# FATIGUE FORECASTERS

## Development of a Machine Learning (ML) Pipeline to Determine Predictive Fatigue and Erosion on Coil Tubing

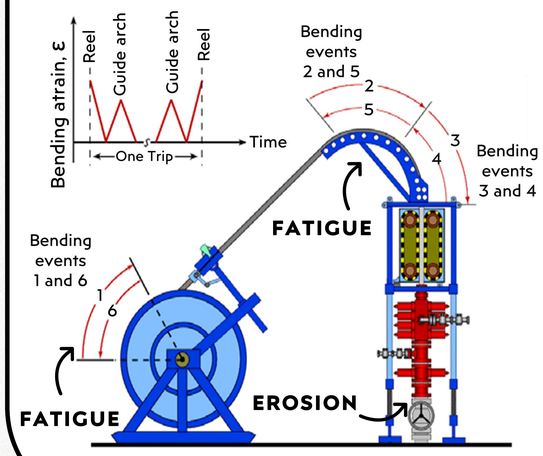
RIPPLE

ELEMENT technical services

UNIVERSITY OF CALGARY

SCHULICH School of Engineering

## THE PROBLEM




[1] Li, YQ, Gao, X, Ni, LD, Hu, QF, & Xin, YA. "Fatigue of Coiled Tubing and its Influencing Factors: A Comparative Study." *Proceedings of the ASME 2016 International Mechanical Engineering Congress and Exposition. Volume 9: Mechanics of Solids, Structures and Fluids; NDE, Diagnosis, and Prognosis.* Phoenix, Arizona, USA. November 11–17, 2016. V009T12A081. ASME.

**Fracking Oil and Gas extraction uses coiled tubing in a wellbore.**

**Eventual bend fatigue and slurry erosion in bottom 200 meters of tubing cause wear and tear that render the coil unusable.**

**Predicting fatigue and erosion improves fracking sustainability for clients.**

## THE GOAL

Our goal is to revolutionize failure prediction of coil tubing, in the oil and gas industry, using machine learning

**ML MODEL**

Predict fatigue to decide on the feasibility of a coil string for a particular job

Predict the optimum area between factors that impact erosion rate of tubing for informed metrics to clients:

**ML PIPELINE**

## WHY ML?

- DATA UTILIZATION
- PROLONG EQUIPMENT
- COST CUTTING
- OPTIMIZE OPERATIONS
- COMPETITIVE ADVANTAGE
- RISK MANAGEMENT


**Our Team**

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**Special Thanks:** John Yeung, P.Eng, ETS


## OUR METHODOLOGY

### SPRINT 1: FATIGUE MODEL

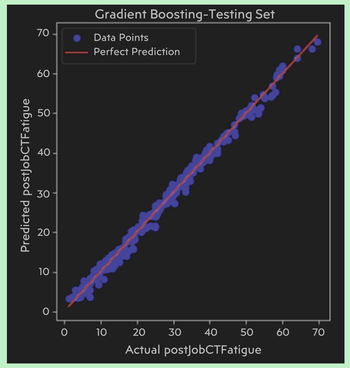
TARGET VARIABLE:

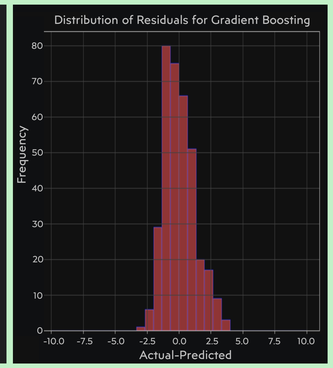
**POST FATIGUE**

FEATURE ENGINEERING

**200+** → **17** → **330+**

**4 MILLION+ MODELS**



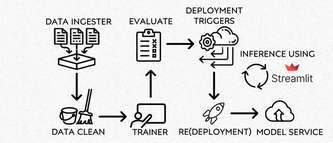




**BEST FATIGUE ML: GRADIENT BOOSTING**

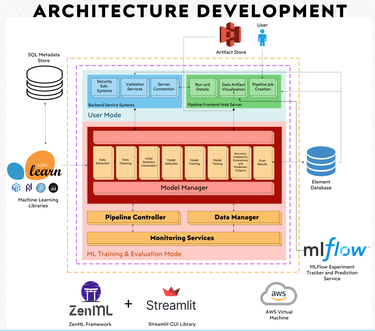
| OURS | | OBJECTIVE |
|---|---|---|
| MEAN SQUARED ERROR **1.34** | | |
| MEAN ABSOLUTE PERCENTAGE ERROR **0.06 %** | VS | MEAN ABSOLUTE PERCENTAGE ERROR **10.0 %** |
| K-FOLD R2 **0.993** | | |

**RESULTS**

### SPRINT 2: EROSION MODEL




**ARCHITECTURE DEVELOPMENT**

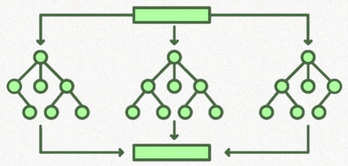



TARGET VARIABLE:

**EROSION RATE**

FEATURE ENGINEERING **29 → 12**

OPTUNA FINETUNING **10 TRIALS**



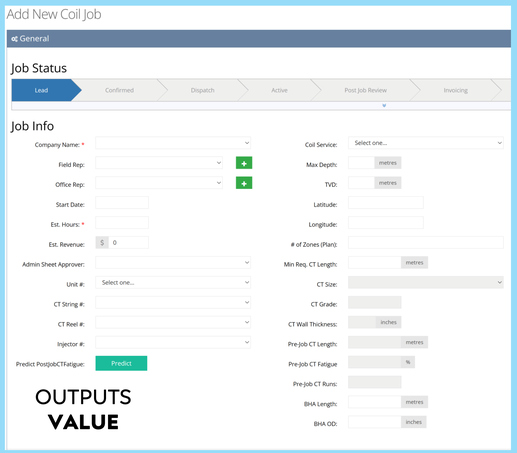
**BEST EROSION ML: RANDOM FOREST**

| OURS | | OBJECTIVE |
|---|---|---|
| MEAN ABSOLUTE PERCENTAGE ERROR **<15 %** | VS | MEAN ABSOLUTE PERCENTAGE ERROR **50 %** |
| MEAN ABSOLUTE ERROR **<0.3** | | MEAN ABSOLUTE ERROR **0.5** |

**RESULTS**

*WILL CONTINUE TO IMPROVE

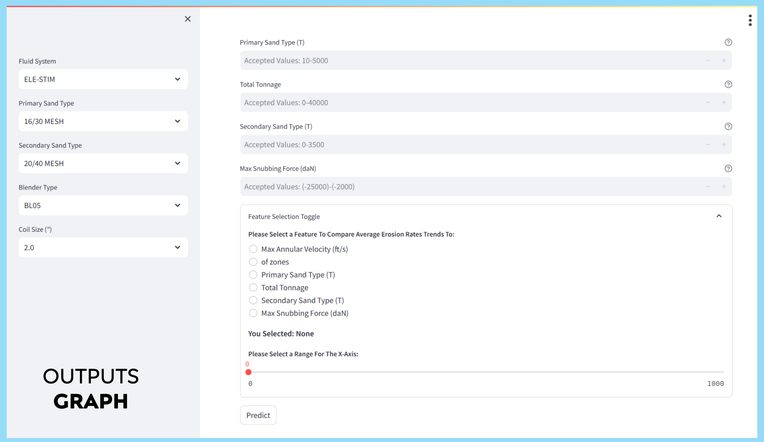
### SPRINT 3: DEPLOYMENT




OUTPUTS **VALUE**

**FATIGUE**

**Both models ready and approved for live deployment and usage on Element Technical Services in-house software. Clients able to use both models with immediate effect.**




OUTPUTS **GRAPH**

**EROSION**