Machine Learning for Improved SNS Accelerator Health and Reliability

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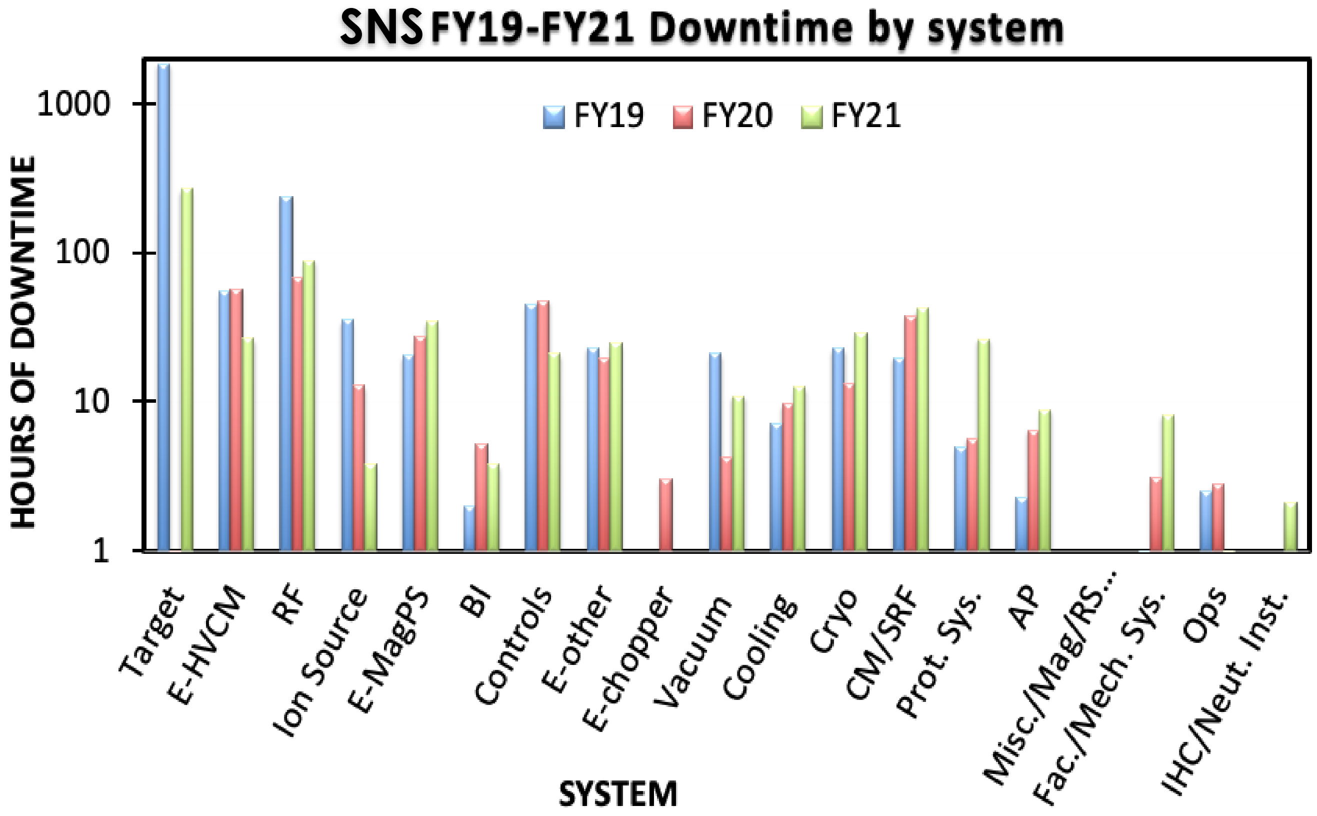
Machine Learning project to reduce downtime

Can we reduce downtime by

- Preventing accelerator failures
- Improving target design

→ **four ML use-cases**



Machine Learning features

- Automatic learning process
- Ability to process big data efficiently
- Ability to model complex non-linearities and identify trends/patterns
- Deep Learning (Neural Nets)
  - Generalize better than statistical methods,
  - Compensate for incomplete physics models,
  - Automatically extract relevant information

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Machine Learning to study four use-cases

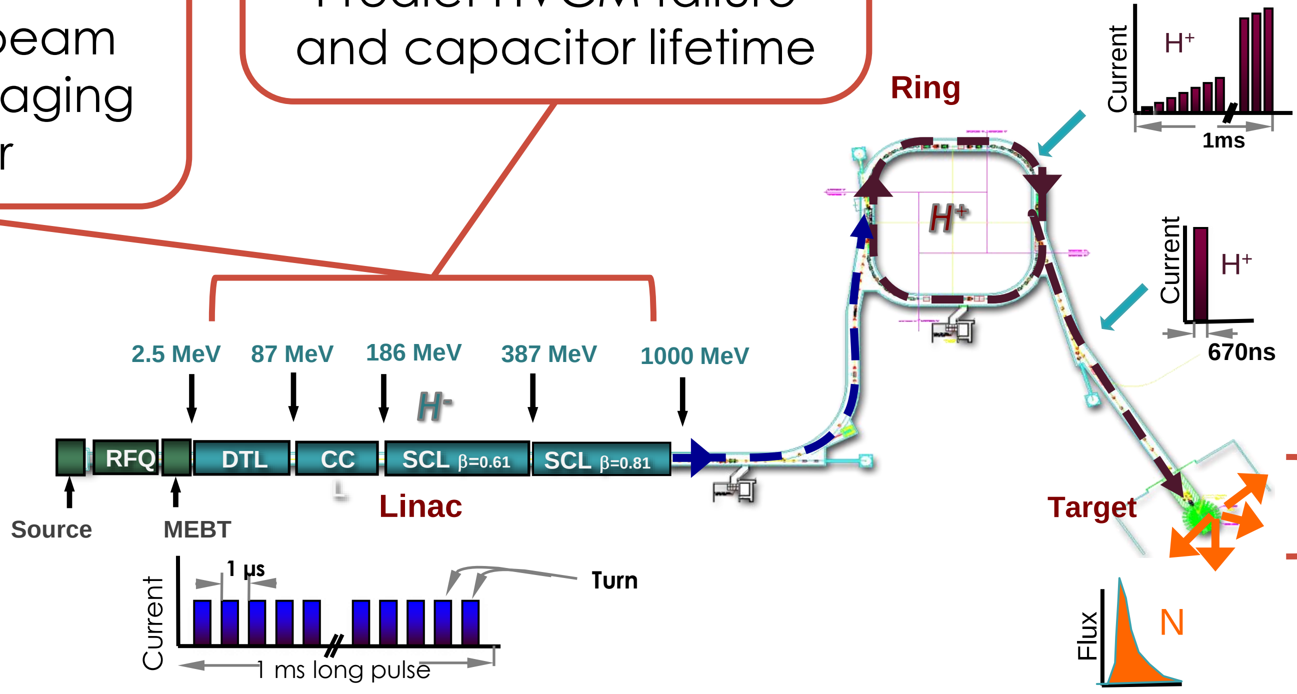
Common goal: Utilize data from existing sensors to apply ML techniques to reduce downtime

1: Beam-based
Prevent errant beam pulses from damaging accelerator

2: High Voltage Converter Modulator
Predict HVCM failure and capacitor lifetime

3: Target
Improve target design by faster simulation

4: Cryogenic Moderator System
Reduce recovery time after trips



#1: Use data from DCM to predict errant beam

Predict upcoming errant beam pulses

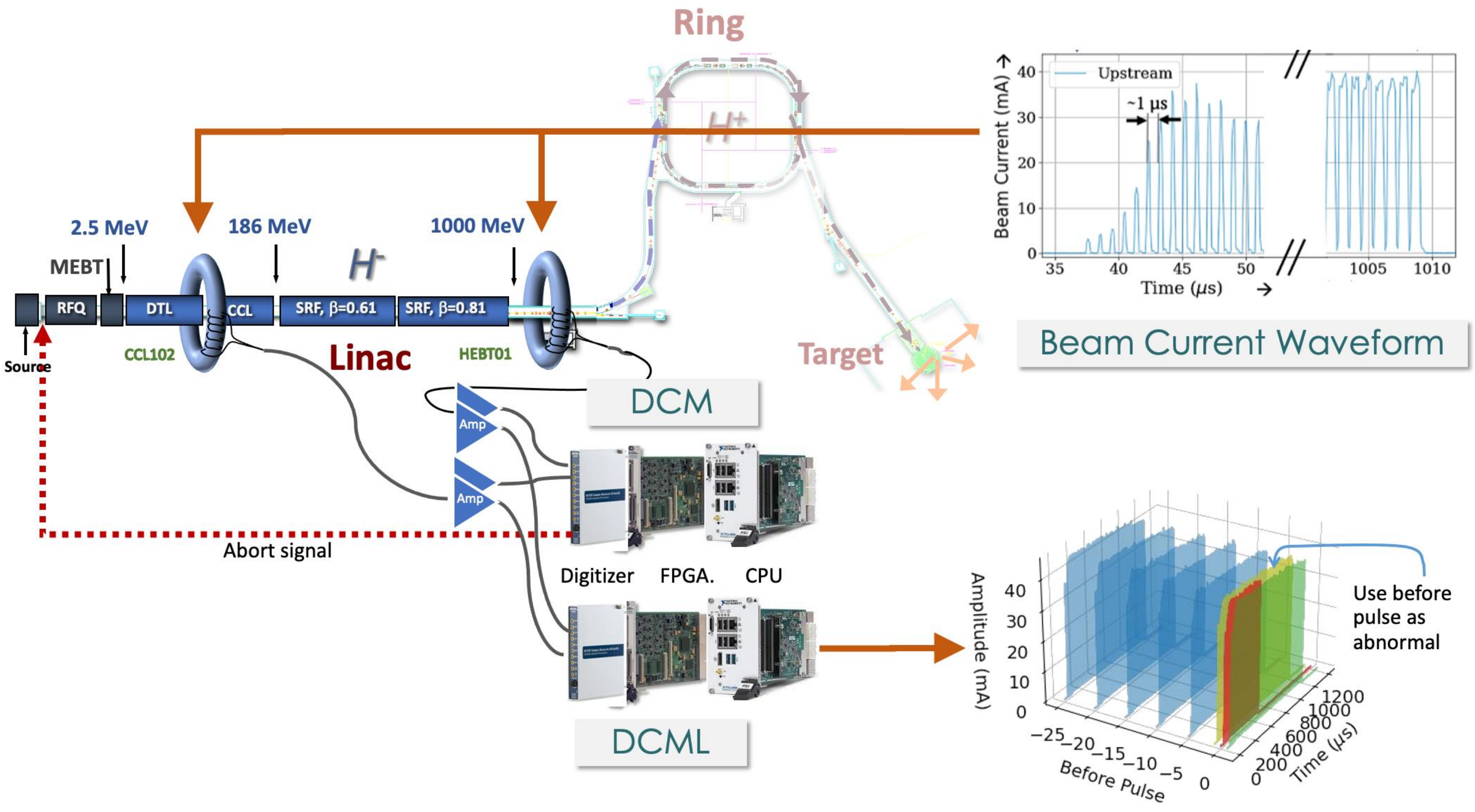
Problem

Errant beam can damage SCL and activate beamlines

Method

Use beam waveforms from before errant beam pulse from Differential Current Monitor

- Use Siamese Model (CPU)
- Use Random Forest (FPGA)



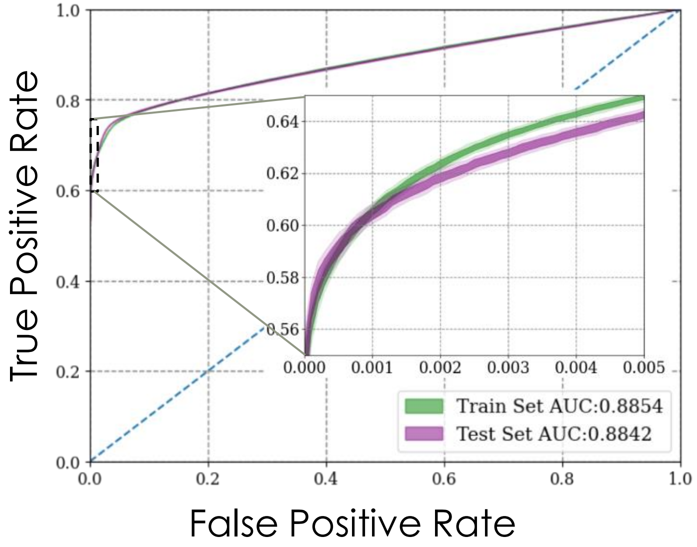
DCM(L) archives up to 25 before the errant beam pulse

Rescic, Miha et al. "Predicting particle accelerator failures using binary classifiers." Nuclear Instruments & Methods in Physics Research Section A-accelerators Spectrometers Detectors and Associated Equipment 955 (2020): 163240.

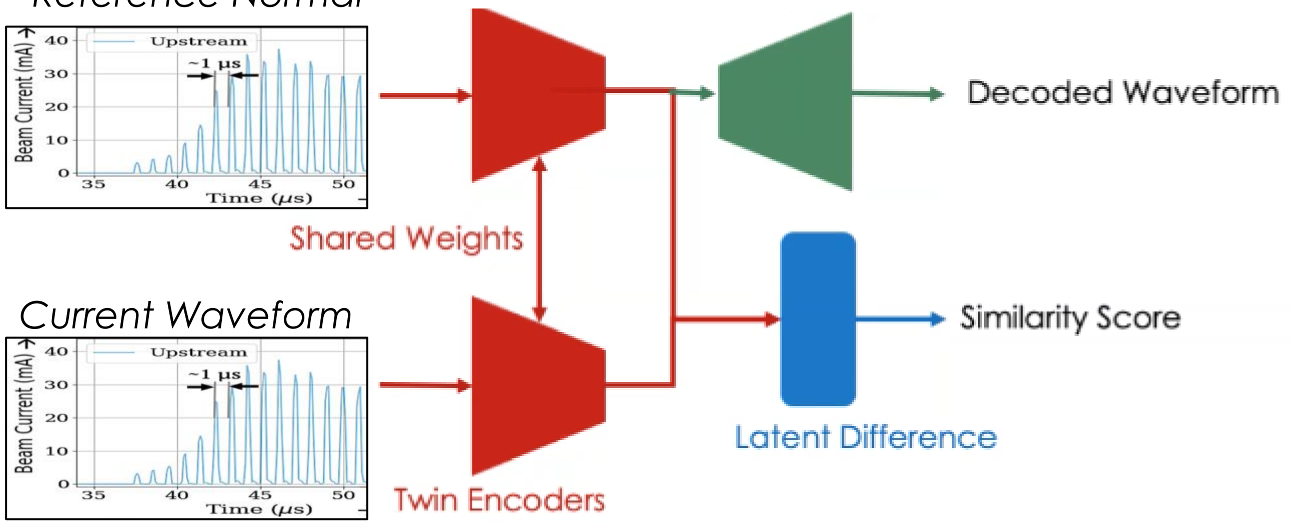
#1: Siamese model detects similarities

Siamese Neural Networks (SNNs):

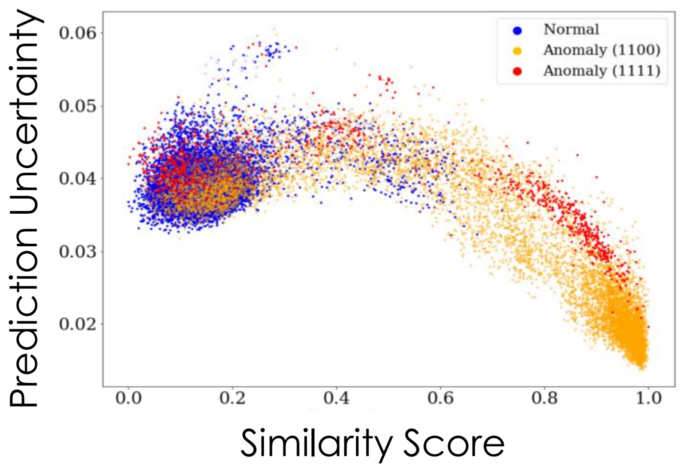
- Learns similarity between two inputs
- Update reference waveforms
- Autoencoder extension verifies waveform encoding
- Gaussian Approximation provides prediction uncertainty



Performance visualization



Siamese Model Overview



Different anomalies and uncertainty

#1: ML Server infers in real-time

Field implementation

DCML

– Random Forest on FPGA of DCML, < 100 μs response time

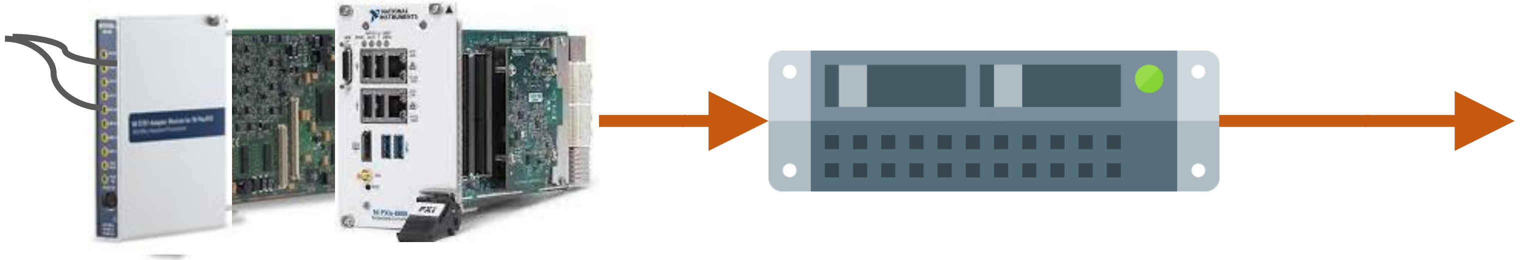
– Siamese model: 1 to 3 inferences per waveform < 16ms (beam rep rate)

ML Server

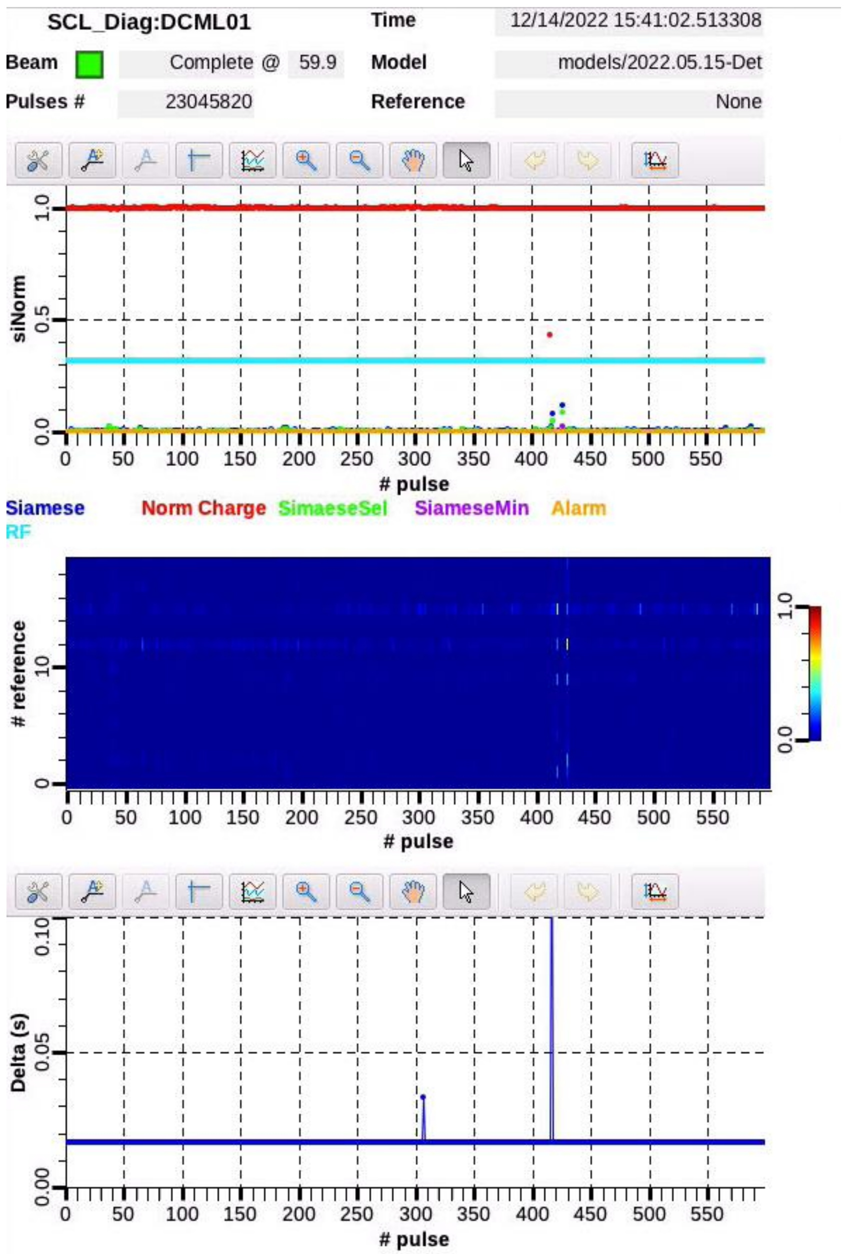
– Takes full raw data from DCML

– Publishes results over EPICS

– Compares recent waveform with multiple reference waveforms



DCML *ML Server*



Lessons Learned

Need to implement continual learning and include accelerator setup parameters as part of training.

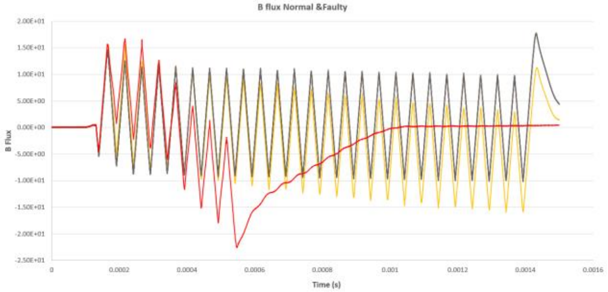
Blokland, W., Rajput, K., Schram, M., Jeske, T., Ramuhalli, P., Peters, C., ... & Zhukov, A. (2022). Uncertainty aware anomaly detection to predict errant beam pulses in the Oak Ridge Spallation Neutron Source accelerator. Physical Review Accelerators and Beams, 25(12), 122802.

#2: Autoencoder predicts HVCM failures

Predict upcoming HVCM failures

Problem

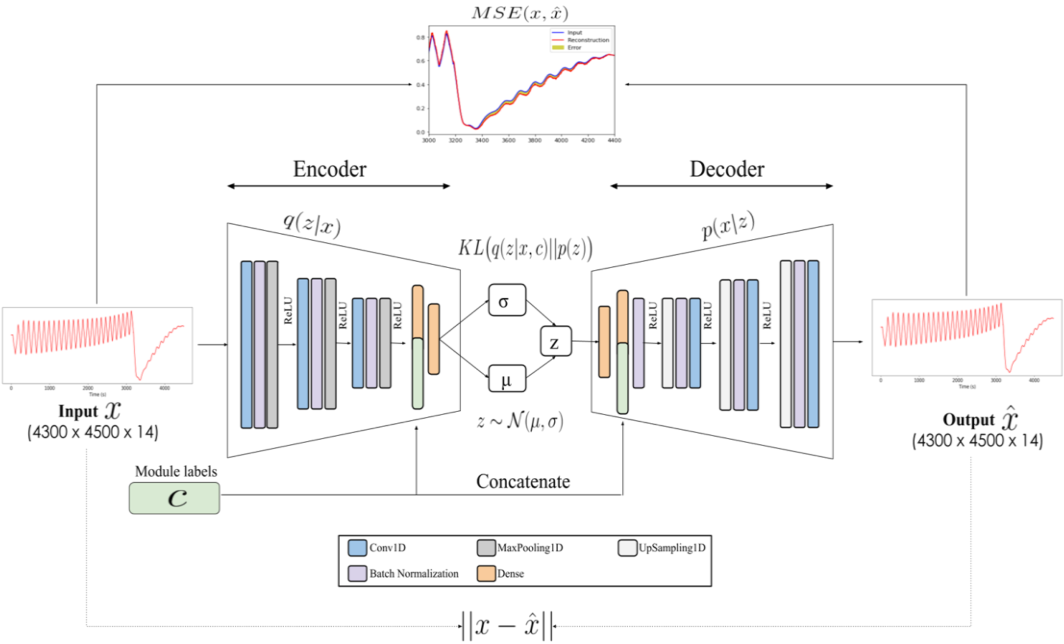
Transistor failure due to transformer saturation



8 normal shots, one in yellow where flux is beginning to drift, one in red when the Insulated Gate Bipolar Transistor (IGBT) exploded.

Method

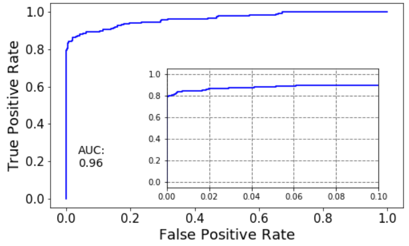
Use auto-encoder to see a difference in the waveforms



Multi-Module Conditional Variational Autoencoder

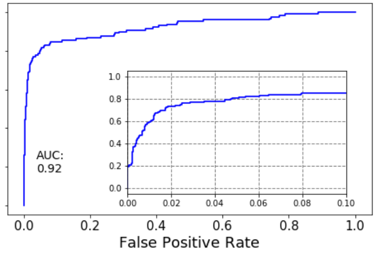
Results

Predict 80-50% of failures with <1% false positive



dV/dT Fault

SRC Fault



Lessons Learned

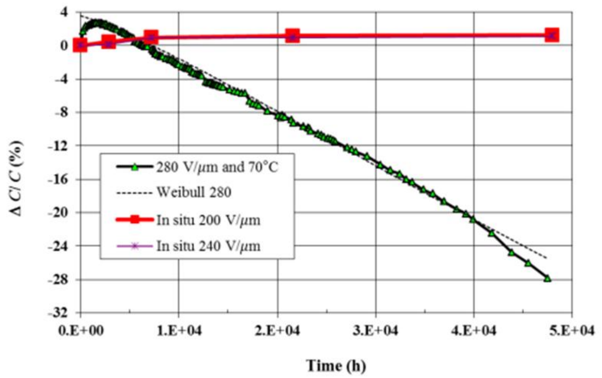
False positive penalty might be too high for application in the field

#2: CNN trained to determine capacitor values

Determine capacitor values from existing data

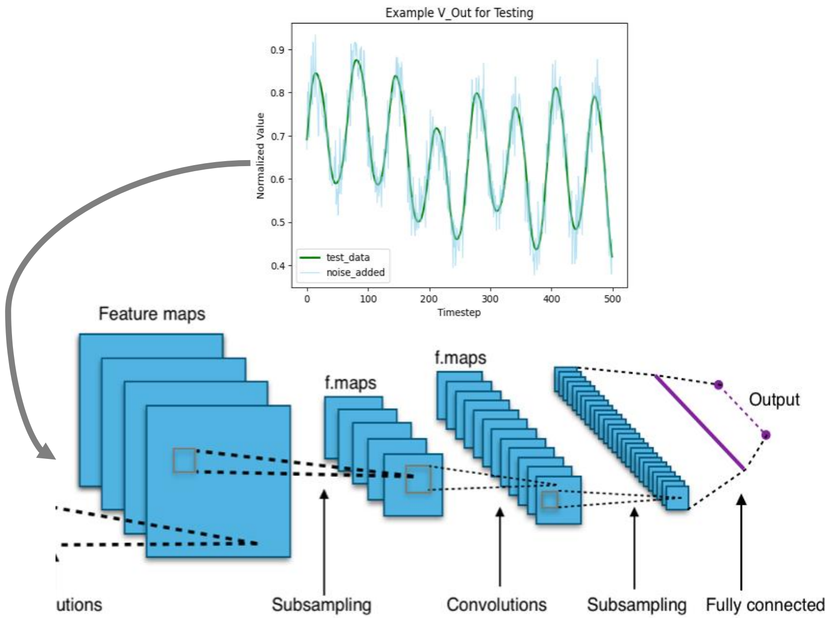
Problem

Capacitor degradation leads to failure. No direct measurement is available.



Method

Use LTSpice to simulate waveforms with varying capacitor values to train neural net Uncertainty-aware convolutional neural network



Results

Error <**1%** for capacitance predictions and low uncertainty

Average Uncertainty	Cap A (pF)	Cap B (pF)	Cap C (pF)
Actual	5.97901	7.39233	8.10603
Noisy	6.57088	8.48543	9.37121

Capacitor nominal value 3200 pF

Lessons Learned

Difficult to apply in the field as HVCM must be taken apart to measure capacitors.

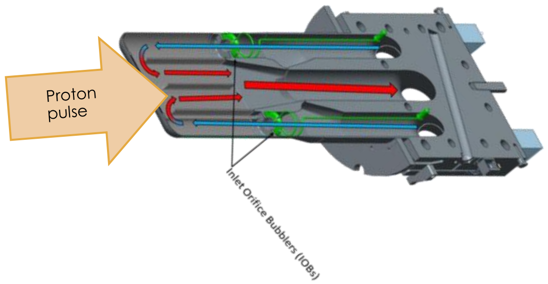
*Radaideh, M. I., Pappas, C., Walden, J., Lu, D., Vidyaratne, L., Britton, T., ... & Cousineau, S. Time Series Anomaly Detection in Power Electronics Signals with Recurrent and Convlstm Autoencoders. Available at SSRN 4069225.

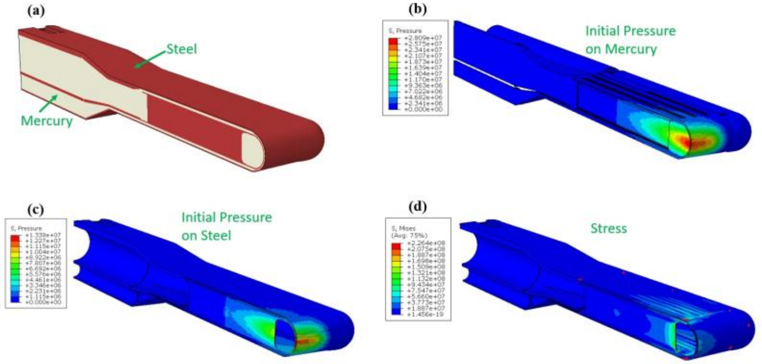
#3: Target surrogate model speeds design cycle

Use ML techniques to speed up design cycle

Problem

Complex multi-phase response to beam pulses requires time intensive simulations

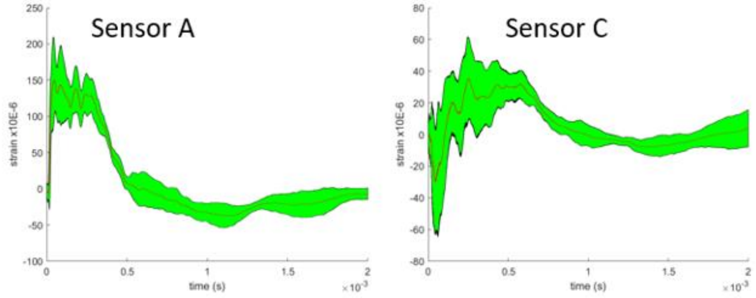




Simulation

Method

- Run simulations on HPC over parameter space
  - Sierra/Solid Mechanics with a 2-phase mercury model to include bubble families
- Train surrogate model over same parameter space
- Use surrogate model to find those parameters that match strain measurements
- Use those parameters in the full simulation while changing the target design



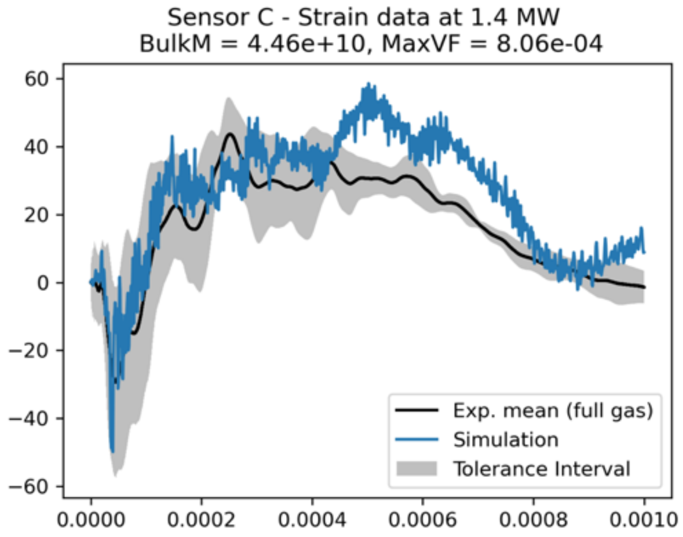
Variation in strain measurements
(Surrogate model results to stay within variation)

*Radaideh, M. I., Tran, H., Lin, L., Jiang, H., Winder, D., Gorti, S., ... & Cousineau, S. (2022). Model Calibration of the Liquid Mercury Spallation Target using Evolutionary Neural Networks and Sparse Polynomial Expansions. arXiv preprint arXiv:2202.09353.

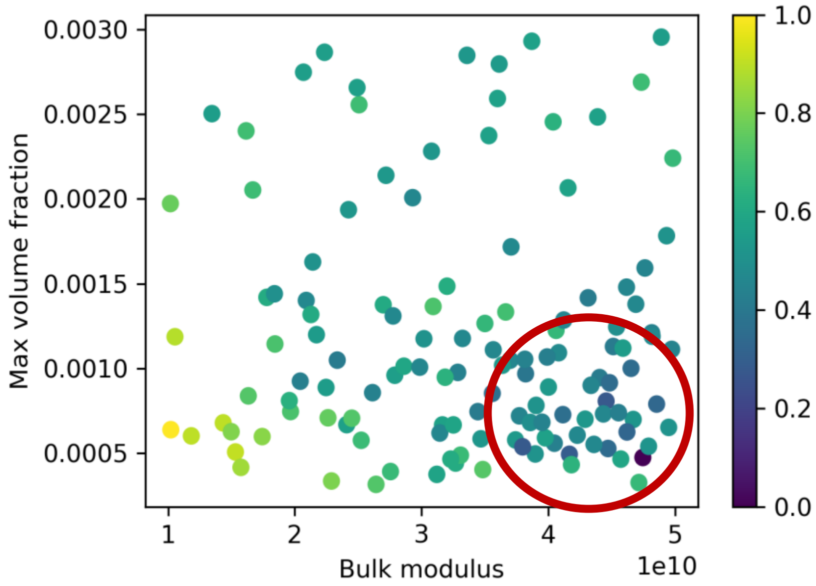
#3: Surrogate model down selects parameter space

Results

Using sparse surrogate based on polynomial expansion model with gas



Matching of strain waveforms



Candidate parameters

Lessons Learned

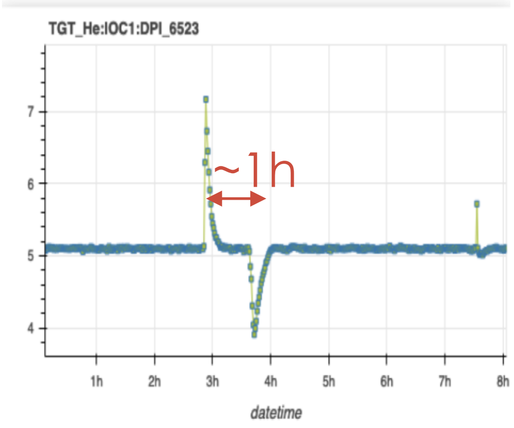
Need enormous amount of HPC simulations to even get started.

#4: Cryogenic Moderator System modeled

Improve overall system responses to the beam trips by better controller parameters and using meta-control methods.

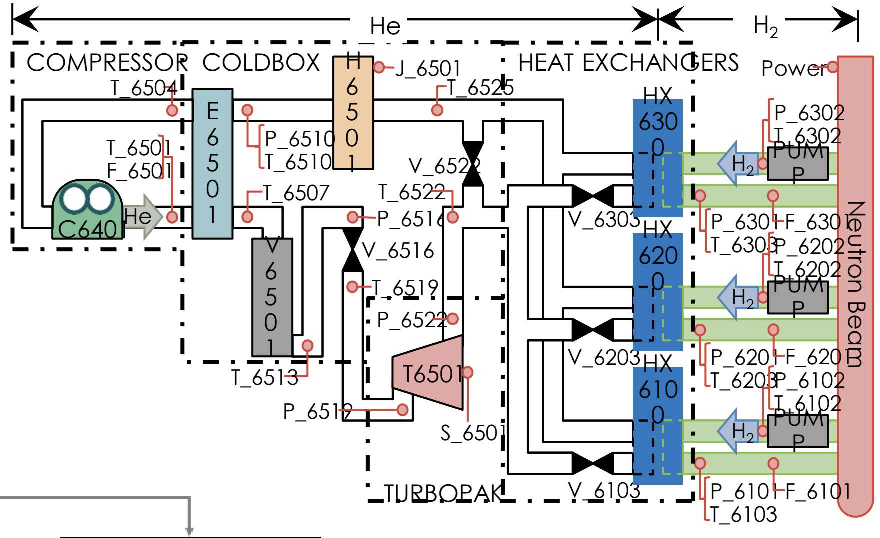
Problem

Long system recovery time due to CMS trips The system is complicated and not well modeled

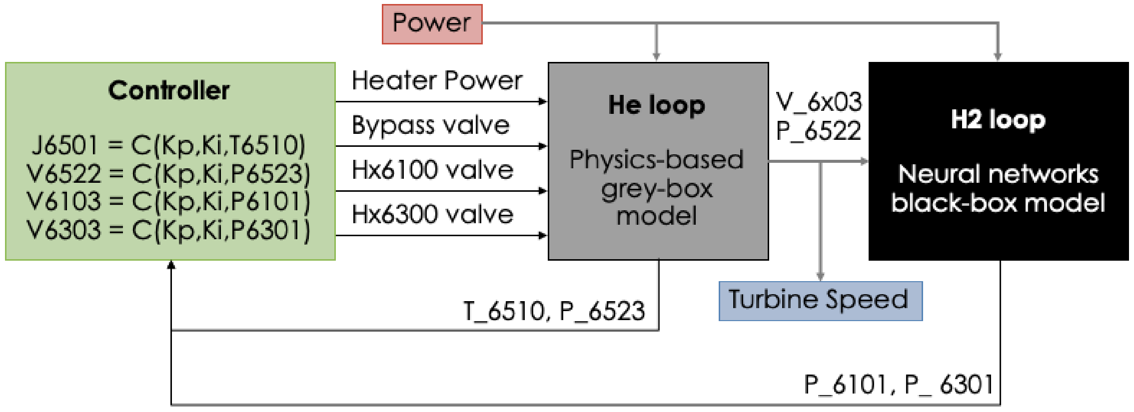


Method

Construct models to simulate subloops. Use ML to augment overall model to complete simulation then retune controllers using simulation



Model



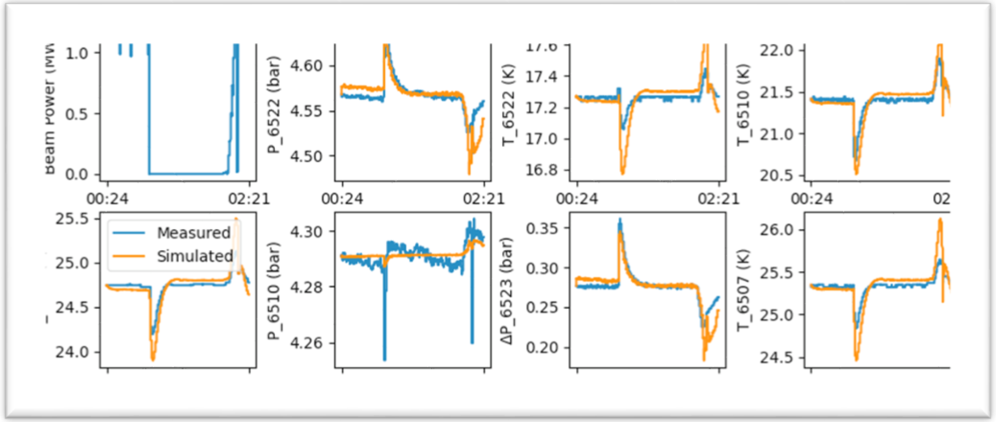
Augmented Model

*Maldonado, B. P., Liu, F., Goth, N., Ramuhalli, P., Howell, M., Maekawa, R. & Cousineau, S. (2022). Data-Driven Modeling of a High Capacity Cryogenic System for Control Optimization. The 22nd World Congress of the International Federation of Automatic Control. Under Review

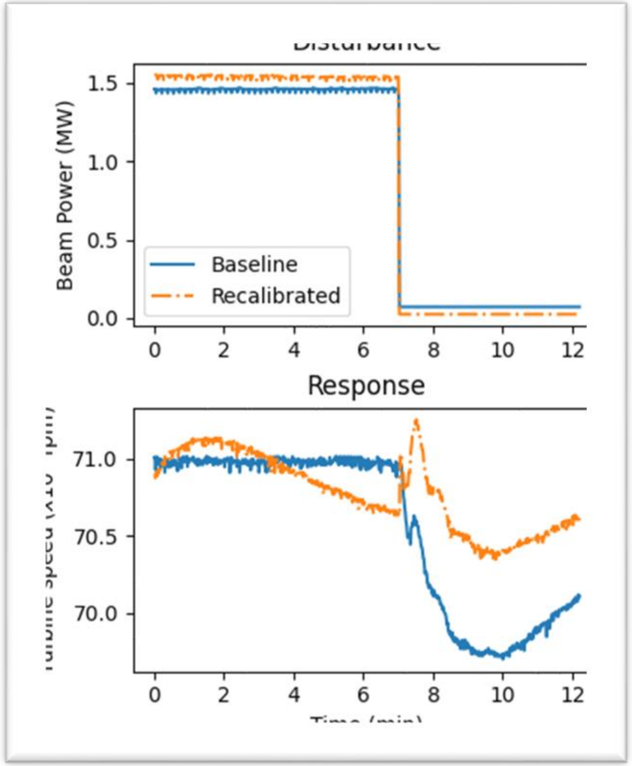
#4: Cryogenic Moderator System modeled

Results

Using new model to calculate controller settings led to reduced pressure transients and factor of ten reduction in time for the system to return to desired state.



Model can simulate disturbances in thermodynamic states (mass flows, pressures, temperatures) due to CMS trip



Turbine fluctuation reduced by 50%

Lessons Learned

First operational improvement using ML. ML (offline) analysis changed existing controllers' setup.

*Maldonado, B. P., Liu, F., Goth, N., Ramuhalli, P., Howell, M., Maekawa, R. & Cousineau, S. (2022). Data-Driven Modeling of a High Capacity Cryogenic System for Control Optimization. The 22nd World Congress of the International Federation of Automatic Control. Under Review
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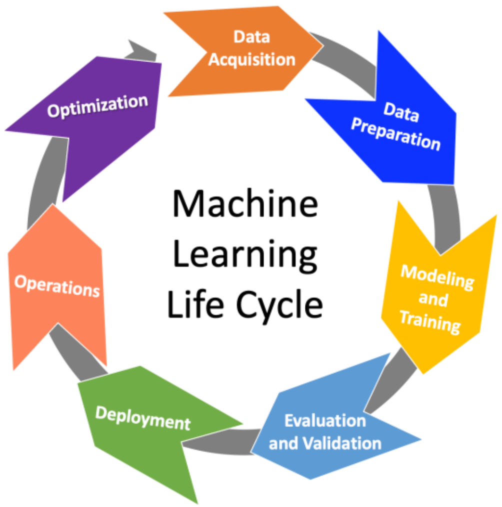
Machine Learning Framework

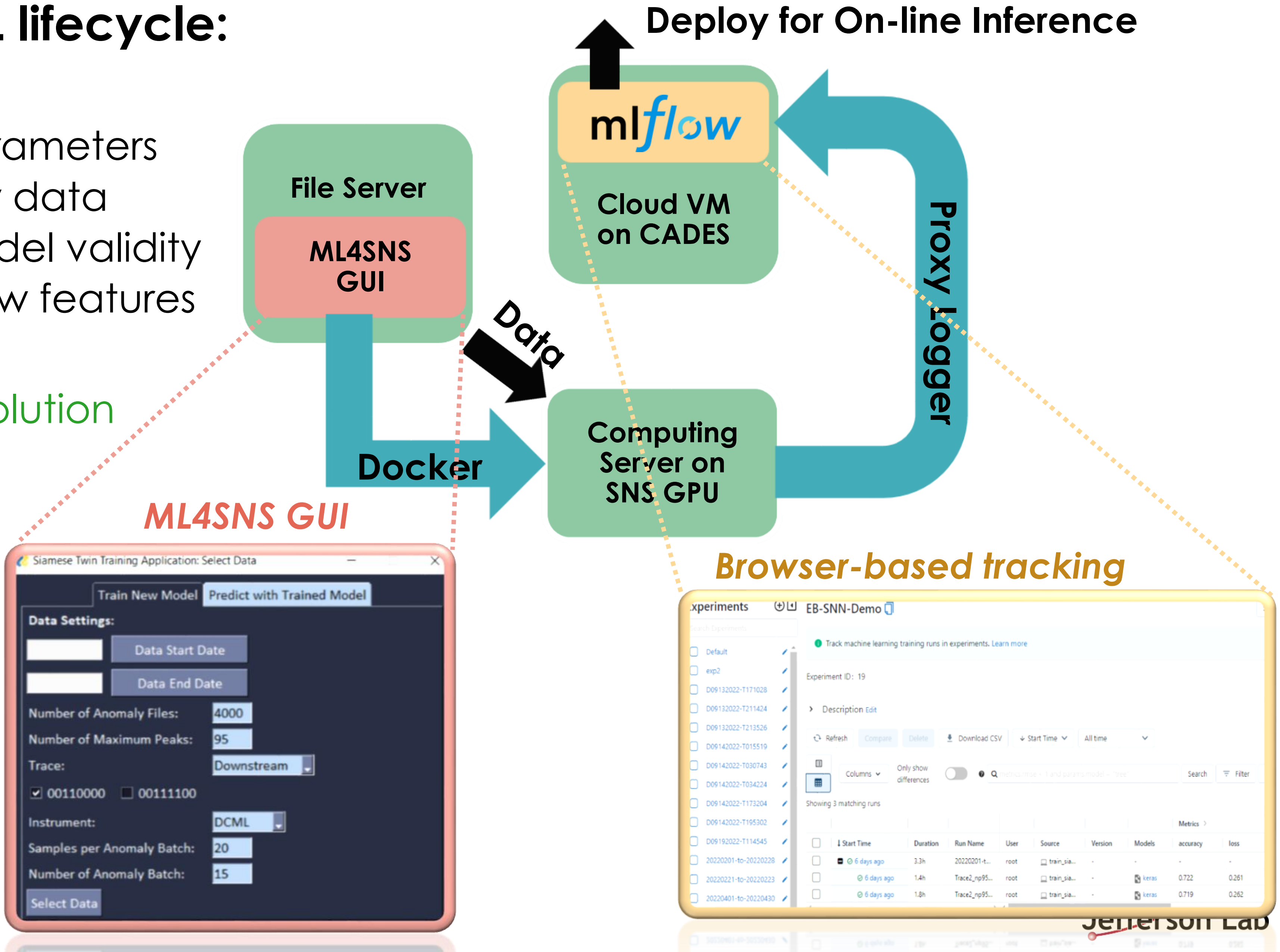
Developed to follow ML lifecycle:

- Version control
- Tracking model hyperparameters
- Updating model per new data
- Routine tests to verify model validity
- Improving model with new features

Lesson Learned

This is crucial to sustain ML solution





Summary

Lessons learned to apply ML to Operations:

- Continual learning and robust models to manage changes
- Success in analysis might not be enough for operational gains
- Modeling of system to generate data can take up most of your time
- Retuning using ML resulted in permanent operational improvement

Thank you for your attention!

Questions?