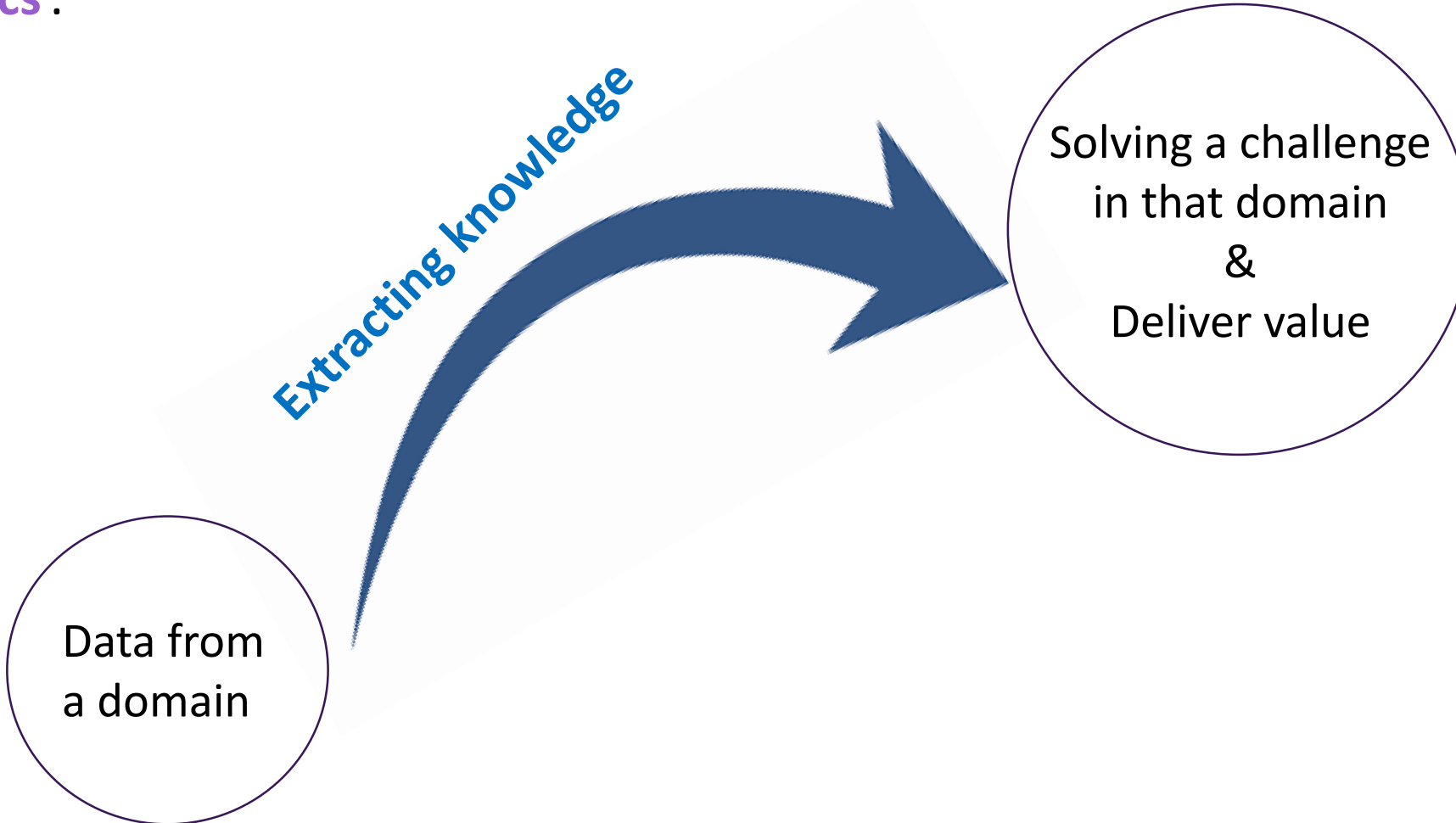# OPTIMISATION OF GAS WELLS USING ADVANCED DATA ANALYTICS
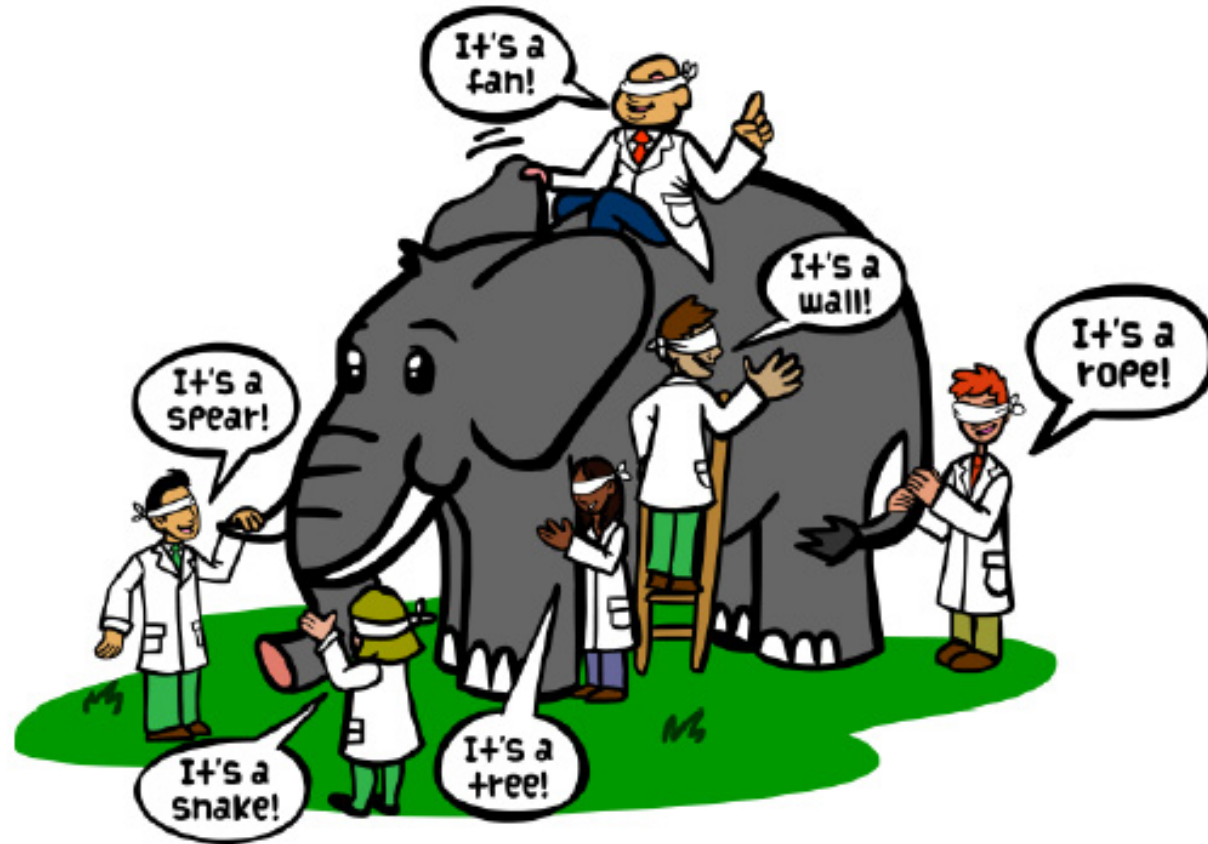
Dr Mahshid Firouzi, The University of Queensland

19 February 2020

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It's almost impossible to read the headlines every day without seeing phrases like '**Big Data**' or '**Analytics**'.

Extracting knowledge

Solving a challenge in that domain
&
Deliver value

Data from a domain

2

http://www.theblindelephant.com/the_blind_elephant_fable.html
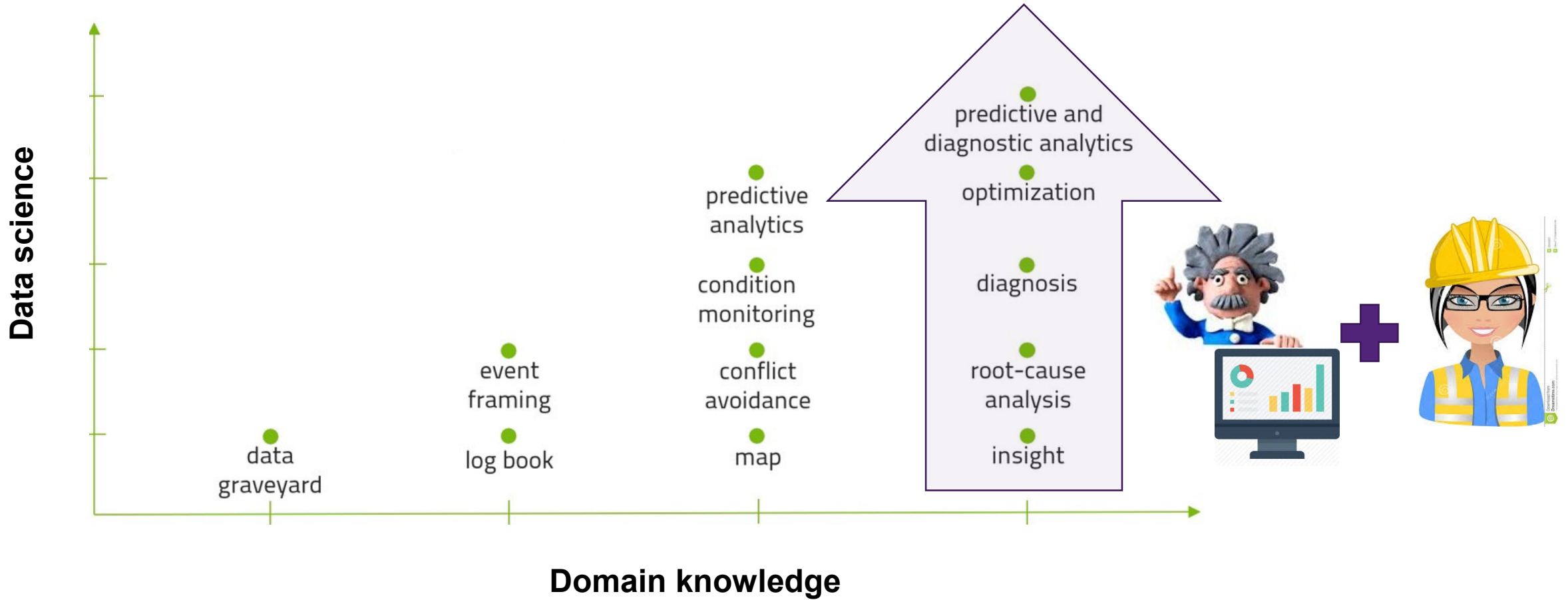
Given the experience of each person, all descriptions are good, but far from the truth

What's missing?

- Contextualised information
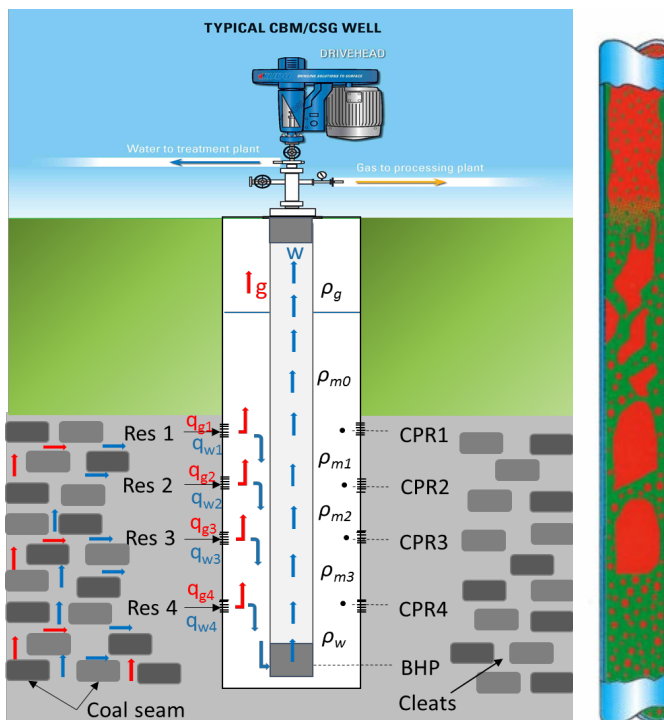- Connection

Modified after P. Bangert (2018)

OUR CASE STUDY

Pump speed

Tubing pressure

Choke position

Separator pressure   **Gas line pressure**

Casing pressure

LCV

Water pressure

Tubing flow

OPEX **&** **Efficiency**

PHYSICS + SIMULATION + SENSORS + DATA ANALYTICS

Surface & sub-surface data

❖ Predict the FBHP
❖ Predict pump failure

FBHP

Basic physics and signals now better understood from UQ well simulator, sensors and new signal processing

WHAT'S THE PROBLEM?

Optimising the dynamic flow pressure (FBHP) allows improvement of the well productivity

Pressure gauges are unreliable and complex to maintain

Flow regimes are key in prediction/measurement of the flow pressure

Aim:

Production optimisation through predicting the FBHP using calibrated response & multi-well data analytics

6

Lab simulation + close collaboration with industry partner

| Parameter	7" well
Casing ID	170 mm (6.69")
Tubing OD	70 mm (2.76")
Rig height	8.0 m
Test section	6.0 m
Max. air flow	7,500 Lpm (380 MScfD)
Max. water flow	1,200 Lpm (10,000 bblD)
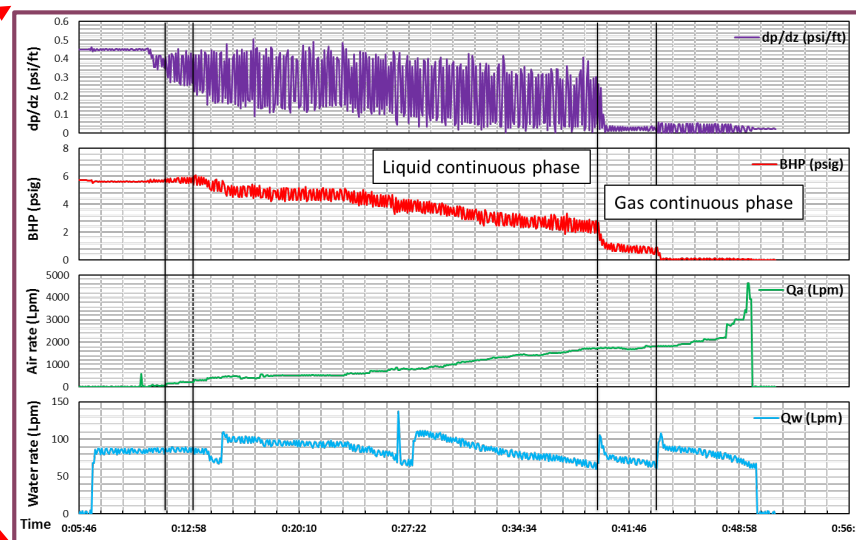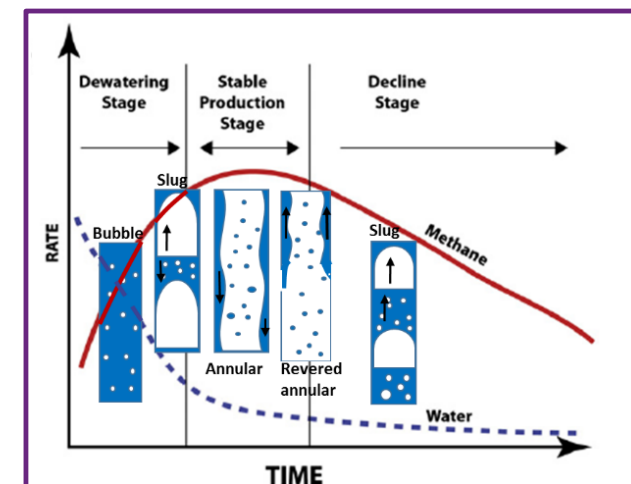
Recorded pressure and flowrate data

Prototype model #1: **Aims to predict the FBHP in the event the pressure sensor fails without interrupting the well**

316 vertical wells from 13 different fields

Production period: 3-27 months

Variables: FBHP, water flow rate, gas flow rate and pump torque
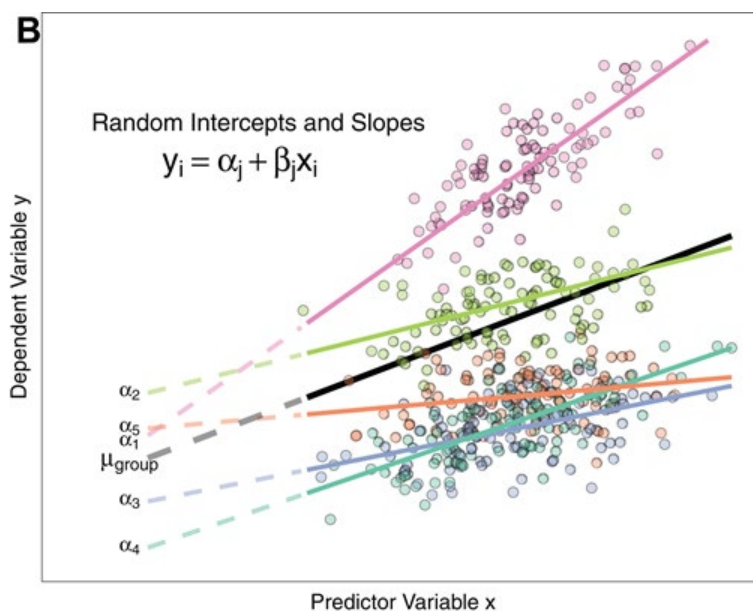
FBHP ~ gas flow + water flow + pump torque + (1 + pump torque | well ID)

With this model, each well can have a different intercept term for FBHP, and coefficient (slope) for the pump torque variable.
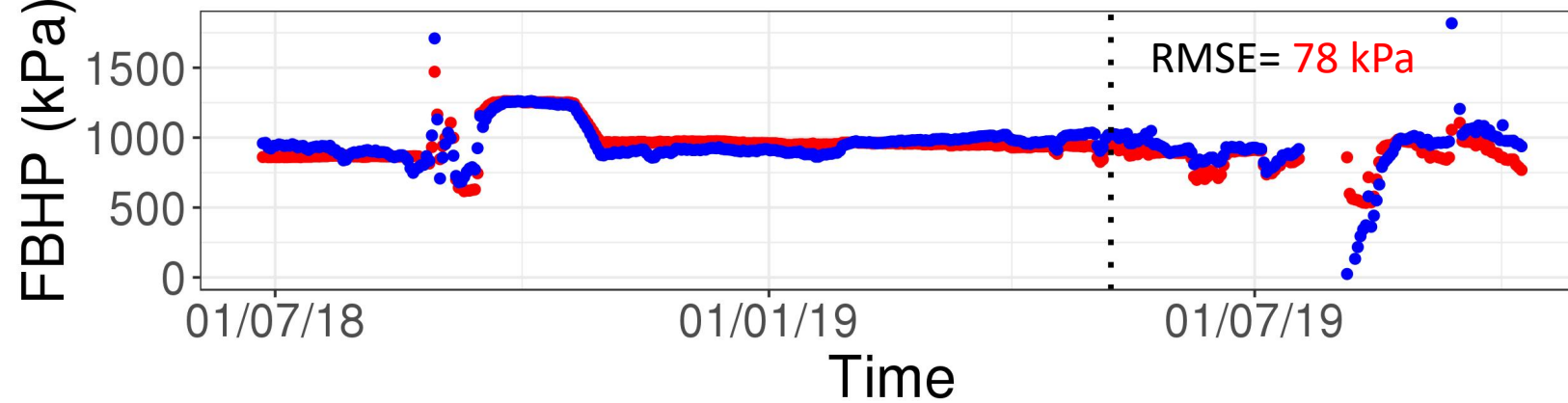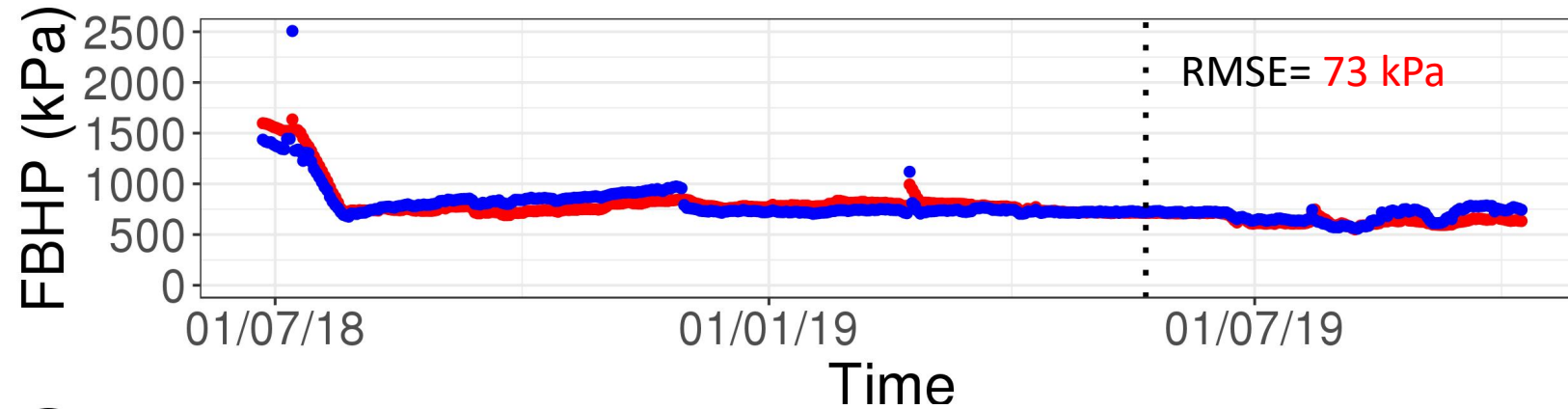
Model assessment:

During each iteration of the cross-validation

- Test set consisted of last 30% of observation from a particular well
- The training data for this consisted of the initial 70% of the data from this well as well as all the data from remaining wells.

B

Random Intercepts and Slopes

$y_i = \alpha_j + \beta_j x_i$

Dependent Variable y

α_2
α_5
α_1
μ_{group}
α_3
α_4

Predictor Variable x

Linear mixed model

PRELIMINARY RESULTS FOR PREDICTION OF THE FBHP

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Our mixed-effect model results show real promise in predicting the FBHP with RMSE 168 kPa (15%)

RMSE= 73 kPa

RMSE= 78 kPa

Randomly samples 1000 data points)

• Actual   • Predicted
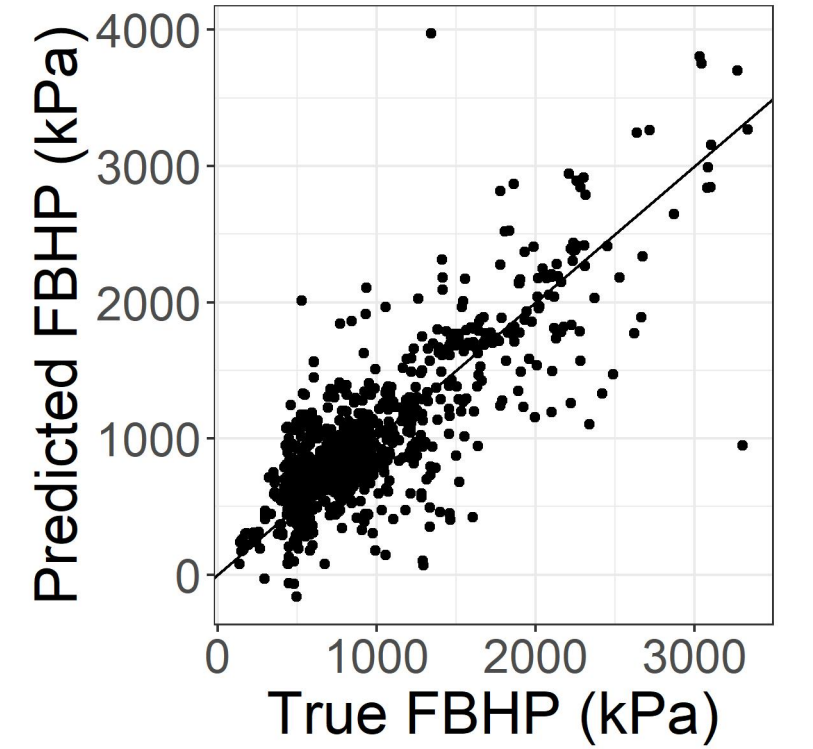
$$RelativeAbsolute\ Error = \left| \frac{(True\ value - Predicted\ value)}{True\ value} \right| \times 100$$

Comparison of the predicted FBHP with the measured FBHP

❖ Enhance the prototype model by incorporating more data from more wells

❖ Detect incipient faults in PC-pumps and predict failure to better plan maintenance and improve pump lifetime - UQ wellbore flow simulator allows us to experimentally investigate the performance of these PC-pumps under harsh conditions in a controlled fashion

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Acknowledgement

Data scientists

Suren Rathnayake

&

Nathaniel Chand