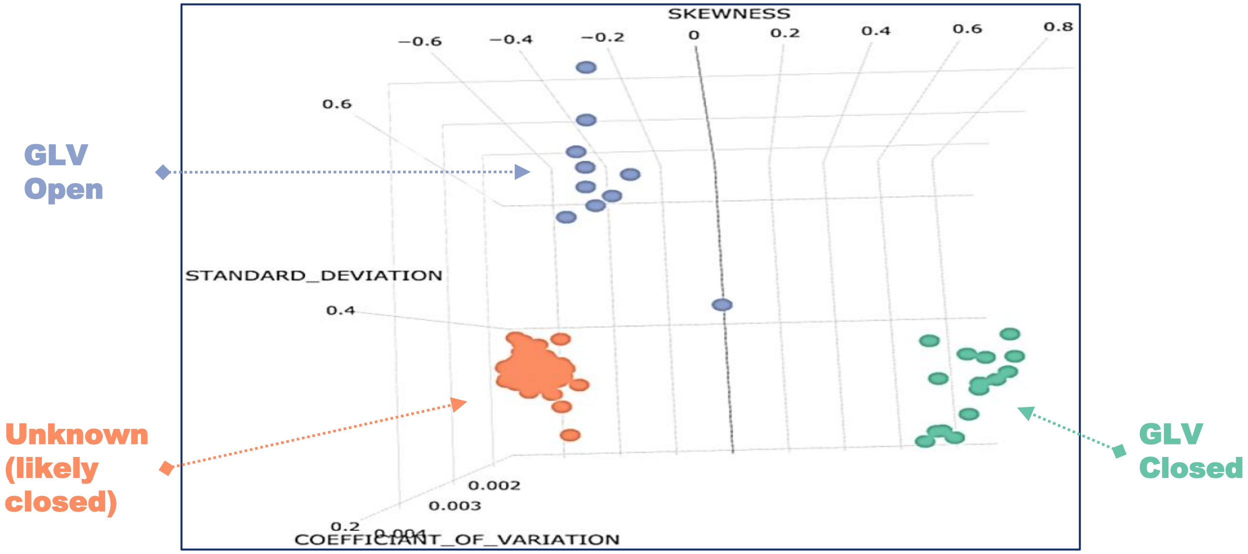
# DTS Analytics for Anomaly Detection in Gas-Lift

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

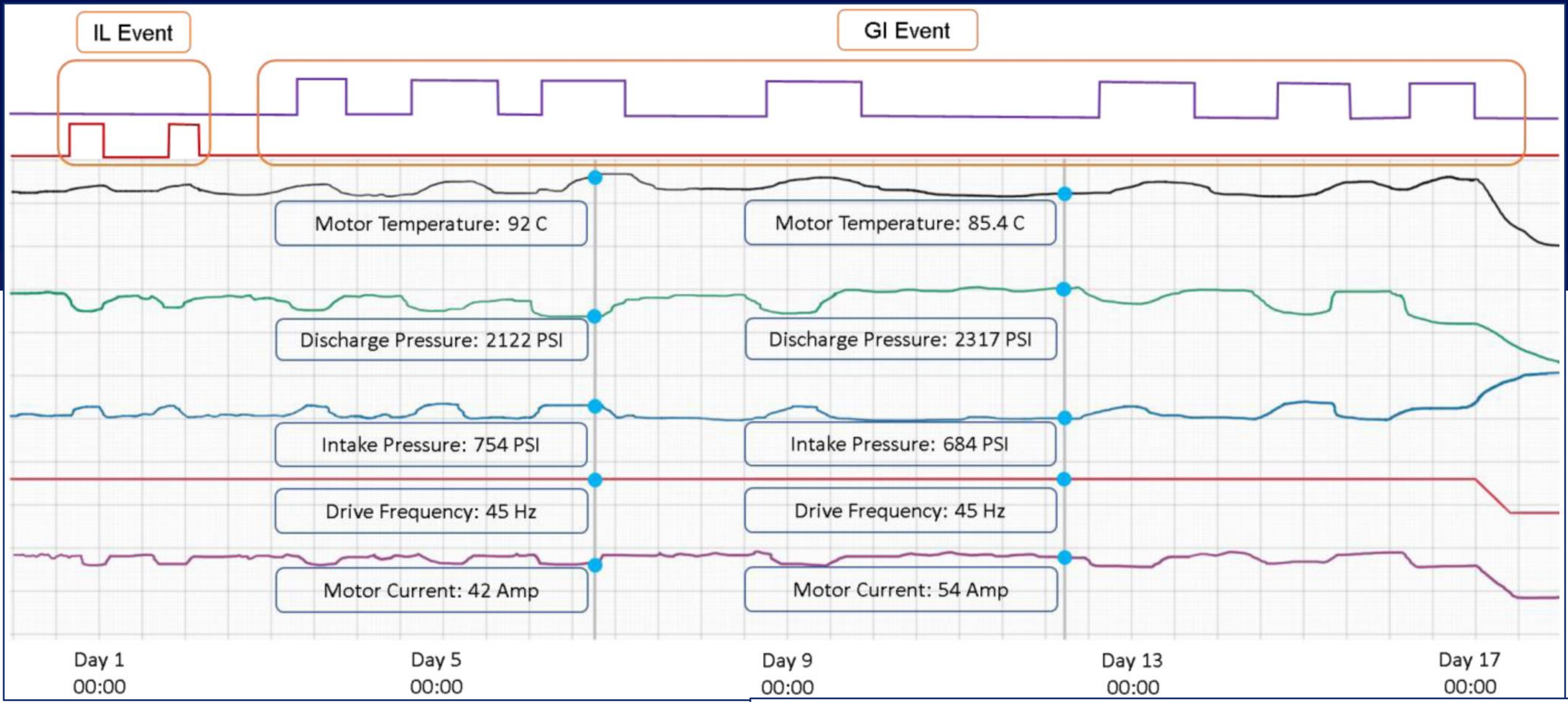


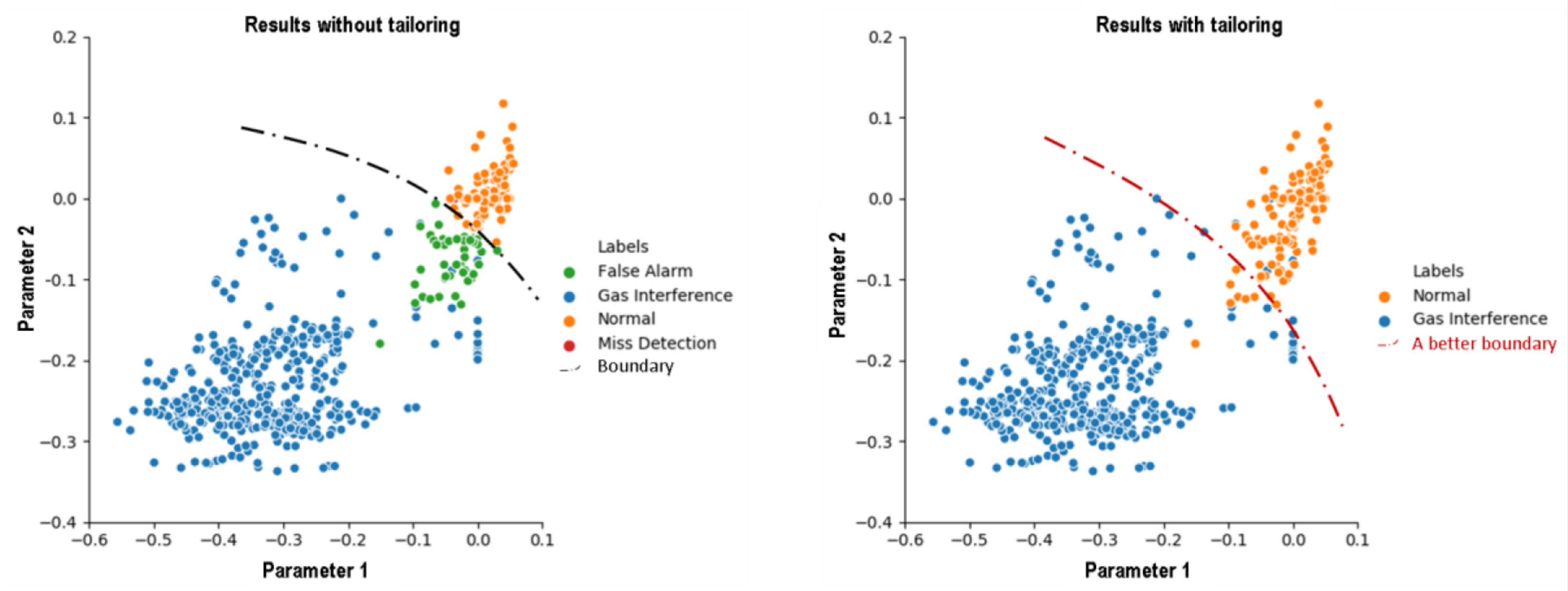



# ESP Anomaly Detection Engine




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



# Failure Prediction
# Physics Based approach

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**Data Analytics Steps:**

**Descriptive analytics = what is happening**
**Predictive analytics = what will happen**
**Prescriptive analytics = how to make an event happen**

## DESCRIPTIVE ANALYTICS

**An accurate analysis of the type of failures should be established:**

- Determine the Failure Frequency Rate (FFR)
- Determine Equipment Failure Frequency (EFF)
- Operating Expense (OPEX )
- Perform RCA

**Apply specific Algorithm decision tools, such as:**

- Decision Tree, Fishbone Diagrams, Pareto/ Bar charts, brainstorm, histograms, system attributes

**Goal: Reach more informed recommendations**

## PRESCRIPTIVE ANALYTICS

**Implement Changes**

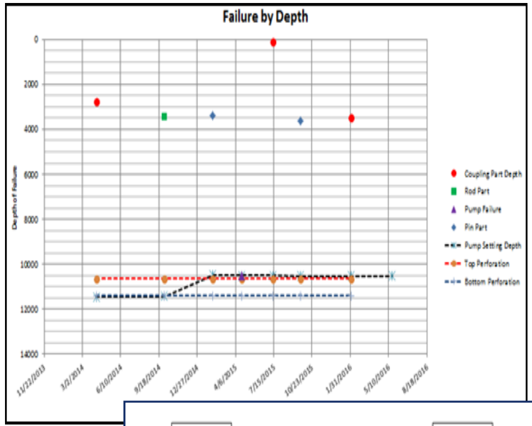
- Define Key Performance Indicators
  - Equipment Load, Production Rates, Failure Index
- Offer recommendations
  - Target to Improve Failure Rate & Maximize Production

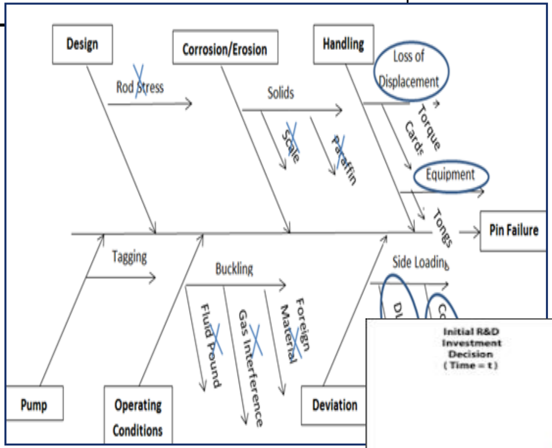
**Offsite Changes**

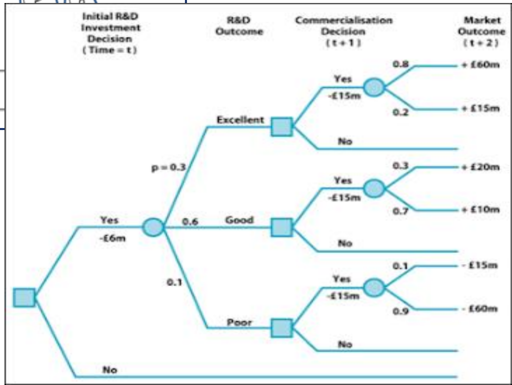
- Manage by Exception
  - Set Alarms (i.e. rod load, gearbox, pump efficiency)
- Modify production set points
  - SPM, stroke length, idle time, etc..

**Field Modifications**

- Future intervention planning
  - (i.e. pump bore change, metallurgy upgrades, gas separators, rod design change, etc.…)

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D. Renteria, “Physics-Based Analytics to Manage Failures”, 2017 WESC

# Failure Prediction
# Machine Learning approach for ESP

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- ESP Well and Component Failure Prediction in Advance using Engineered Analytics - A Breakthrough in Minimizing Unscheduled Subsurface Deferments
  - Introduction
  - Analytical Data Modeling
    - Machine Learning
    - Approach and Process
  - Data Preparation
    - Data Gathering
    - Data Pre-Processing
  - Model Building
    - Dataset Sample Selection
    - Model Training
    - Feature Selection and Engineering
    - Parameter Tuning
  - Model Testing
    - Creating a Dataset for Model Testing
    - Model Scoring
    - Test Results
  - Model Evaluation by Well Owners (Operator's Blind Test)
    - Methodology
    - Operator's Blind Test Results
  - Value Generated by the Analytical Model
  - Conclusions and the way ahead
- References

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### Static Data

Installation and Commissioning data

Well Completion information

ESP Well Failure history

Ad-hoc information (emails, spreadsheet, reports, photos)

### Dynamic Data

Downhole Gauge: Pump Discharge & Intake pressures, Motor temperature, Intake temperature, vibration etc.

Motor Controller: Electrical readings, well running status and trip conditions.

Surface Pressure Gauges: Tubing head pressure, Flow line pressure

### Calculated Data

Well Model Based Calculated Data: Inferred production and Pump Efficiencies calculated from the Physics based models in Real Time

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

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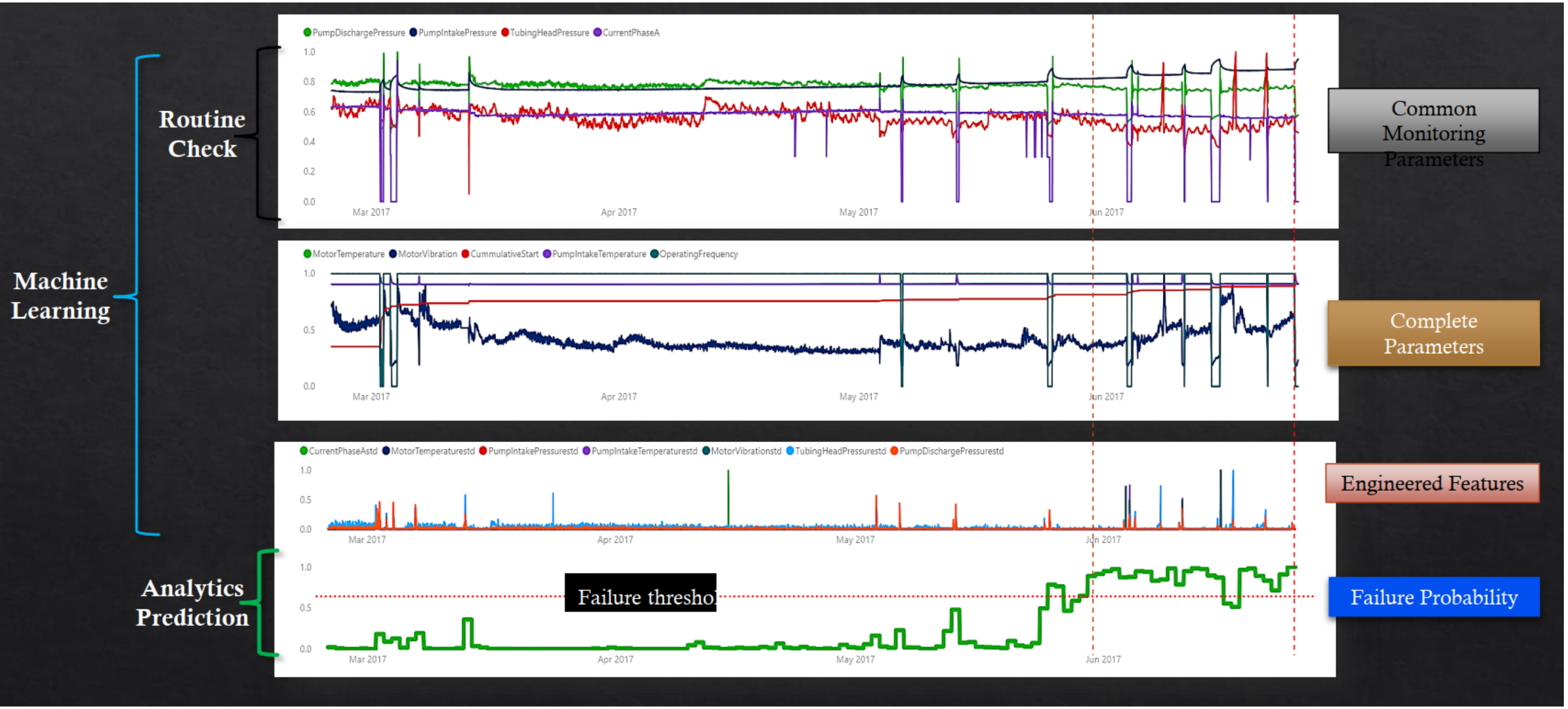


- Data driven models captured 58.62% of the well failures and 66.66% of the pump failures while keeping all false alarms negligible.
- The Blind Test confirmed that ESP Well Failure model scored a high precision of 89.47% and 75.86% accuracy, the ESP Pump (component) Failure model scored a very high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

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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

# Pattern Recognition – Data Analytics

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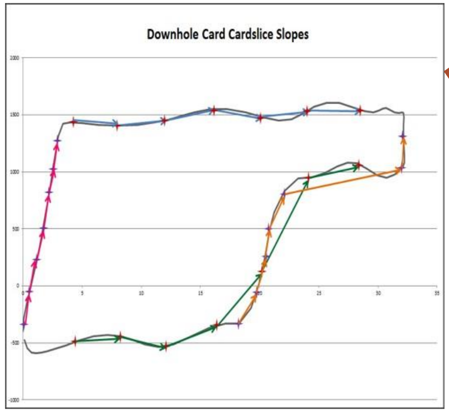
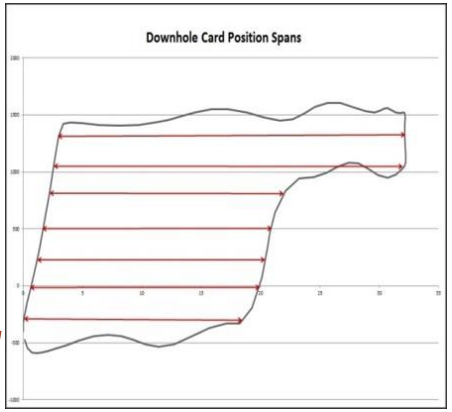
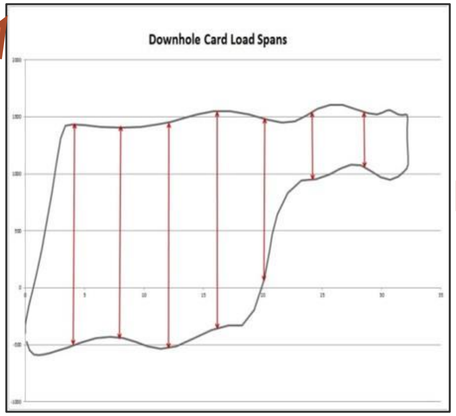
**Objective:**
Identify downhole conditions using downhole data

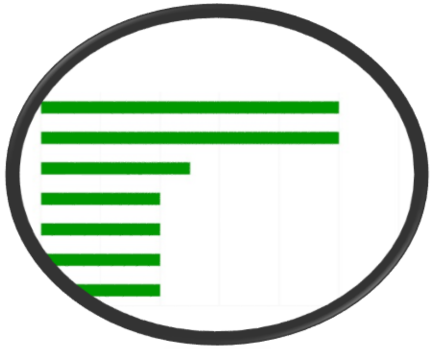



V. Pons, "Accurate Rod Pumped Well Control Using Modern Techniques, 2016 Sucker Rod Pumping Workshop, OK



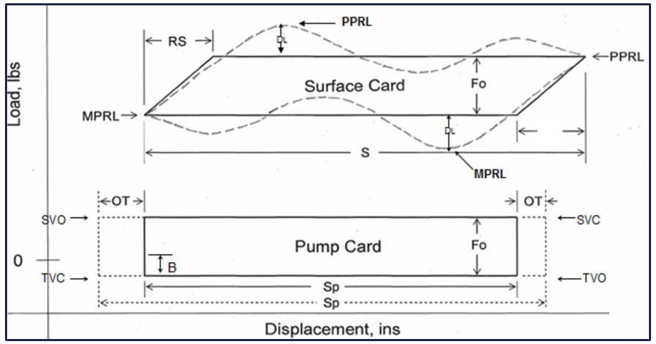

Segment data into load and position segments

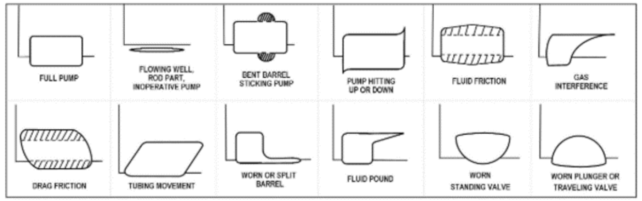


Position and load segments can be analyzed as distributions

- A library of downhole conditions can be saved in the form of a position and load distribution
- Every new card is segmented the same way and it's position and load distribution compared to the library




WellWorx – Rod Pumping Course

**Limitations:**
- Downhole conditions are finite but can take many different shapes in downhole data
- A large library of downhole data slows down the process
- Combination of downhole conditions are difficult to predict
- Success rate of pattern matching varies depending on data

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# Pattern Recognition – Machine Learning

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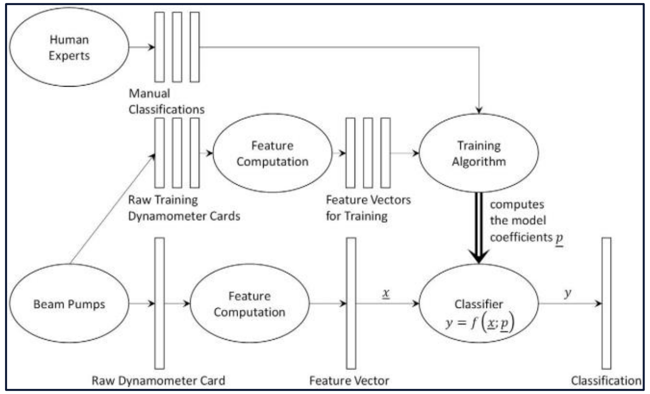
**SPE 195295 – “Predictive Maintenance for Rod Pumps” – Dr. P. Bangert, Sayed Sharaf**

- Objective: Diagnose rod lift downhole cards in real time
- Dataset: 35292 cards from 299 beam pumps from Bahrain
- Process – Evaluate different methods for feature engineering and compare results on data set

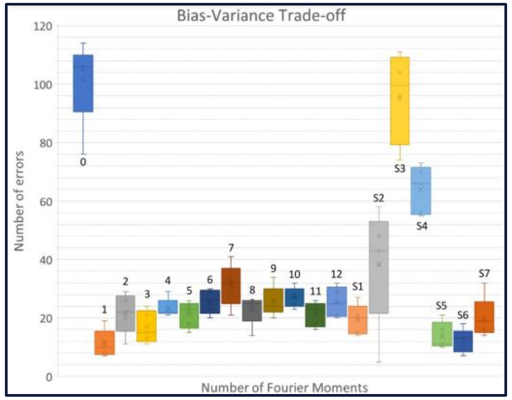
**Models Considered:**

- Library based
- Model based
- Segment based
- Other

Different models and data treatment methods were investigated to return best possible result.




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




**Bias vs. Variance:**

Vertical position = bias = average number of errors

Vertical span = variance of error

Table 2—Classification performance of the best model on the test data set. For each class, we specify how many training and testing samples were used. The model performed perfectly on all training samples but made a few errors on testing samples, as specified.

| Category | Training Samples | Testing Samples | Incorrect |
|---|---|---|---|
| Normal | 8557 | 1529 | 0 |
| Fluid Pound (Slight) | 5347 | 955 | 0 |
| Fluid Pound (Severe) | 93 | 15 | 0 |
| Inoperative Pump | 1981 | 379 | 0 |
| Pump Hitting Down | 1740 | 303 | 2 |
| Pump Hitting Up and Down | 2258 | 407 | 2 |
| Inoperative Pump, Hitting Down | 9045 | 1626 | 1 |
| Traveling Valve or Plunger Leak | 98 | 15 | 1 |
| Standing Valve, Traveling Valve Leak, or Gas Interference | 345 | 62 | 0 |

**Results:**

Using stochastic gradient-boosted decision tree model

Accuracy = 99.9%

Evenly distributed errors

Library data set of over 35,000 downhole cards

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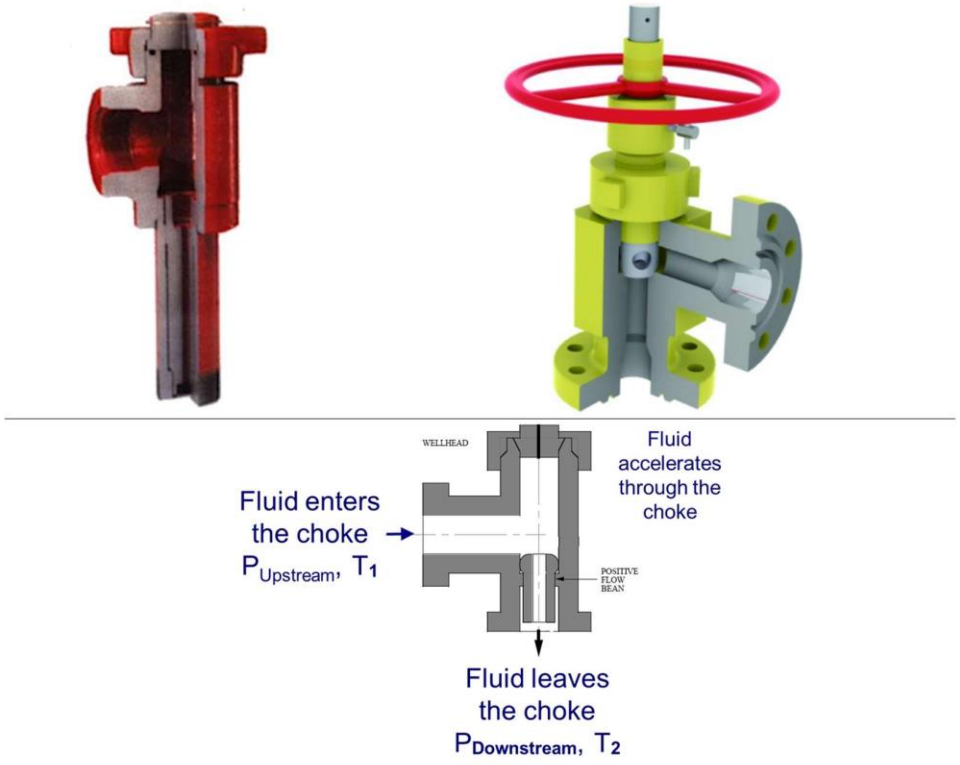
# Virtual Flow Meter – Choke Flow Prediction

Source: Barjouei *et al.* (2021) Prediction performance advantages of deep machine learning algorithms for two-phase flow rates through wellhead chokes. J Petrol Explor Prod Technol 11, 1233–1261 (2021). https://bit.ly/3vRbUiH




- Paper provides details on the methodologies, workflows, and complete dataset.

**Table 11** Data record statistical characterization of the variables in this study

Dataset Variables for Prediction Two-phase Flow Rate from Wellheads in the oil Fields

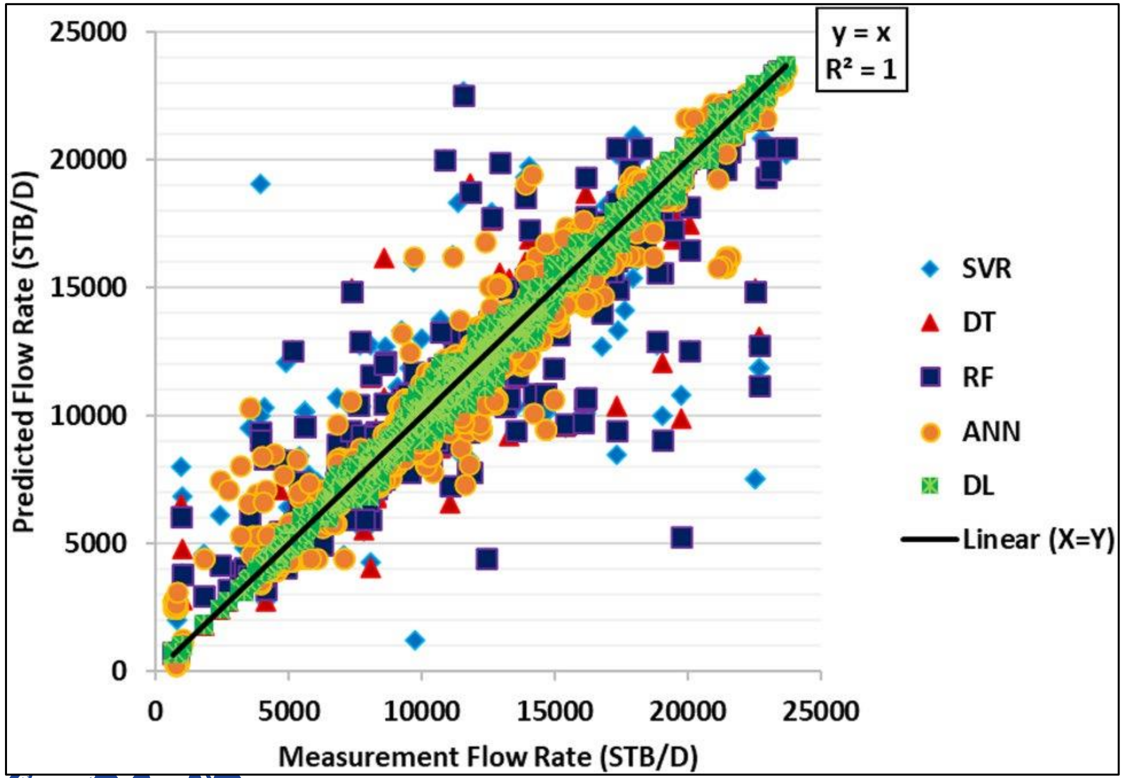
| Field | Variables | Wellhead Choke Diameter | Wellhead Pressure | Oil Specific Gravity | Gas to Liquid Ratio | Two-Phase Flow Rate |
|---|---|---|---|---|---|---|
| | Symbol | D64 | Pwh | Yo | GLR | QL |
| | Units | inch/64 | psig | % | Scf/STB | STB/day |
| 7245 dataset records from Sorush Oil Field | Mean | 65.7 | 319 | 1.00 | 135.3 | 11,667 |
| | Std. Deviation | 15.2 | 169 | 0.06 | 42.9 | 3625 |
| | Variance | 231.5 | 28,718 | 0.00 | 1840.1 | 13,137,230 |
| | Minimum | 33.8 | 131 | 0.93 | 3.0 | 660 |
| | Maximum | 111.9 | 1024 | 1.07 | 217.0 | 23,700 |
| 113 dataset records from Oil Field of South Iran | Mean | 54.5 | 1280 | 0.86 | 858.6 | 8549 |
| | Std. Deviation | 16.9 | 349 | 0.02 | 440.3 | 5376 |
| | Variance | 282.4 | 120,507 | 0.00 | 192,106.3 | 28,641,000 |
| | Minimum | 24.0 | 50 | 0.81 | 107.0 | 1324 |
| | Maximum | 80.0 | 2940 | 0.92 | 3660.0 | 22,150 |

Entire dataset in spreadsheet format is available here: **https://bit.ly/2SZDlJK**

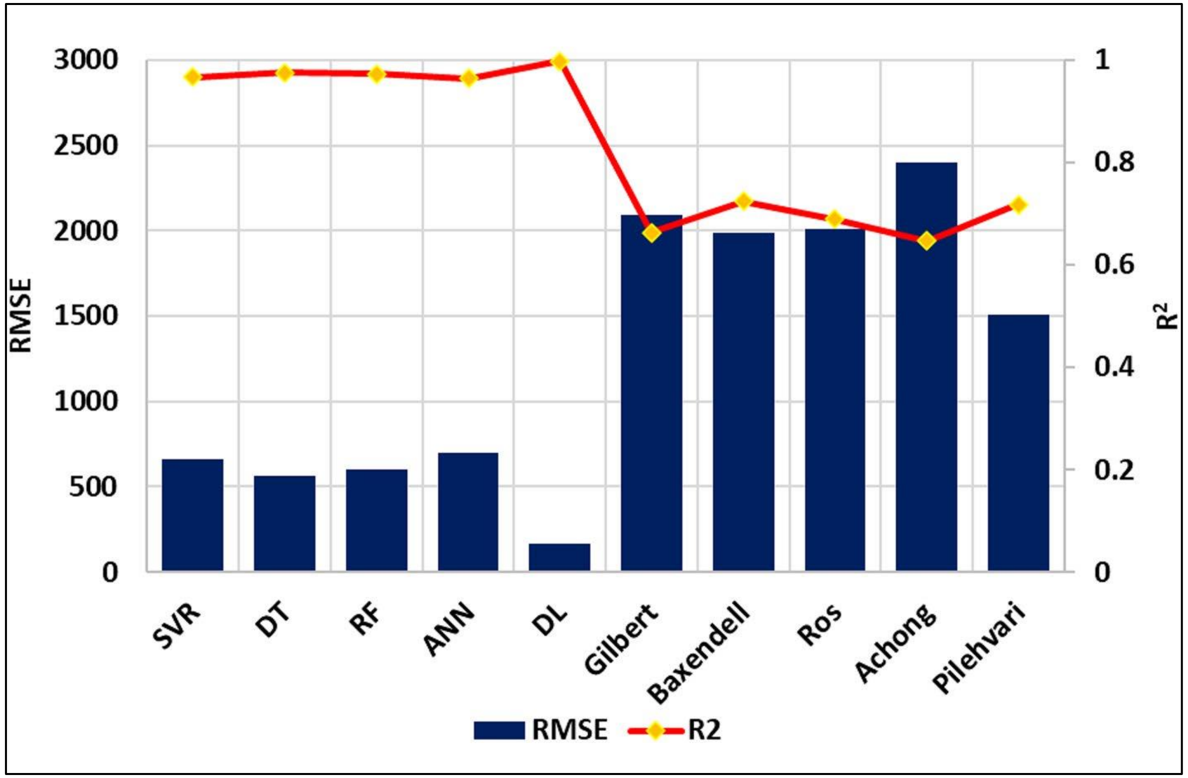
# Choke Flowrate Prediction Results

Source: Barjouei *et al.* (2021) Prediction performance advantages of deep machine learning algorithms for two-phase flow rates through wellhead chokes. J Petrol Explor Prod Technol 11, 1233–1261 (2021). https://bit.ly/3vRbUiH [Accessed 3 Jun 2021]

## Predicted vs Measured Flow Rates



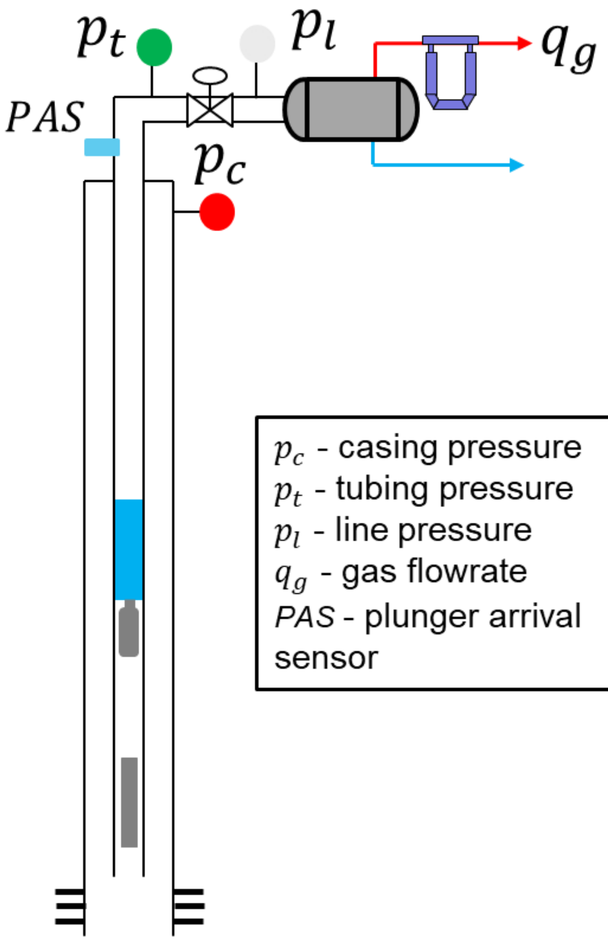

## Ql Prediction Accuracy



# Virtual Flow Meter – Plunger Lift

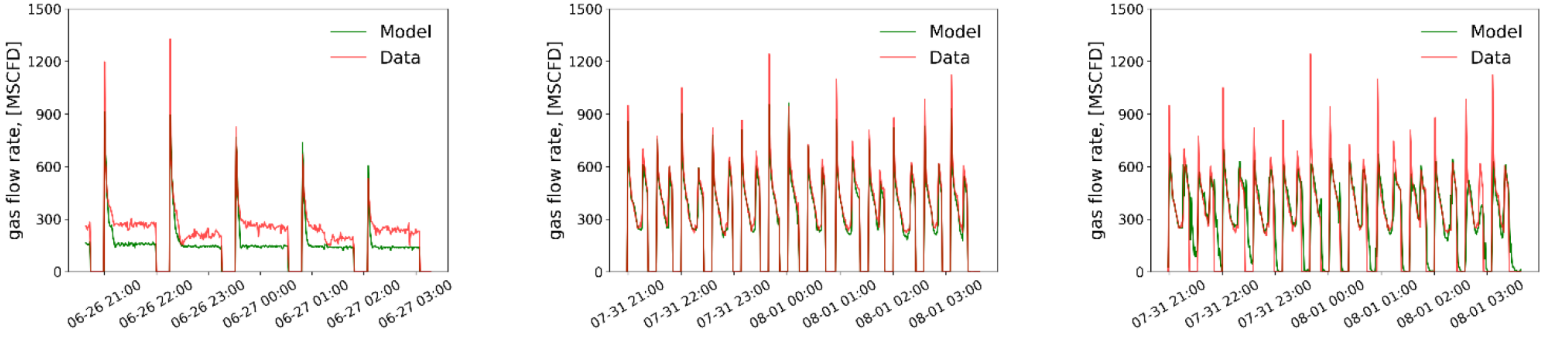
Source: Akhiiratdinov *et al.* (2020) Data Analytics Application for Conventional Plunger Lift Modeling and Optimization, SPE 201144

- 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.



# Virtual Flow Meter – Plunger Lift

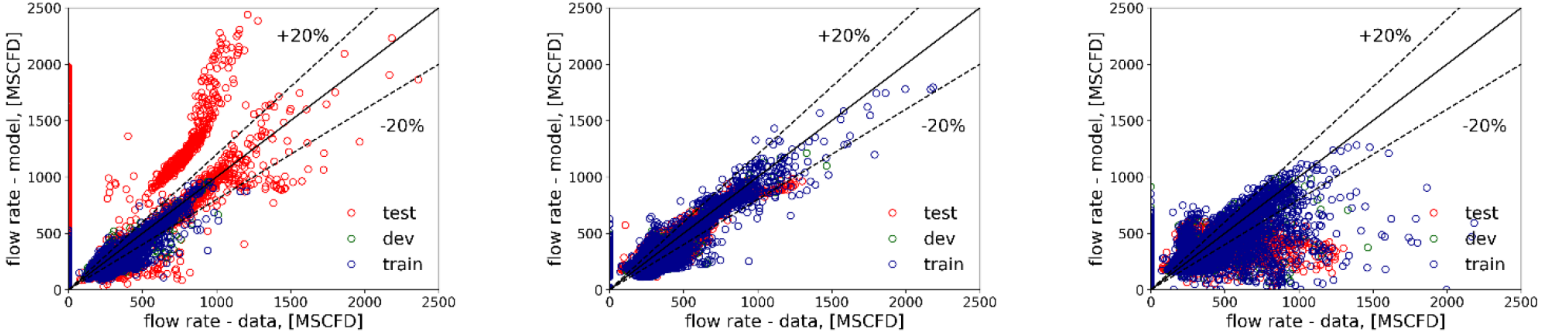
Source: Akhiiratdinov *et al.* (2020) Data Analytics Application for Conventional Plunger Lift Modeling and Optimization, SPE 201144




(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.

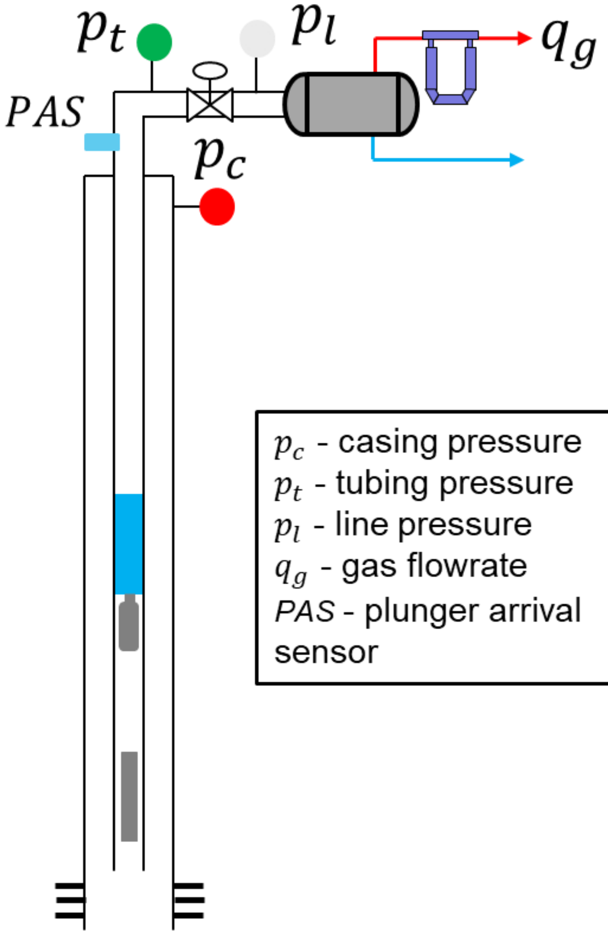
(c) Brute force model predictions for 6 hours of the test set – 9 days training set.




(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.



# Conclusion

Webinars

- 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
- Only about 5% of data collected is being used with great results – imagine the possibilities if we could automate learning for all collected data. This would maximize efficiency and can only be done with ML techniques

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# 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.