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Machine Learning Methods for Estimating Down-Hole Depth of Cut

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Metrics for Drilling Efficiency and Dysfunction

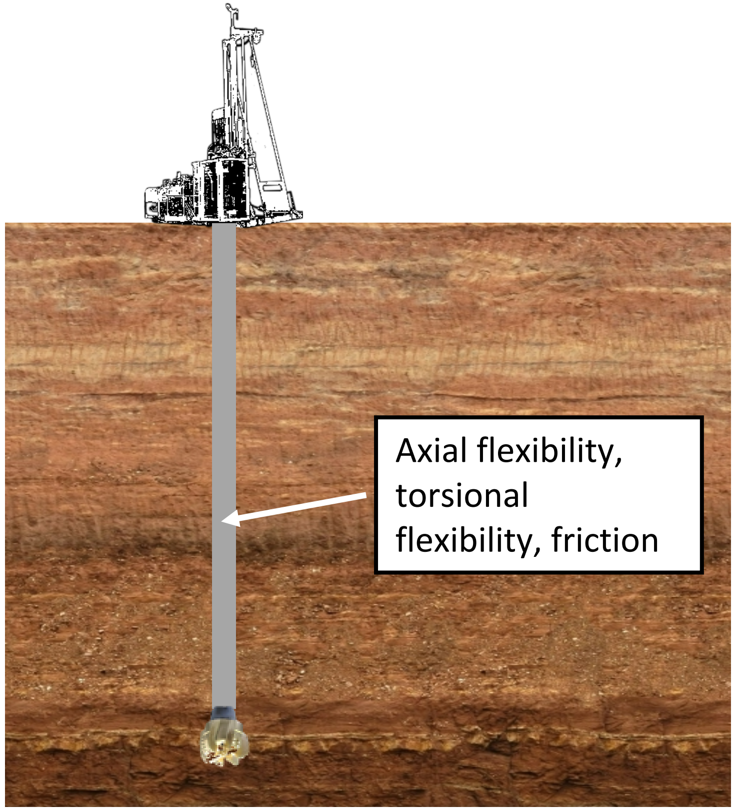
- Depth of cut (DOC)
  - Measures bit penetration into rock
  - Indicator of drilling efficiency and bit behavior

$$DOC = \frac{ROP}{RPM}$$

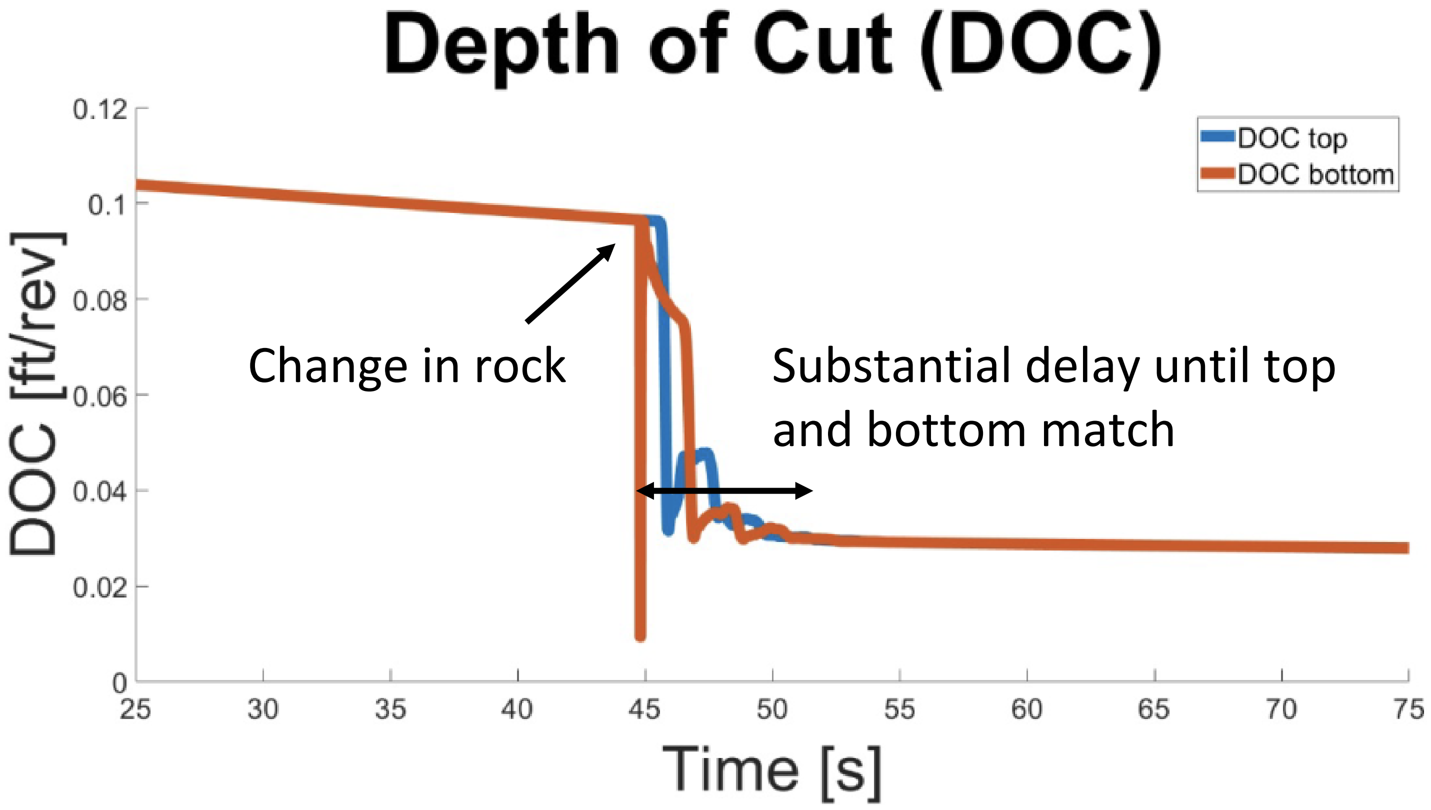
- Rate of penetration (ROP)
  - Reflects rate at which drill moves through rock
  - Used by many control and optimization algorithms
  - Enables closed-loop drilling control

Measuring ROP and DOC

- Position or displacement sensors at surface for drill depth and rate of rotation
- Errors and mechanical lag due to flexibility of drill string
- Poor and slow indicator of drilling dysfunction (e.g. whirl, stick-slip, interfacial severity, bit bounce)



Example of Rock Property Transition

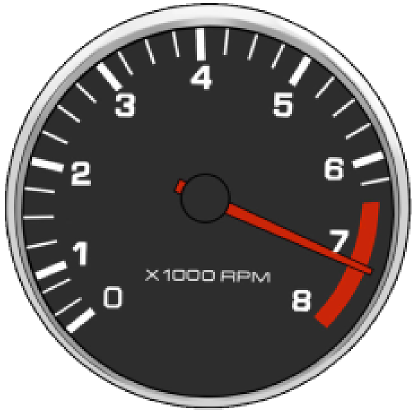


Down-Hole Measurements

- Down-hole measurements bypass friction and elasticity
  - Hard to measure DOC and ROP due to lack of ground reference

- Can measure signals correlated with ROP

Axial Force + Torque

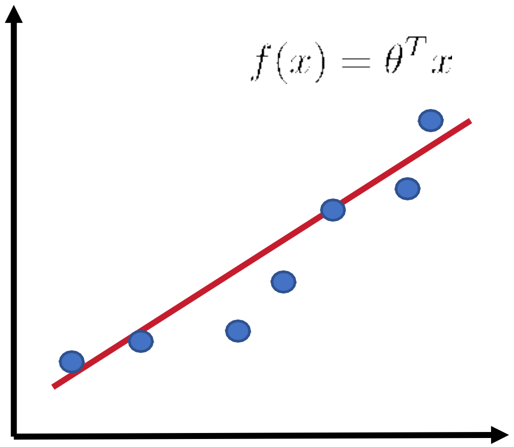


RPM

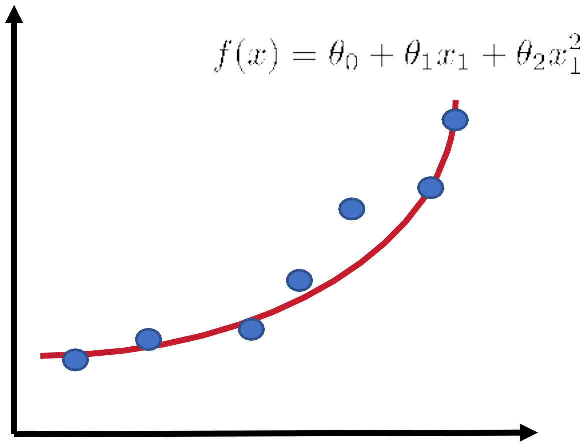
Our Approach

- Use machine learning to estimate ROP from weight-on-bit (WOB), torque, and RPM
- Many options to choose from:

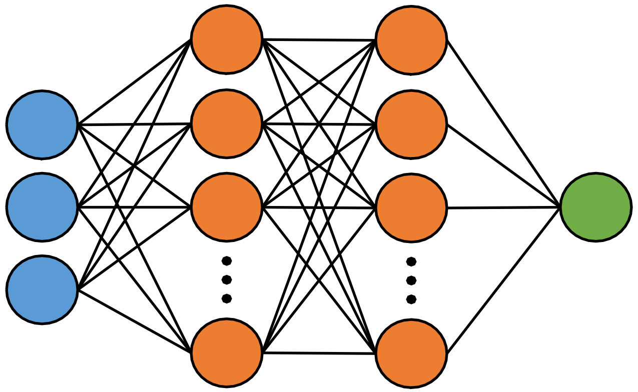
Linear Model



Polynomial Model



Neural Network



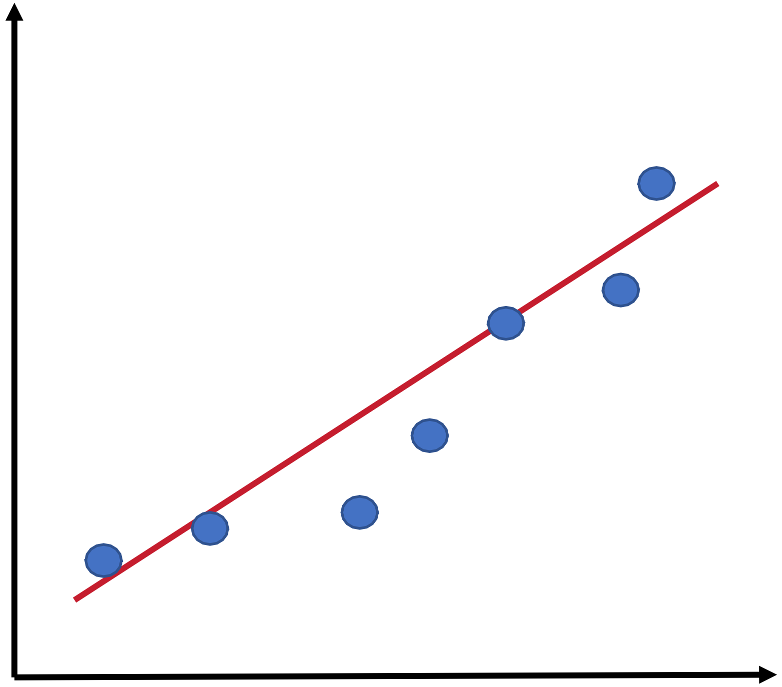
Estimating ROP via Regression

- Given N training examples of input signals and target outputs $\{(x_1, y_1), \ldots, (x_N, y_N)\}$
- We find model parameters using regularized least squares regression

$$\underset{\text{Model Parameters}}{\theta^*} = \text{argmin}_\theta \overbrace{\sum_{i=1}^{N} (\underset{\text{Ground Truth}}{y_i} - \underset{\text{Model Prediction}}{\hat{y}_i})^2}^{\text{Loss Function}} + \overbrace{\lambda \sum_{j=1}^{M} \theta_j^2}^{\text{Regularization}}$$

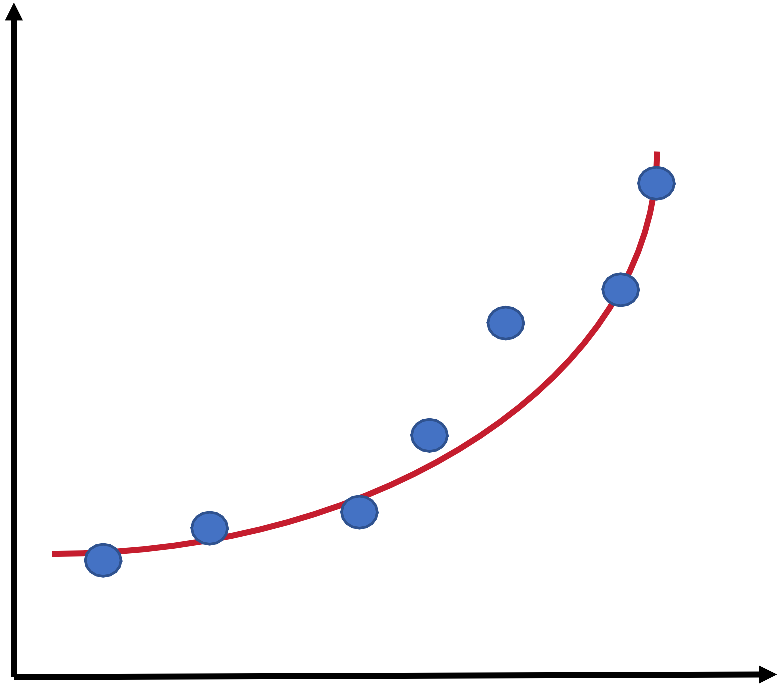
Linear and Polynomial Models

Linear



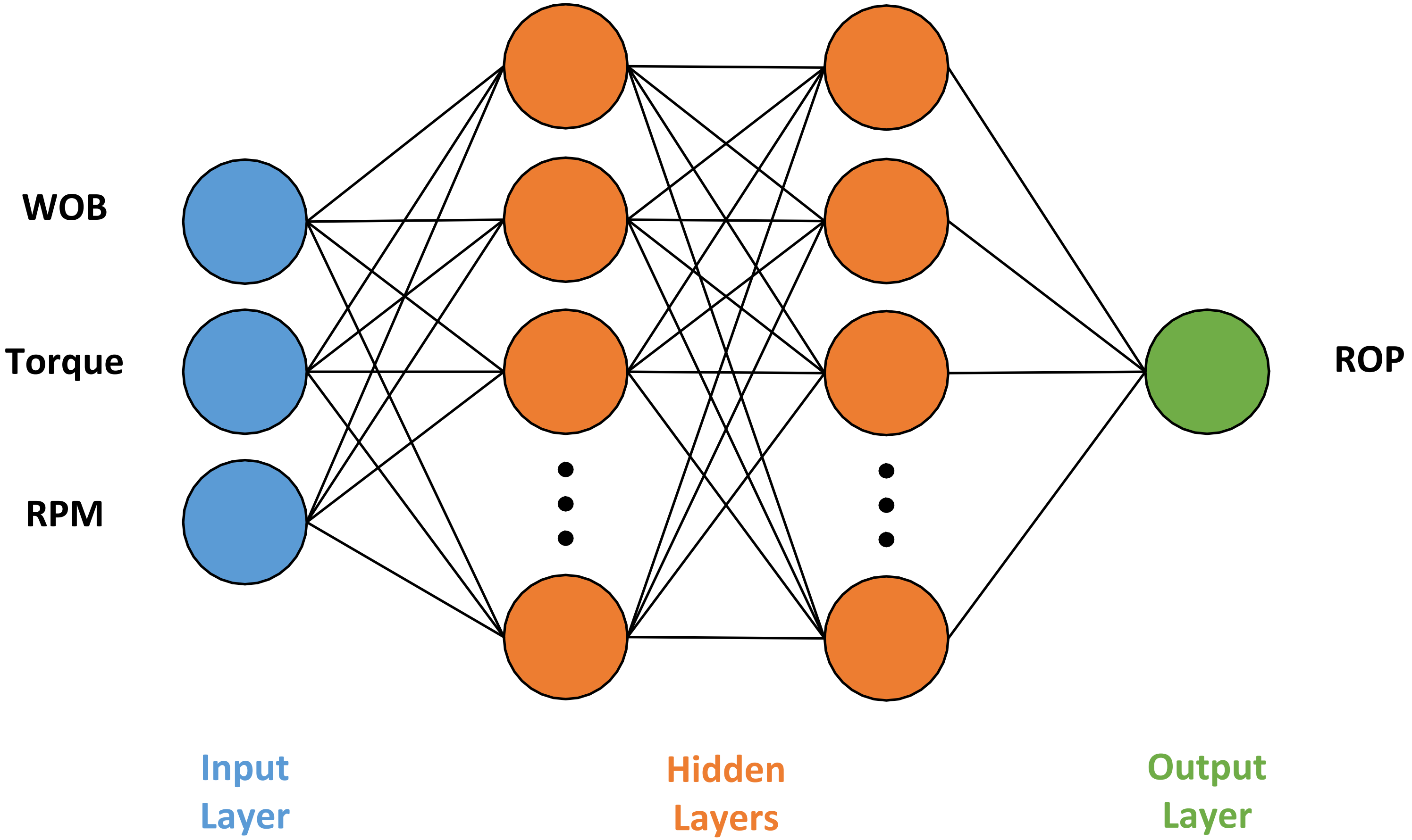
$$f(x) = \theta^T x$$

Polynomial



$$f(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_{11} x_1^2 + \theta_{22} x_2^2 + \theta_{12} x_1 x_2$$

Neural Network Models



$$f(x) = W_2\phi(W_1x + b_1) + b_2$$

$$\phi(x) = \max(0, x)$$

$$\theta = \{W_1, W_2, b_1, b_2\}$$

Experimental Laboratory Drilling Dataset

- Drilling data collected at Sandia National Lab's Hard Rock Drilling Facility (HRDF)

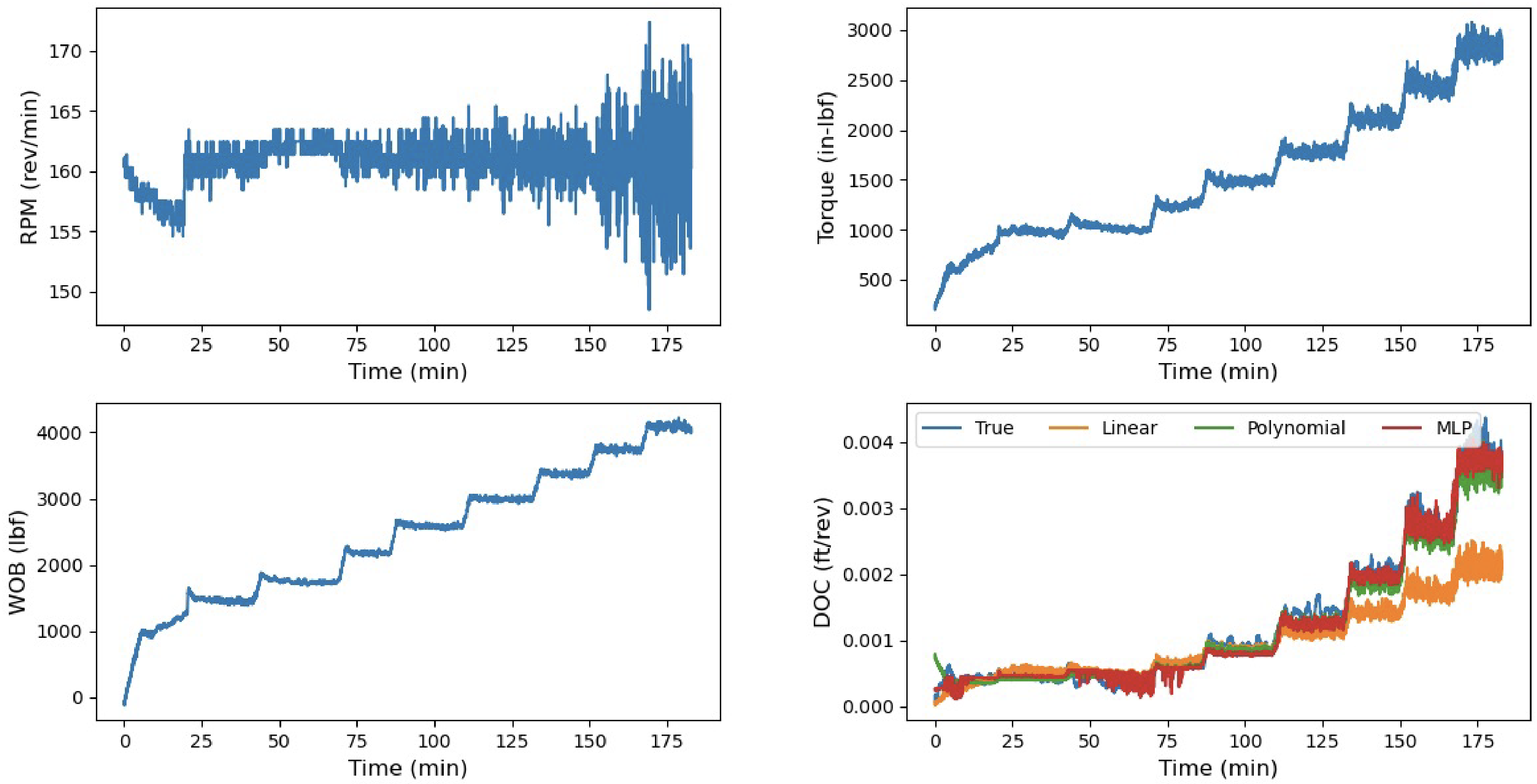
- Measurements
  - Down-hole WOB, RPM, torque, and DOC
  - Filtered with a moving average filter (window length ~0.2 sec)

- Ground truth ROP estimated using finite forward-difference of DOC

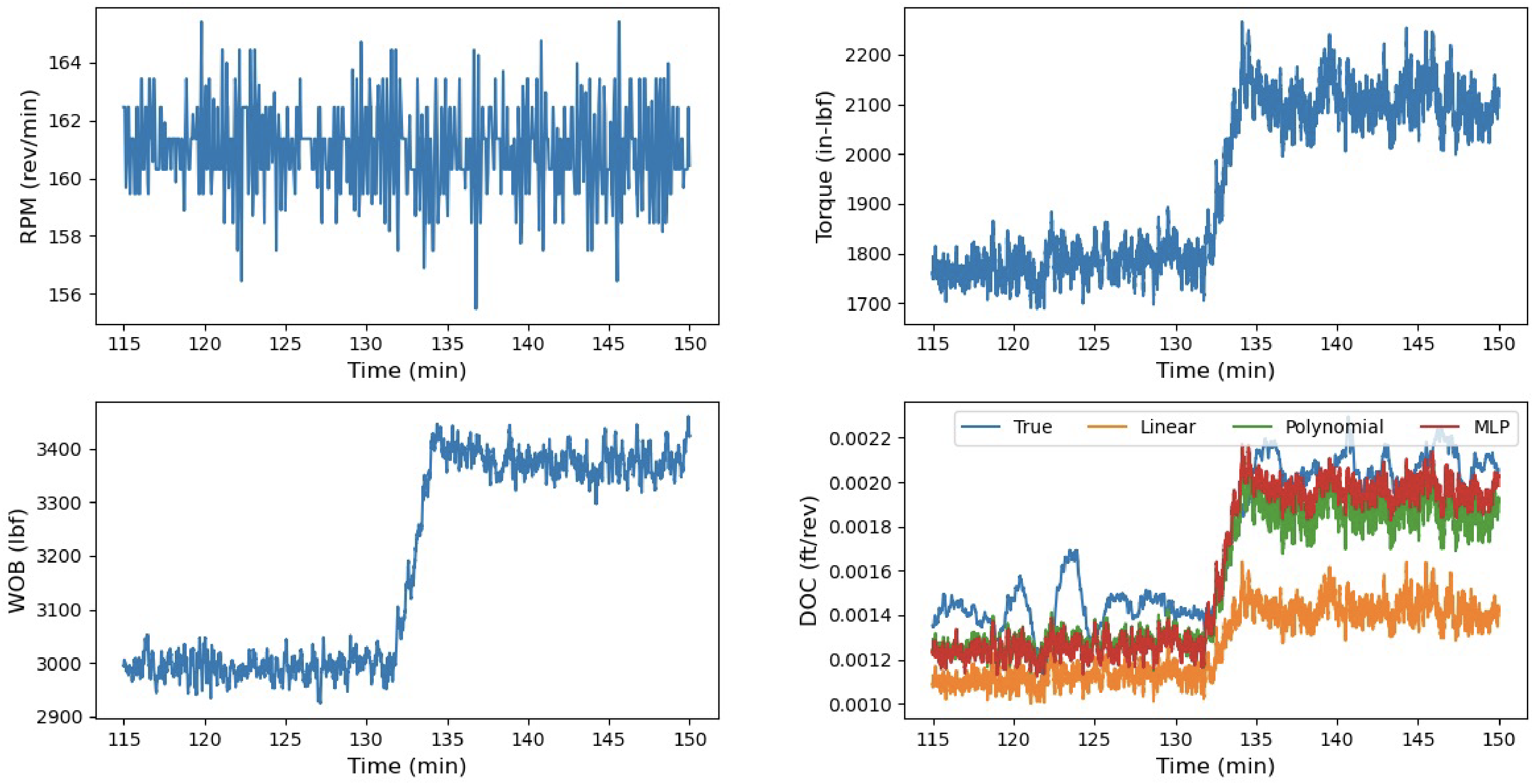
Results: Mean Absolute Error Across Models

Models	Train MAE	Validation MAE	Test MAE
Linear	1.81	3.00	3.63
Polynomial	0.906	1.46	1.89
MLP	**0.876**	**1.27**	**1.79**

Results: Model Performance on Test Sequence



Results: Sudden Change in WOB



Conclusions

- Successfully shown that machine learning can be used to predict down-hole ROP and DOC

- Neural network models proved to perform best across different depth-of-cuts

- Results indicate the potential to enable:
  - Better drilling assessment
  - Improved control
  - Extended component life-times

- Next step: incorporate neural network with down-hole sensing sub and integrate into HRDF