Application of Machine Learning to Predict the Response of the Liquid Mercury Target at the Spallation Neutron Source

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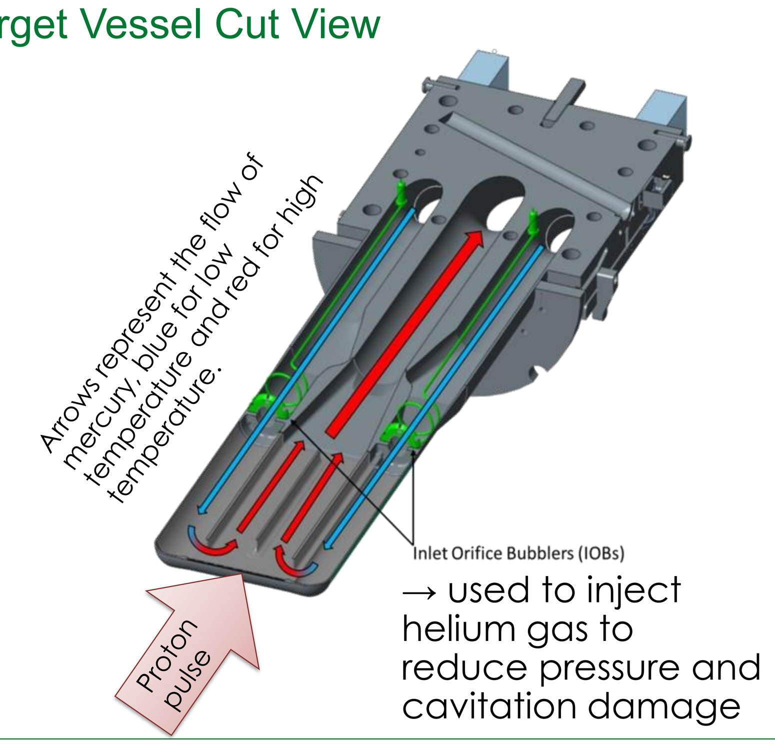
Abstract

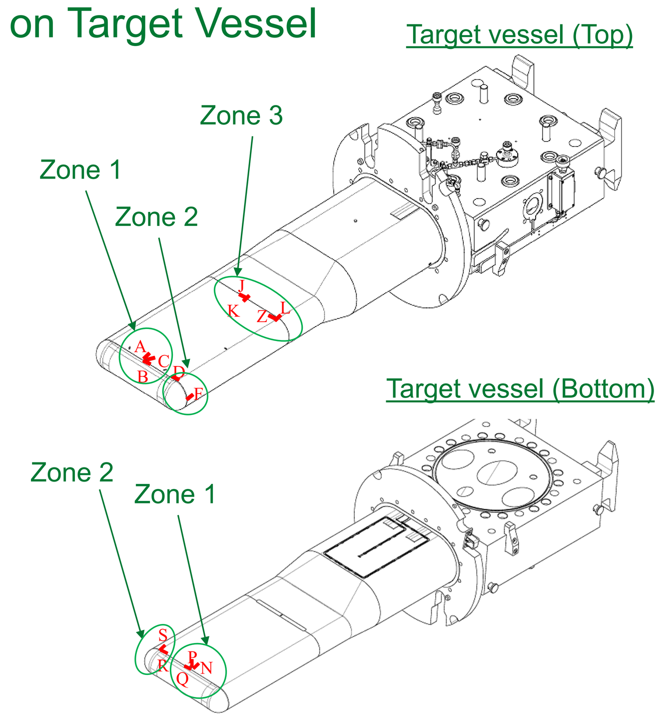
- The Spallation Neutron Source (SNS) at Oak Ridge National Laboratory is currently the most powerful accelerator-driven neutron source in the world. The intense proton pulses strike on SNS's mercury target to provide bright neutron beams, which also leads to severe fluid-structure interactions inside the target. Prediction of resultant loading on the target is difficult particularly when helium gas is intentionally injected into mercury to reduce the loading and mitigate the pitting damage on the target's internal walls [1, 2]. Leveraging the power of machine learning and the measured target strain, we have developed machine learning surrogates [3] for modelling the discrepancy between simulations and experimental strain data. We then employ these surrogates to guide the refinement of the high-fidelity mercury/helium mixture model to predict a better match of target strain response.

Target Model and Strain Sensors

Target Vessel Cut View

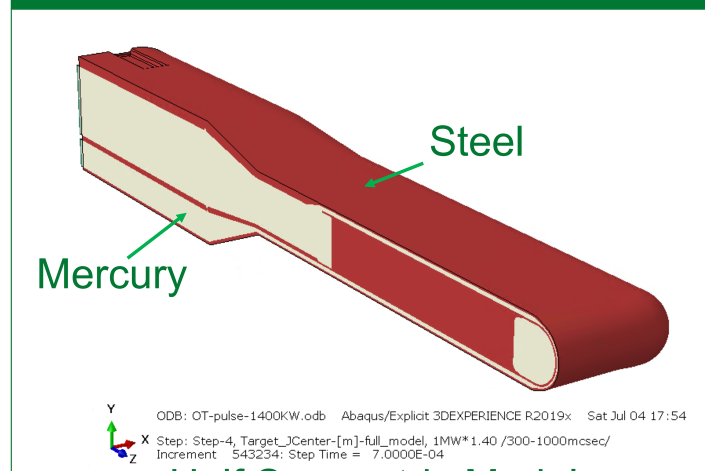


Strain Sensors on Target Vessel

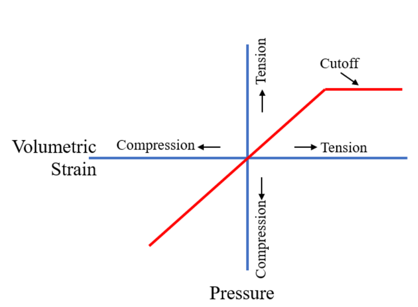


Target Finite Element Simulation

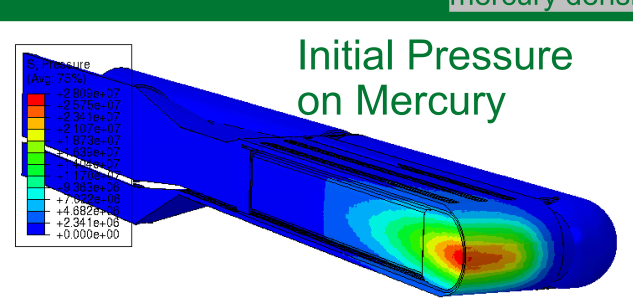
mercury density: 13500 kg/m³, sound speed: 1456 m/s, tensile cutoff:150000 Pa



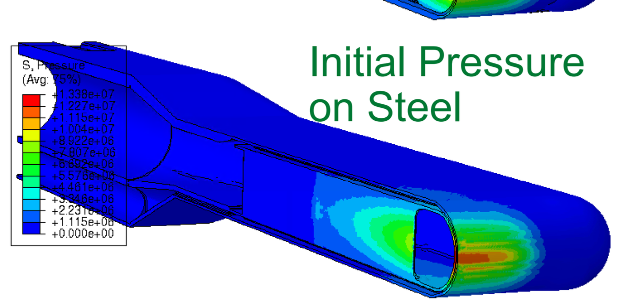
Half Symmetric Model



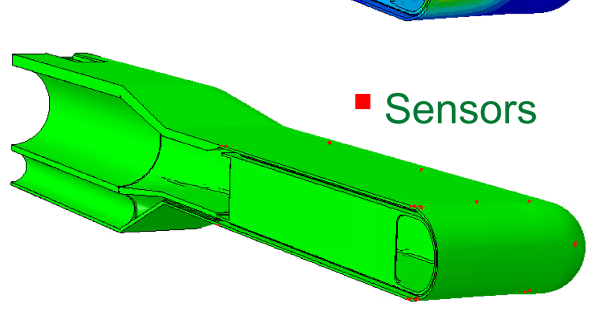
Equation of State Mercury Model



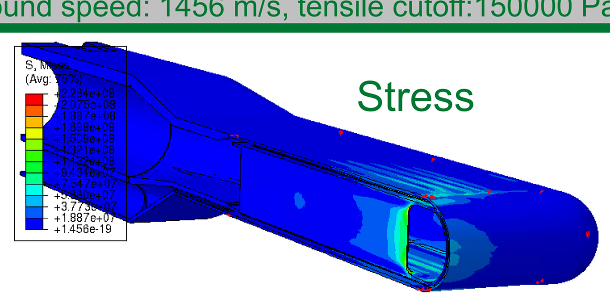
Initial Pressure on Mercury



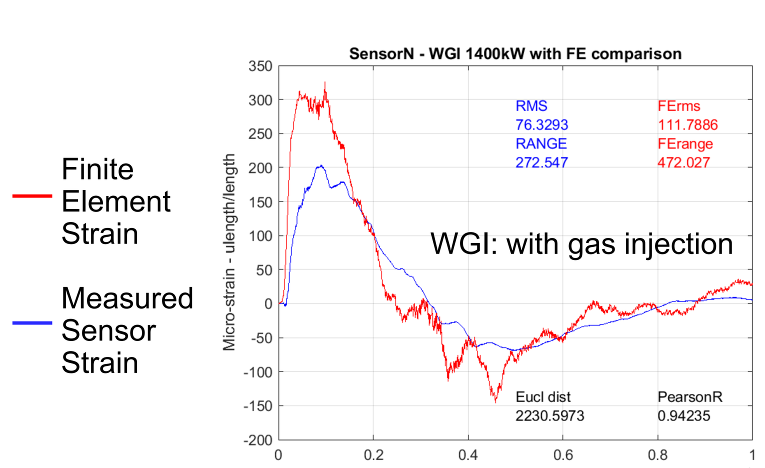
Initial Pressure on Steel



■ Sensors



Stress



RMS: root-mean-square of strain values
RANGE: Max strain – Min strain
Eucl dist: Euclidean distance
Pearson R: Pearson Correlation Coefficient

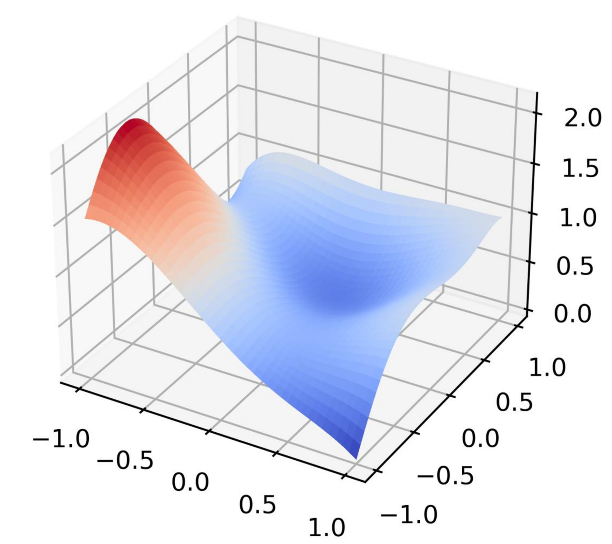
Tuning Parameters in Mercury Material Model

Run#	Tensile Cutoff (Pa)	Density (kg/m³)	Sound Speed (m/s)
1	1.5517E+06	4.3069E+03	4.8793E+03
2	3.1035E+06	1.3500E+03	7.9517E+03
3	6.2069E+06	2.1948E+03	2.4897E+03
4	1.3966E+07	1.0643E+04	3.8552E+03
5	9.8276E+06	7.2638E+03	4.5379E+03
6	2.5862E+06	5.9966E+03	8.6345E+03
7	1.0000E+01	9.7983E+03	7.2690E+03
8	1.0345E+06	3.4621E+03	1.1241E+03
9	1.1379E+07	1.3178E+04	1.4655E+03
10	1.2414E+07	2.6172E+03	2.8310E+03
11	1.1897E+07	1.7724E+03	6.5862E+03
12	5.6897E+06	1.2333E+04	6.9276E+03
13	4.6552E+06	8.1086E+03	5.5621E+03
14	1.3448E+07	6.8414E+03	1.8069E+03
15	7.7586E+06	3.0397E+03	9.6586E+03
16	7.2414E+06	1.1488E+04	3.5138E+03
17	4.1379E+06	1.0221E+04	1.0000E+04

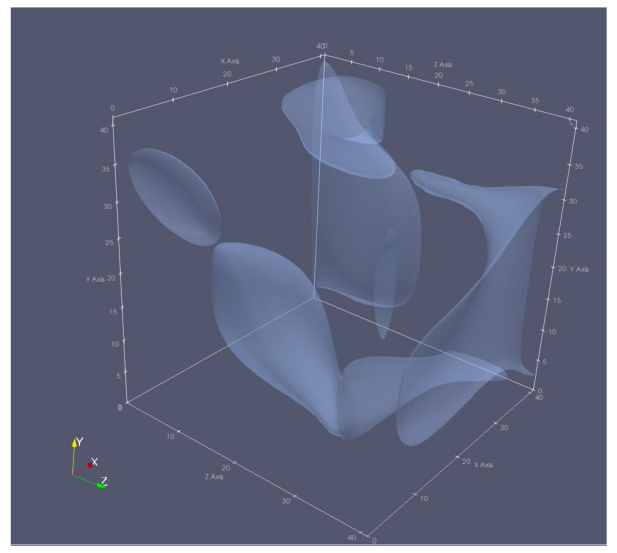
Run#	Tensile Cutoff (Pa)	Density (kg/m³)	Sound Speed (m/s)
18	8.2759E+06	7.6862E+03	8.2931E+03
19	1.0345E+07	1.1910E+04	9.3172E+03
20	1.5000E+07	5.5741E+03	5.2207E+03
21	1.4483E+07	8.9534E+03	7.6103E+03
22	6.7241E+06	3.8845E+03	6.2448E+03
23	8.7931E+06	9.3759E+03	4.4138E+02
24	1.0862E+07	1.3600E+04	5.9034E+03
25	3.6207E+06	1.1066E+04	7.8276E+02
26	5.1724E+06	6.4190E+03	2.1483E+03
27	5.1725E+05	8.5310E+03	3.1724E+03
28	2.0690E+06	1.2755E+04	4.1966E+03
29	1.2931E+07	5.1517E+03	8.9759E+03
30	9.3103E+06	4.7293E+03	1.0000E+02
31	1.5000E+07	5.3310E+03	1.0000E+03
32	1.5000E+07	5.6370E+03	1.5000E+03
33	0.0000E+00	1.1762E+04	2.2500E+03
34	1.5000E+07	5.3310E+03	7.5000E+02

Varying Tensile Cutoff, Density and Sound Speed values are randomly selected from Latin hypercube sampling points [4]; strain data calculated from these new finite element runs provide training dataset for machine learning.

Current Machine Learning Result



By comparing with one set of experimental strain sensor data, 34 sets of FE sensor data build trial ML surrogates. Projections of trial surrogates on random 2d planes show multimodality, which indicates some optimized parameters that can reduce the strain discrepancy in FE simulation due to the existence of gas bubbles.



Isosurface plot of the ML surrogates shows regions that likely contain candidate parameters, which helps refine the parameters search space in next stage.

Future Work

- Introduce more physics-based bubble models into mercury material model for parameter tuning.
- Increase the number of FE simulations to improve the accuracy of machine learning surrogates and enable more machine learning methods.
- Refine the parameter space and develop optimization framework for an efficient parameter search.

References

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[3] A. Chkifa, N. Dexter, H. Tran, C. Webster, Polynomial approximation via compressed sensing of high-dimensional functions on lower sets, Math. Comp. 87 (311), 1415-1450.
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