

Lateral Buckling VAS Model

Prediction by Surrogate Modelling

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Why Surrogate Models?

Engineering Simulations are slow and fragmented, and learnings are lost.

Phase	Category	Challenges	Solutions Using Surrogate Models				
	Time & Resource Constraints	 Simulations take months to run Limited ability to iterate quickly High computational and human effort required Bids are lost because we cannot meet schedule 	 Surrogates deliver fast predictions Support rapid iteration and design validation Reduce compute and labour overhead Completing project ahead of schedule is incentivised 				
Projects	Large Design Space & Manual Optimisation	·	 Use DoE and surrogate models to reduce needed simulations Enable automated, global optimisation Instant parametric/sensitivity analysis 				
	Knowledge Loss	 Engineers rework from scratch for each project No reuse of past simulation results 	 Develop reusable surrogate models from historical data Enable cross-project learning and adaptation Run additional simulations off-critical path for model training 				
Foulty Change (Duining)	Time & Resource Constraints	 No time for detailed simulations Fast cost and solution estimates needed Reliance on engineering judgment, not data Risk of inaccurate early-stage cost predictions 	 Use surrogates for instant predictions based on previously trained models Support early-stage design without compromising on insight Enable reliable and consistent, data-driven predictions 				
Early Stage (Pricing)	Subjectivity & Lack of Analytics	 No structured comparison of options Decisions made without traceable analytics No way to quantify risk of design or cost estimates 	 Support dashboard-driven FEED analysis Provide visual insights for trade-off and what-if studies Use surrogate models with uncertainty quantification (e.g., GP) - Inform prediction bounds and confidence intervals 				

The inability to reuse knowledge, the reliance on manual processes, and the absence of fast, data-driven predictions expose the company to **delays, cost overruns, and lost bids**.

Lateral Buckling Analysis

Predict pipeline behaviour on the seabed

Analysis Goal

Do we need any external mitigations? If yes, how many and where?

How?

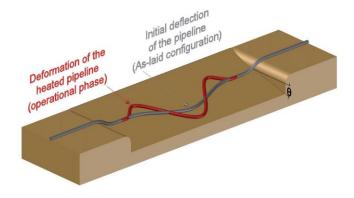
Predict pipeline behaviour through FEA. We check for:

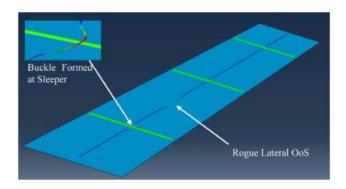
- 1. Pipeline buckle probability: Is it going to buckle (controlled)?
- 2. Pipeline Stress (Is it going to break?)
- Post buckle amplitude (How long the sleeper need to be?)
- 4. End Loads (Is it safe for the connected structures?)
- 5. ...

Optimisation Criteria

Cost: Lowest number of mitigations (Each mitigation = 2 to 4 million)

Achieved by: Running large case matrix of cases and select least number mitigation configuration that does not break the pipeline.





Analytical Equations?

- Analytical Equations for Lateral Buckling response.
- These equations can be used to estimate buckle mitigations solutions without doing FEA.
- Required Abaqus cases (4.2 million)
 - Single sleeper
 - Full factorial approach
 - 3 cases per variable
- Uncertain efficiency of equations.
 - Non-linearity may not be sufficiently captured
 - More simulations may be required to improve equations.
 - Difficult to ascertain which cases to run to improve equation's reliability.

Time Consuming | Low Reliability (?)

Input	Range	Output
Pipe OD	[6" – 14"]	Buckle Initiation Force
Pipe WT	[0.375" – 1.5"]	Post Buckle EAF
External coating	[0"-3"]	Max Longitudinal Stress
Temperature	[0 - 350°F]	Max Longitudinal Strain
Pressure	[4 – 15ksi]	Buckle Amplitude
Axial pipe/soil friction	[0.2 - 0.8]	Axial Stress Range
Lateral pipe/soil friction	[0.5 - 1.3]	
Sleeper height	[2 – 4ft]	
Sleeper friction	[0.05 - 0.6]	
Contents Density	[20 – 65 pcf]	
Mode shapes	2 Modes	
•••		

Proposed Solution

Machine Learning Based Prediction

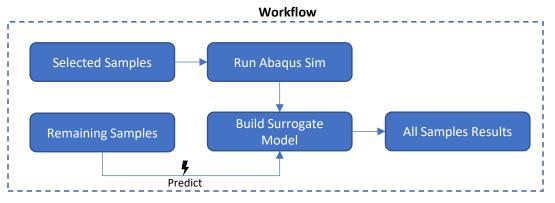
Low Data Requirement:

- Identifies data points that exhibit non-linearity.
- Informative data points.
- Better mapping of input-output space.

Mapping Complex Relationships

- Automatic learning (Input output relationship)
- Wide range of off the shelf algorithms available.
- Predictions are quick and can be integrated with Excel/Mathcad based tools.

Faster Development | High Reliability



Input	Range	Output
Pipe OD	[6" – 14"]	Buckle Initiation Force
Pipe WT	[0.375" – 1.5"]	Post Buckle EAF
External coating	[0"-3"]	Max Longitudinal Stress
Temperature	[0 - 350°F]	Max Longitudinal Strain
Pressure	[4 – 15ksi]	Buckle Amplitude
Axial pipe/soil friction	[0.2 - 0.8]	Axial Stress Range
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Sleeper friction	[0.05 - 0.6]	
Contents Density	[20 – 65 pcf]	
Mode shapes	2 Modes	

Proof-of-Concept

Objective

- Identify a dummy case
- Small subset of variables.
- Other parameters are kept constant.
- Comprehensive testing of predictions.
- ML model with low complexity.
- Evaluate errors and validate the approach

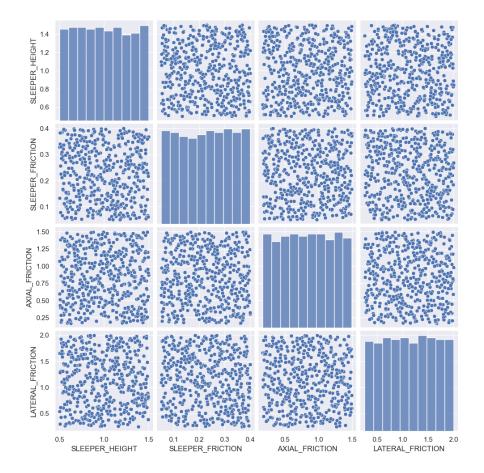
Subsequent Objective

- Identify real cases to start the model building
- Incremental expansion of the variables
- · Add models with higher complexity

Input	Range	Output			
Pipe OD	273.1mm	Buckle Initiation Force			
Pipe WT	22.2mm	Post Buckle EAF			
External coating	3.2mm	Max Longitudinal Stress			
Temperature	60°C	Max Longitudinal Strain			
Pressure	22 MPa	Buckle Amplitude			
Axial pipe/soil friction	[0.2 – 1.5]	Axial Stress Range			
Lateral pipe/soil friction	[0.5 – 1.5]				
Sleeper height	[0.17 – 1.5m]				
Sleeper friction	[0.05 – 0.6]				
Contents Density	650 kg/m ³				
Mode shapes	1 Mode				

Data Generation

- 1000 data points generated (For Training and Testing)
- Sampling using Latin Hypercube Sampling (LHS)
- Abaqus simulations on Rescale (8 x 4 cores)
- FastFEA used for postprocessing
- Total Simulation time: 24 hours



Data Snapshot (1000 Rows)

	SLEEPER_HEIGHT	SLEEPER_FRICTION	AXIAL_FRICTION	LATERAL_FRICTION	ESF1	AMP_Y	AMP_Z	SM2	SM3	EE11	BIF	S11
ı	1.383	0.3688	1.2726	0.2517	-126327		1.20117		29.8416	-6.01983e-05	-126327	-1.23726e+07
l	0.801 1.089	0.2079 0.1924	0.7698 1.089	0.6367 1.5188	-80851.3 -95804.5		5.30714 5.19107		81.653 93.4727	-0.00118891 -0.00141417	-133029 -131241	-2.41507e+08 -2.87266e+08
ĺ	1.059 1.435	0.2968 0.266	0.8736 1.0731	0.7732 0.8502	-89953.1 -94054.5		5.23108 4.31907		99.1745 96.9502	-0.00116227 -0.000942134	-155988 -143827	-2.36095e+08 -1.92065e+08
l	0.847	0.1764	0.8337	1.6552	-101457	0.843122			79.3145	-0.00159016	-134527	-3.23015e+08
- [0.893	0.3234	0.6262	1.5328	-110042	0.889122	5.40639	131365	85.5863	-0.00156445	-169952	-3.17791e+08

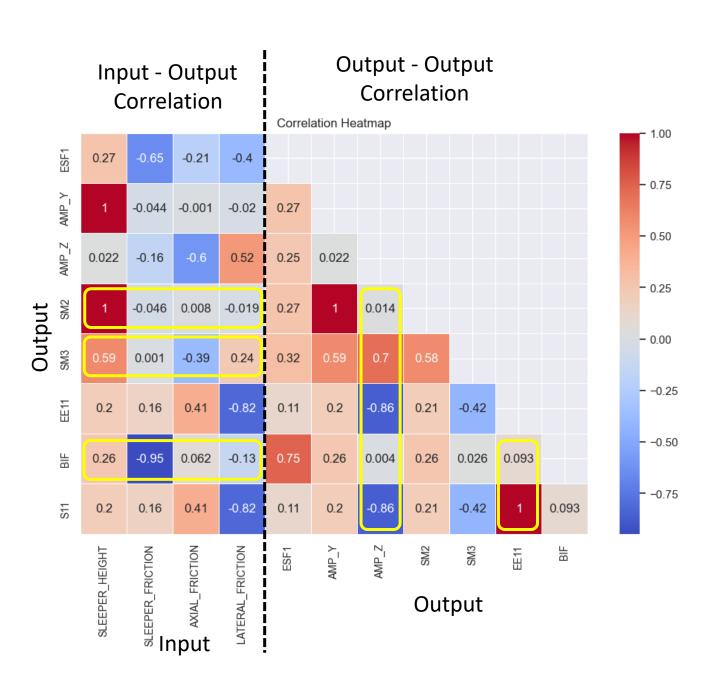
Input

Output

A measure of dependency

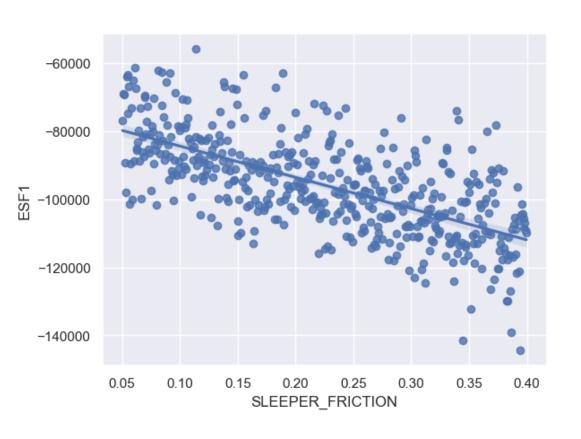
Types of Correlation:

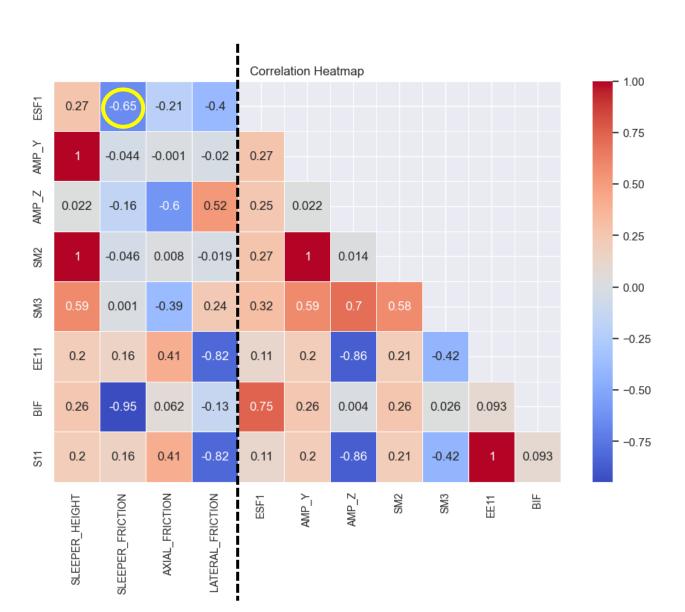
- Positive (Red Colour)
 - Strong (Dark Colours, Value close to 1)
 - Weak (Light Colours, Value close to 0)
- Negative (Blue Colour)
 - Strong (Dark Colours, Value close to -1)
 - Weak (Light Colours, Value close to 0)



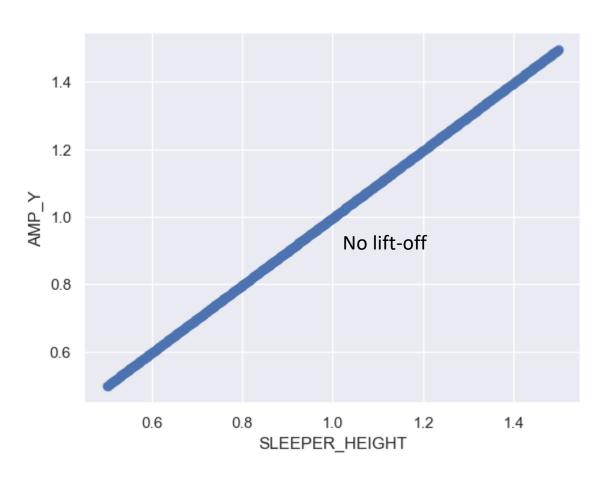
^{*} No plastic strain (PE11) observed in the data points

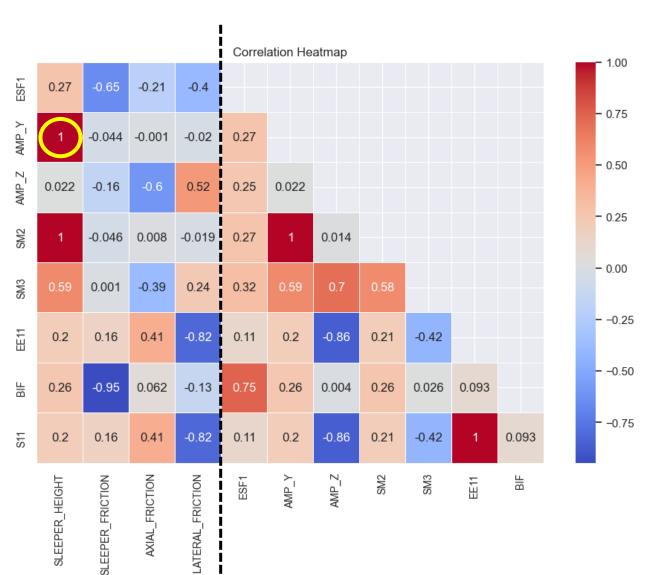
Effective Axial Force



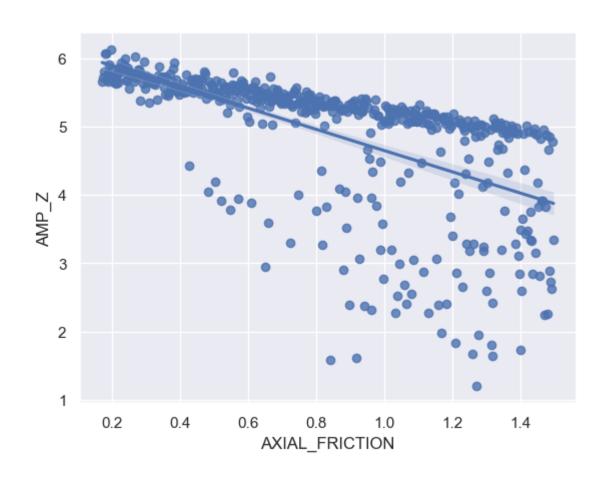


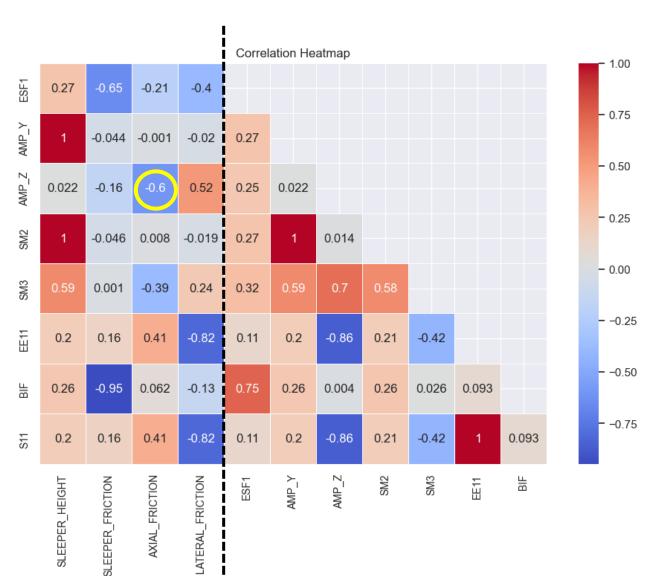
Buckle Amplitude (Vertical)



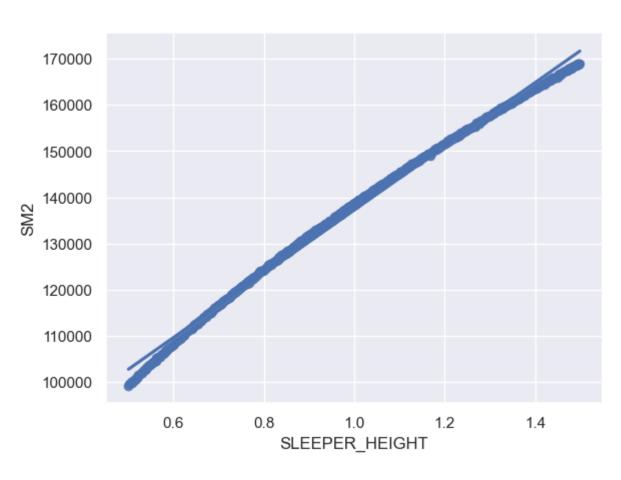


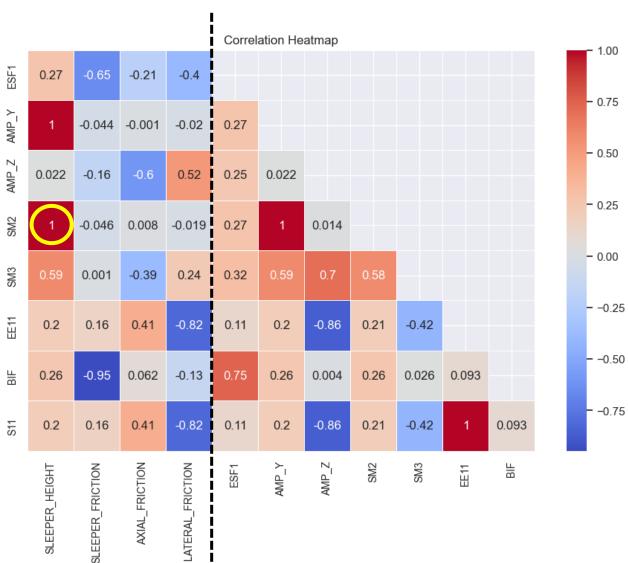
Buckle Amplitude (Lateral)



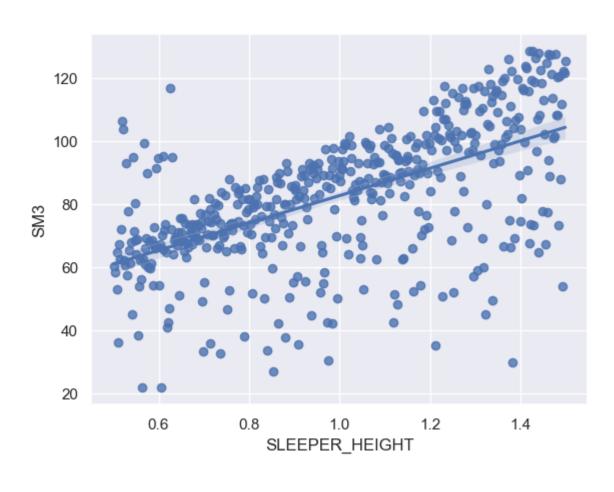


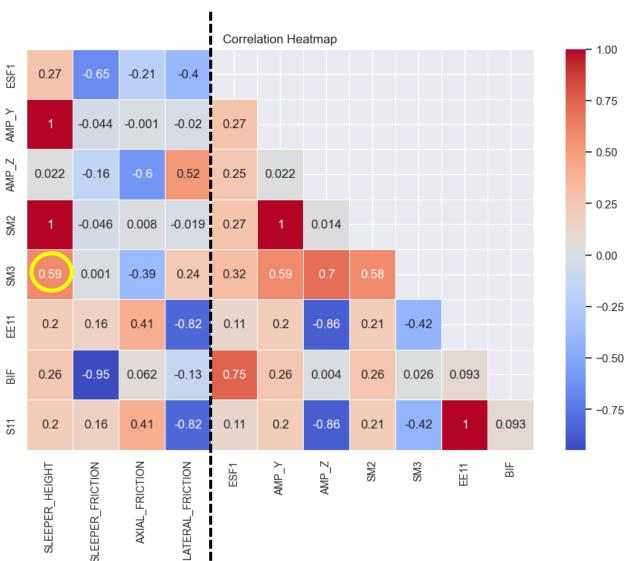
Section Moment (Vertical Plane)



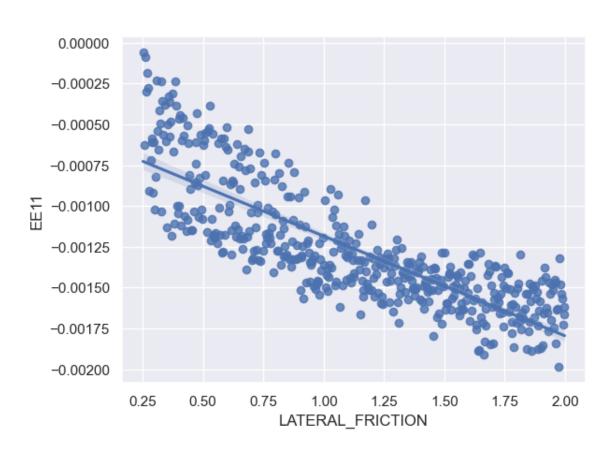


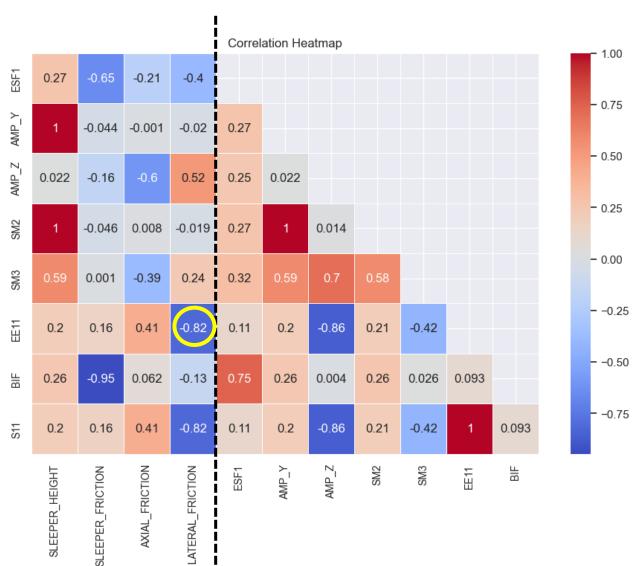
Section Moment (Lateral Plane)



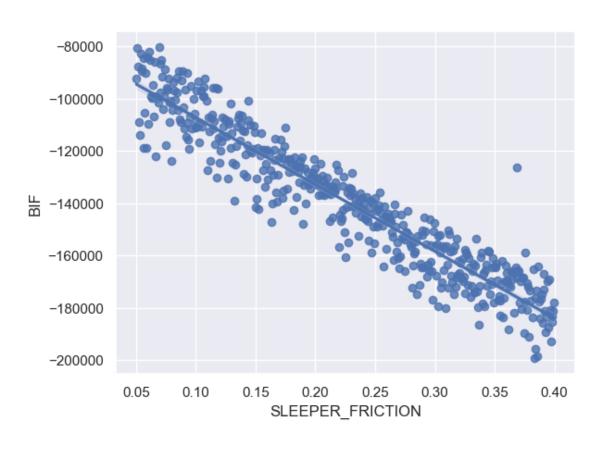


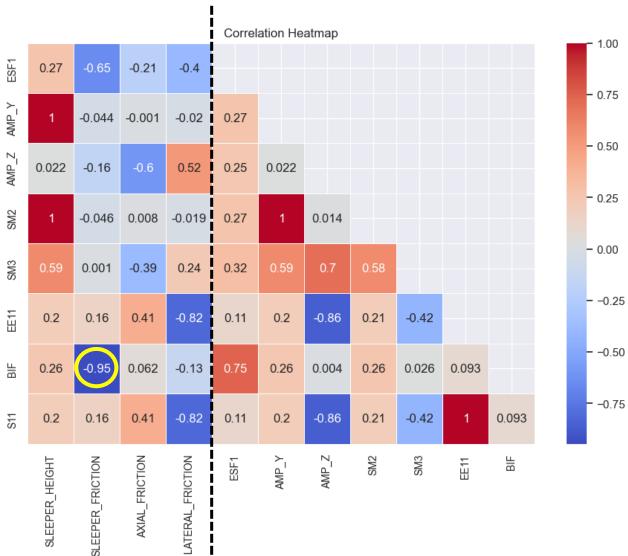
Elastic Strain



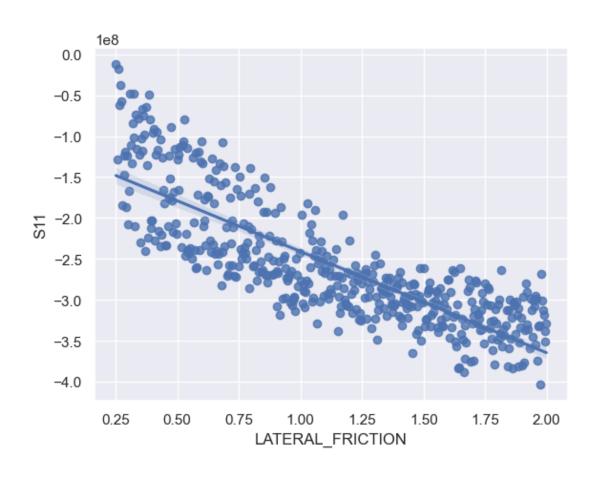


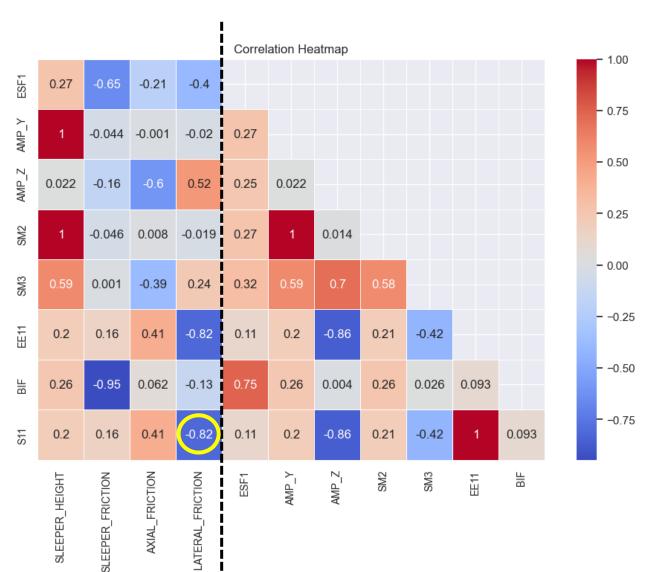
Buckle Initiation Force



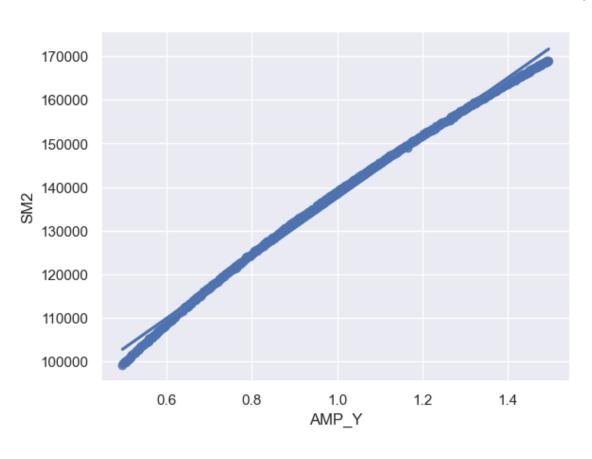


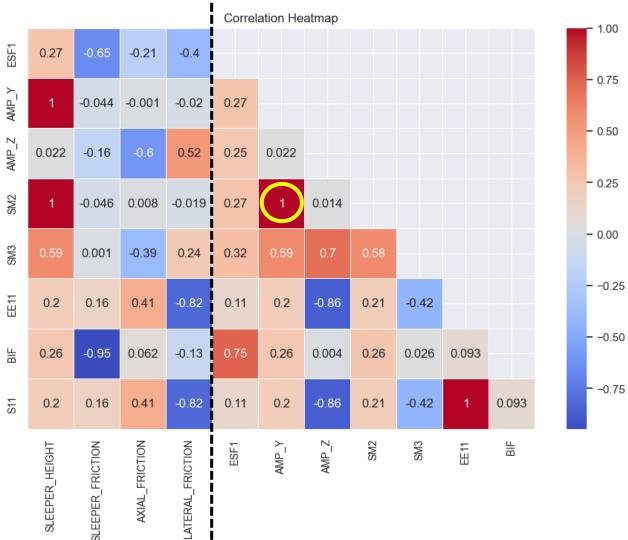
Axial Stress



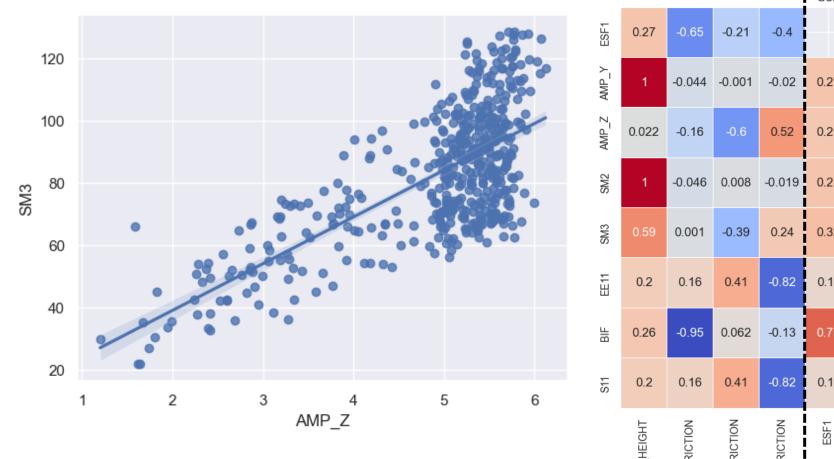


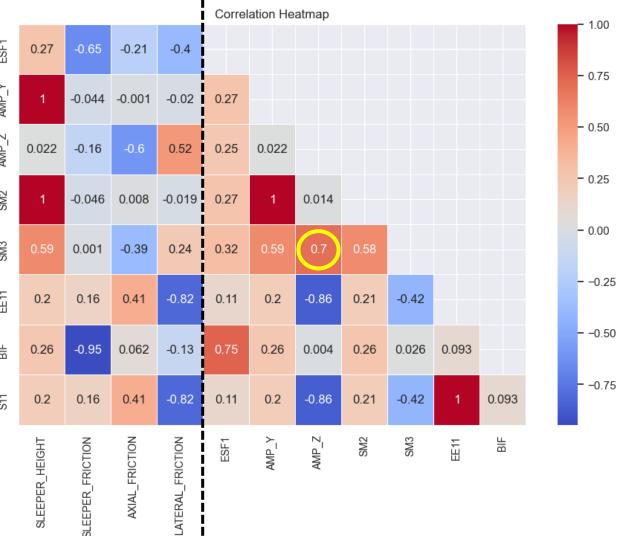
[Vertical] Section Moment vs Buckle Amplitude



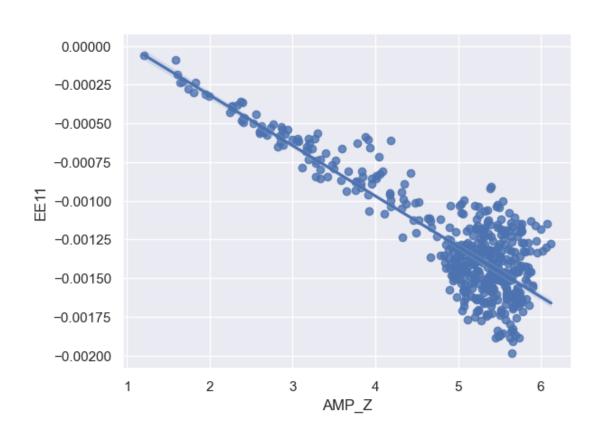


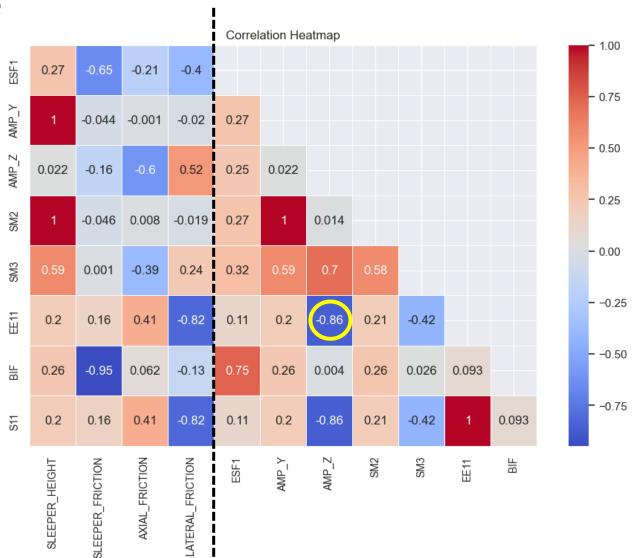
[Lateral] Section Moment vs Buckle Amplitude



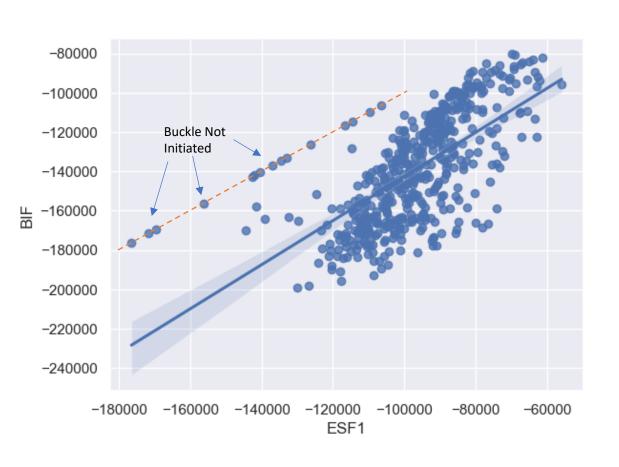


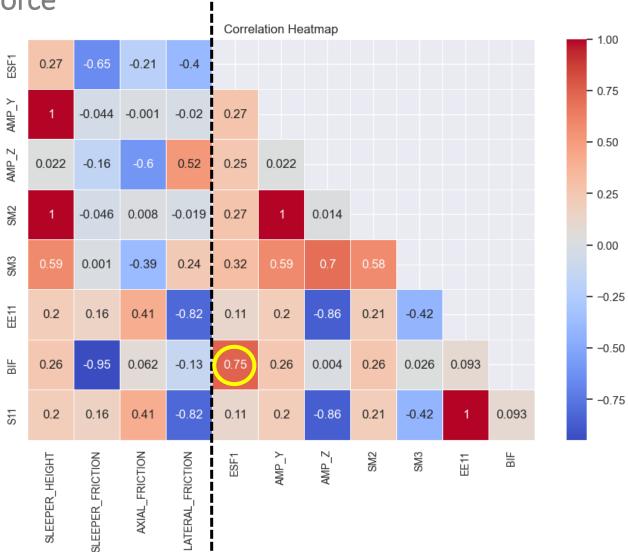
Elastic Strain vs Lateral Buckle Amplitude



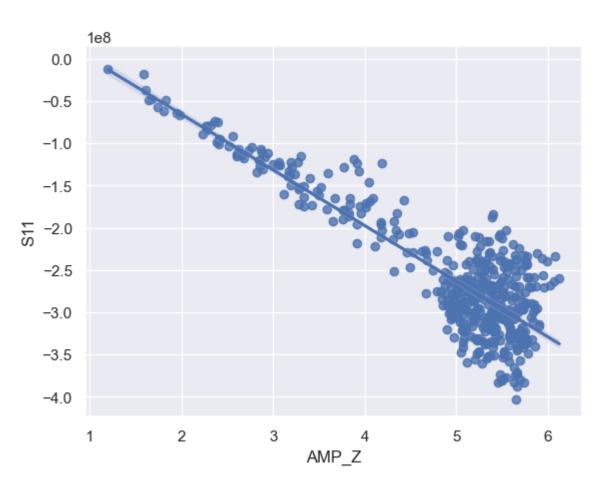


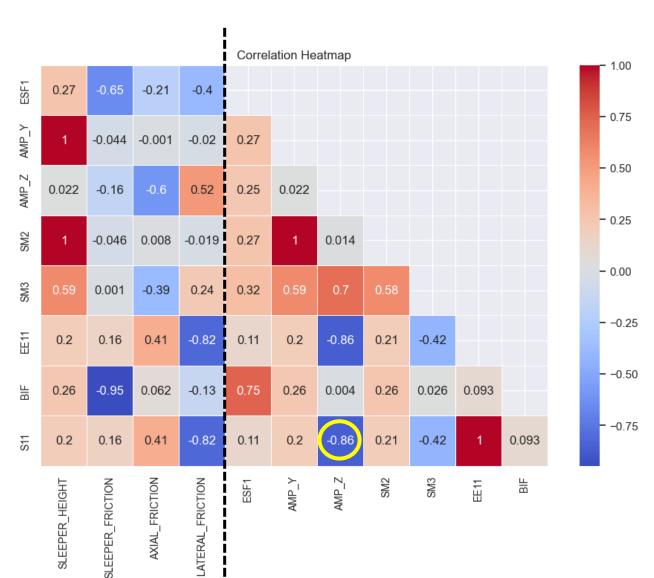
Buckle Initiation Force vs Effective Axial Force



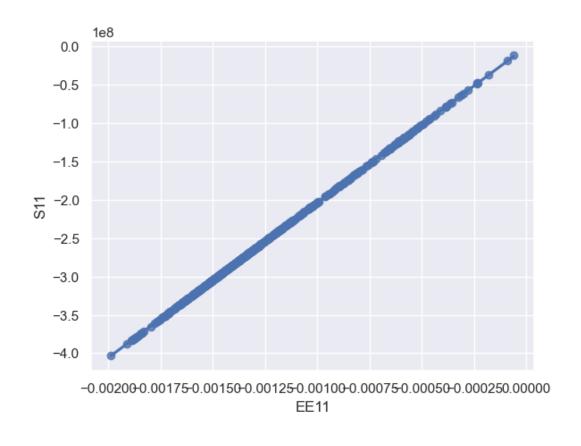


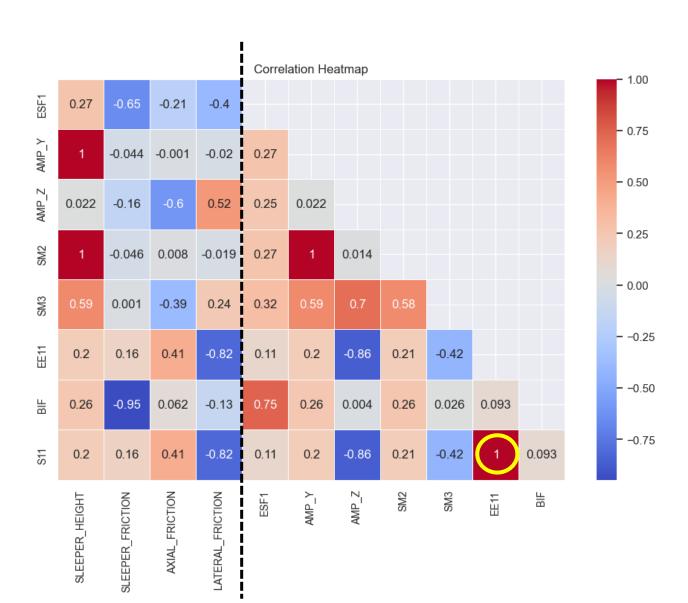
Axial Stress vs Lateral Buckle Amplitude



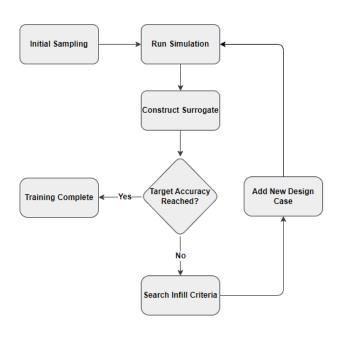


Axial Stress vs Elastic Strain

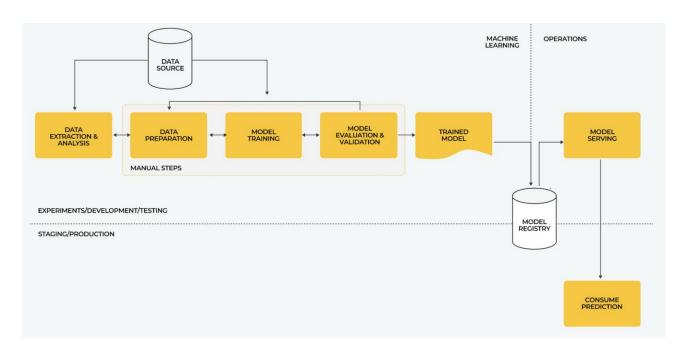




Surrogate Model Development and Serving



Model Training



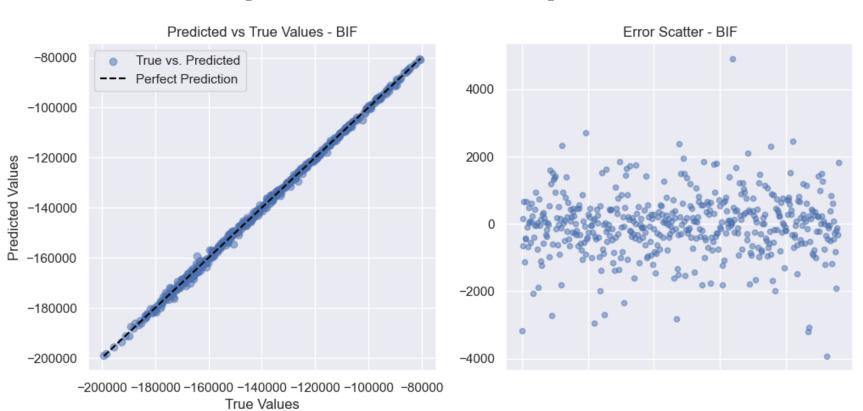
ML Pipeline

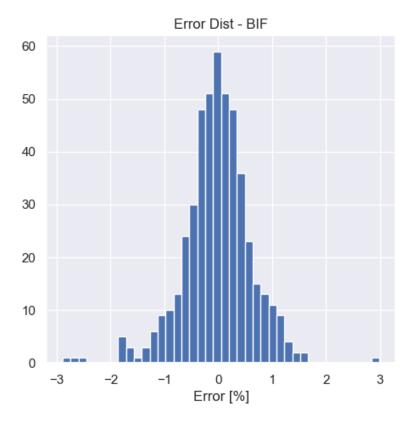
Buckle Initiation Force (min ESF1)

Train/Test Ratio: 83/1000

Median Value: -140.5 kN

Error 2xSTD : [-0.9208 kN, -0.9311 kN]





Analytical Equation - BIF

BUCKLE_INITIATION_FORCE

(Polynomial Degree = 2; 15 Parameters)

```
8953.177 + 122121.43 * SLEEPER_HEIGHT -410.68

* SLEEPER_FRICTION + 628.01 * AXIAL_FRICTION -
117.21 * LATERAL_FRICTION -26079.75 *

SLEEPER_HEIGHT^2 + 1415.82 * SLEEPER_HEIGHT *

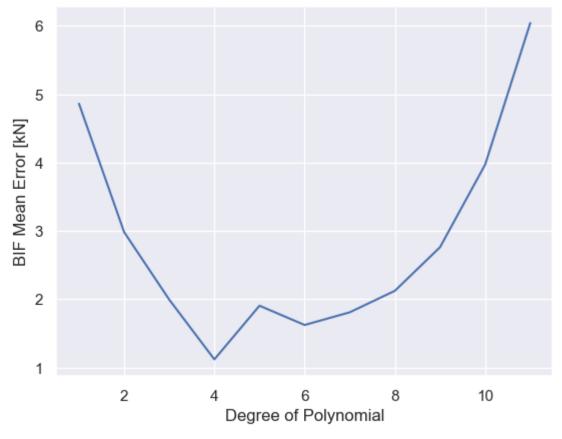
SLEEPER_FRICTION -168.37 * SLEEPER_HEIGHT *

AXIAL_FRICTION + 200.59 * SLEEPER_HEIGHT *

LATERAL_FRICTION 2724.85 * SLEEPER_FRICTION^2
-1499.433 * SLEEPER_FRICTION * AXIAL_FRICTION
-188.181 * SLEEPER_FRICTION * LATERAL_FRICTION
-158.17 * AXIAL_FRICTION^2 + 185.08 *

AXIAL_FRICTION * LATERAL_FRICTION -119.39737 *

LATERAL_FRICTION^2
```

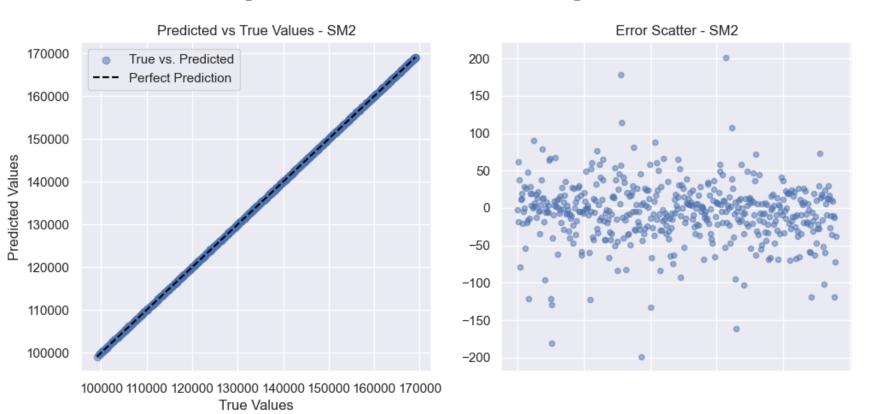


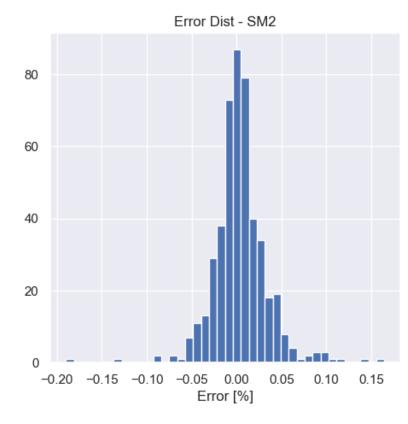
(Polynomial Degree = 4; 70 Parameters)

Section Moment (SM2)

Train/Test Ratio: 52/1000 Median Value: 138.3 kN.m

Error 2xSTD : [0.0208 kN.m, 0.0136 kN.m]

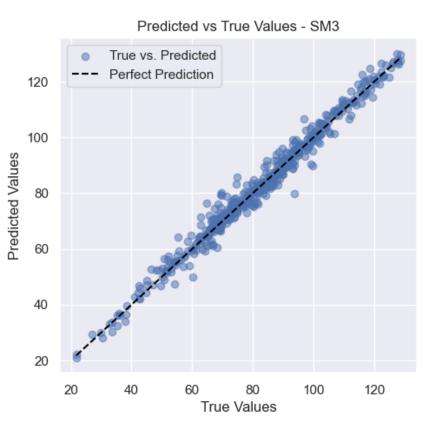


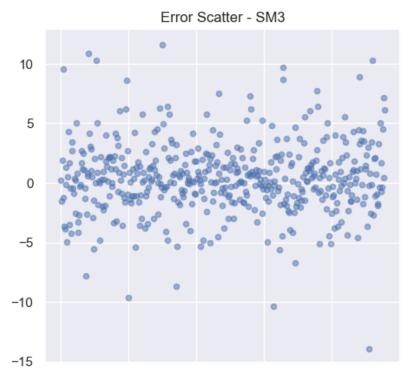


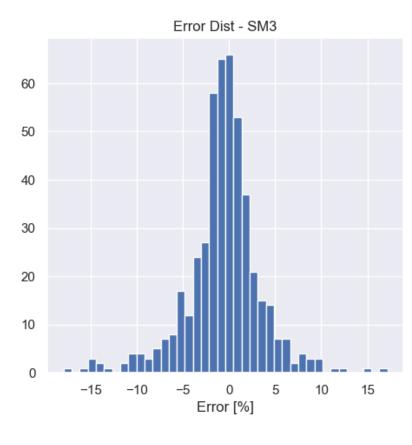
Section Moment (SM3)

Train/Test Ratio: 95/1000 Median Value: 82.47 kN.m

Error 2xSTD : [0.0111 kN.m, 0.0112 kN.m]





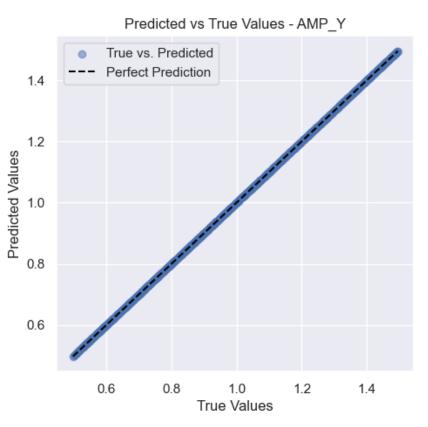


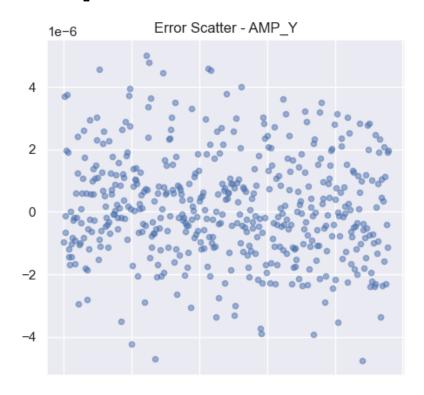
Vertical Amplitude (AMP_Y)

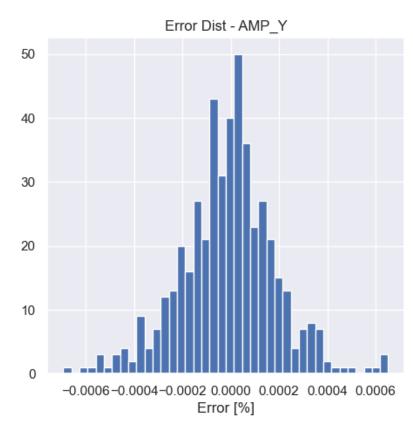
Train/Test Ratio: 29/1000

Median Value: 1.01 m

Error 2xSTD : [0.00051 m, 0.00053 m]





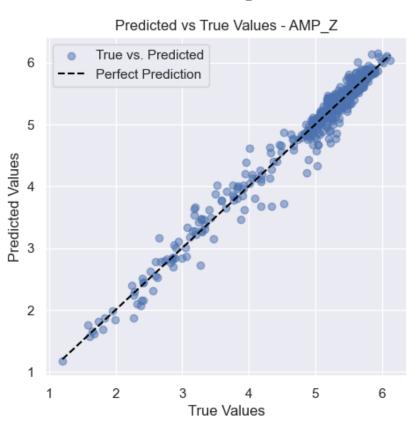


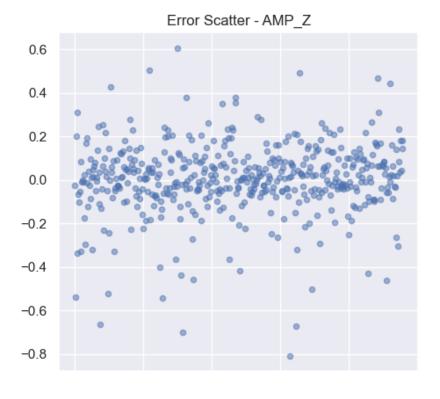
Lateral Amplitude (AMP_Z)

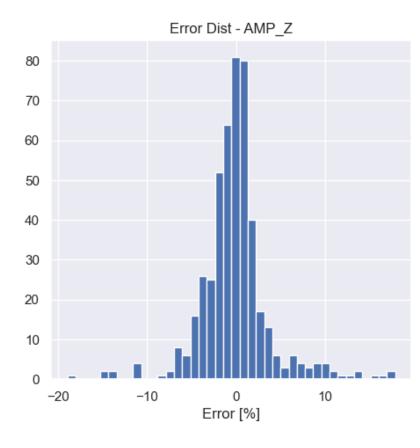
Train/Test Ratio: 100/1000

Median Value: 5.25 m

Error 2xSTD : [-0.051 m, -0.053 m]





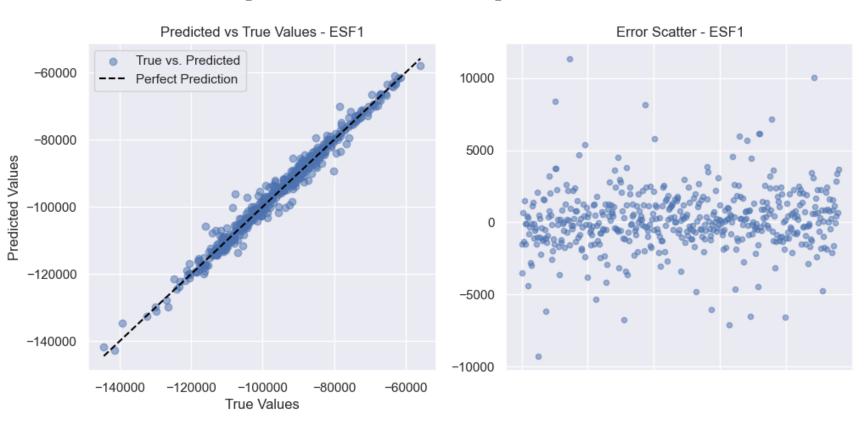


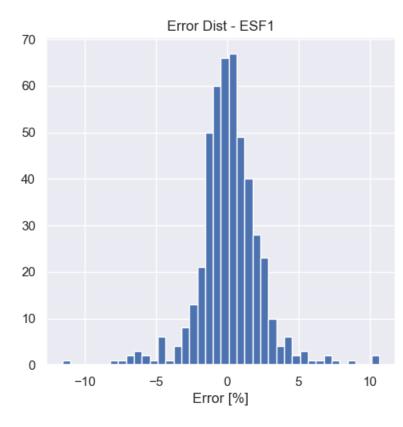
Effective Axial Force (ESF1)

Train/Test Ratio: 100/1000

Median Value: -96.32 kN

Error 2xSTD : [1.841 kN, 1.834 kN]



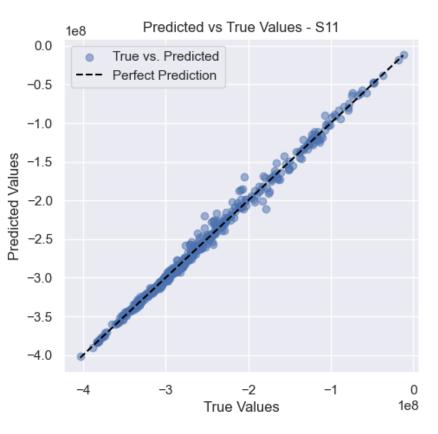


Axial Stress (S11)

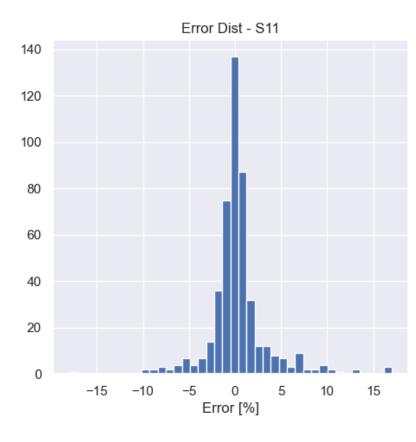
Train/Test Ratio: 87/1000

Median Value: -275 MPa

Error 2xSTD : [-0.0834 MPa, -0.0837 MPa]



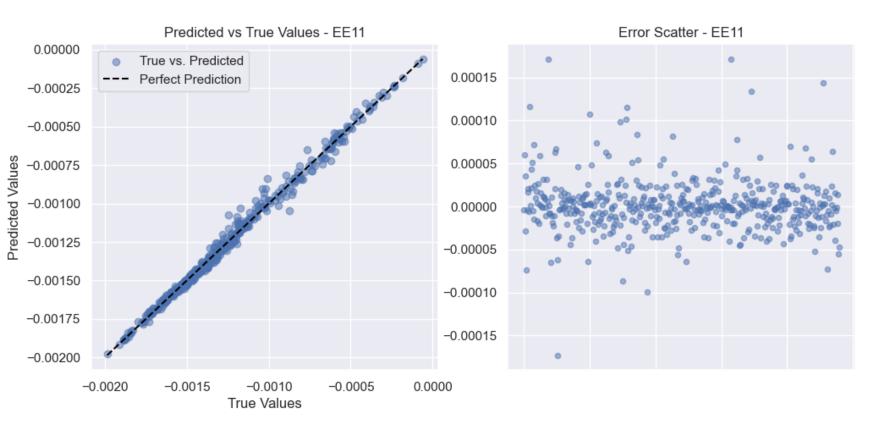


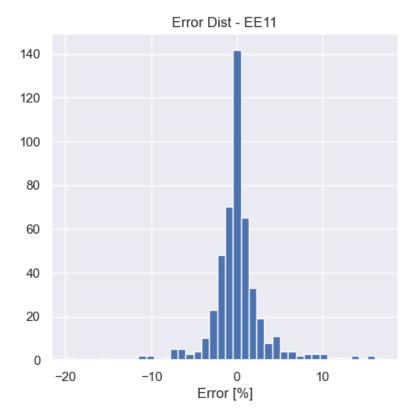


Total Strain (E11). PE11 = 0

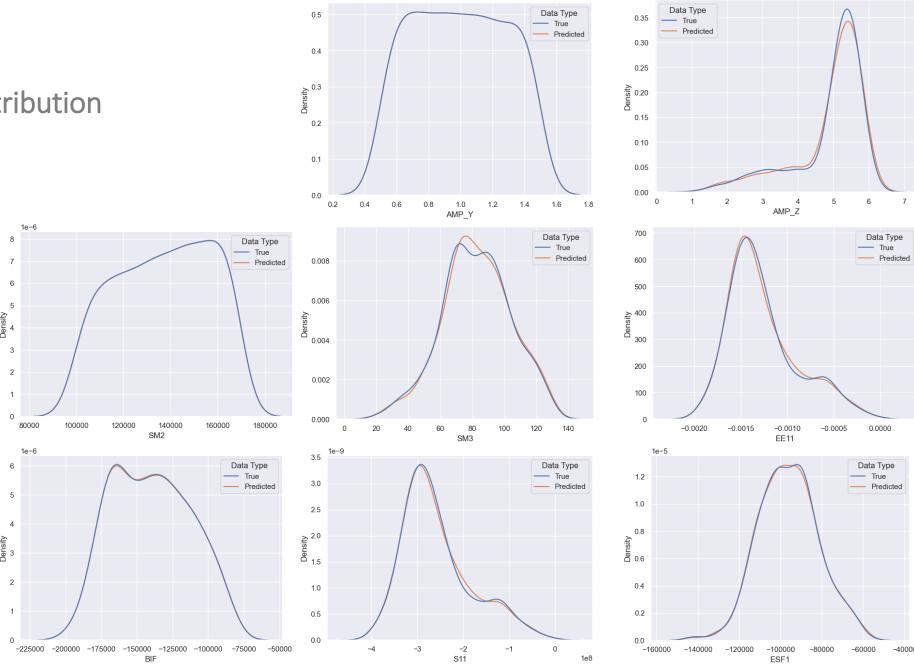
Train/Test Ratio: 69/1000 Median Value: -0.001353

Error 2xSTD : [0.0000365, 0.0000364]

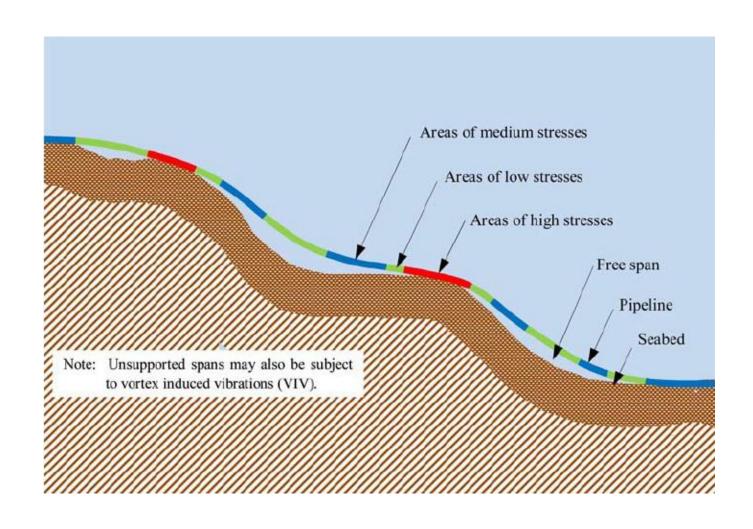




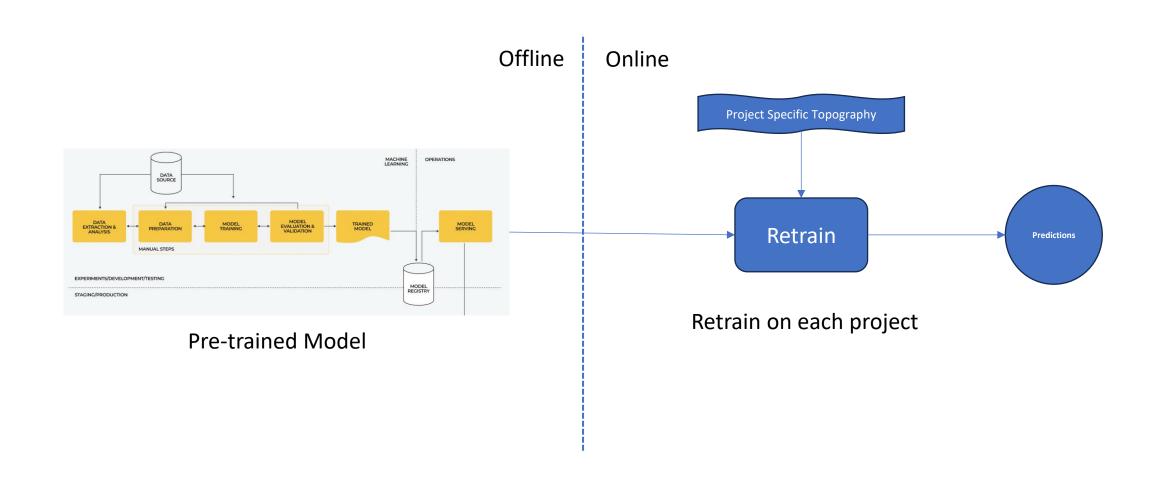
True vs Predicted Distribution



Seabed Topography



ML Pipeline for Uneven Seaved



Thank you