Progress on Machine Learning for the SNS High Voltage Converter Modulators

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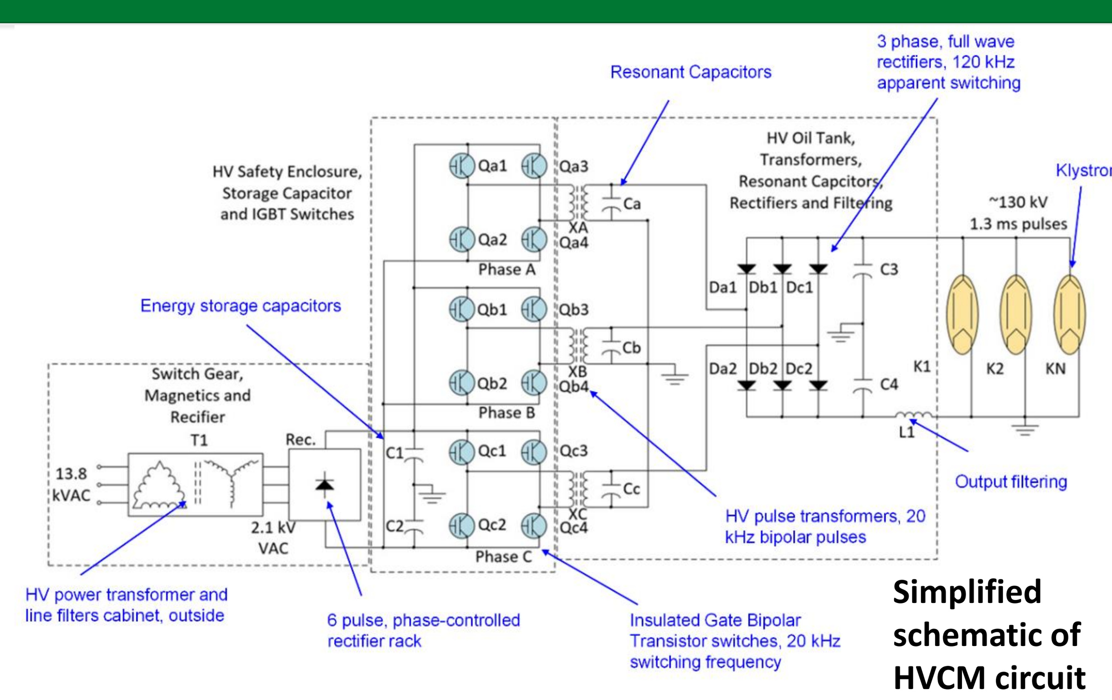
Introduction

The High Voltage Converter Modulators (HVCM) used to power the klystrons in the Spallation Neutron Source (SNS) linac were selected as one area to explore machine learning (ML) due to reliability issues in the past. HVCMs continue to be problematic for the SNS that experience a wide range of failures from mild to catastrophic, causing lost beam time for the SNS. **HVCMs are ranked as the 2nd source of downtime behind the liquid mercury target.** There are 15 HVCMs in the SNS powering 92 klystrons in the SNS, distributed over 4 sections: RFQ (radio-frequency quadrupole), DTL (drift-tube linac), CCL (couple-cavity linac), and SCL (super-conducting linac). Progress in the past 2 years has resulted in generating a significant amount of simulated and measured data [1] for ML models. Applications in anomaly detection, fault classification, and capacitor degradation prognosis were pursued, and promising results were achieved. This work discusses the progress to date and present results from these efforts.

Methods

- **HVCM Operation**

- The three-phase (A, B, C), 13.8 kVAC line power is input and converted to ±1300 VDC by the transformers and a six-pulse controlled rectifier. The output voltage is filtered with two capacitors (C1, C2) that store sufficient charge to produce 1.3 ms pulses. The DC voltage is provided to three IGBT-based H-bridge circuits operating at a nominal 20 kHz switching frequency [2].



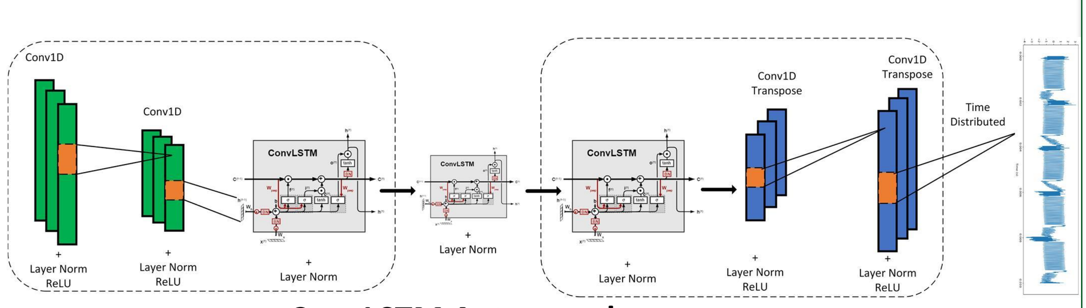
Simplified schematic of HVCM circuit

- The high voltage pulses from the resonant capacitors are recombined and rectified by diodes (Da1 to Dc2), forming the output pulses with a 120 kHz switching frequency, which are then filtered by (C3, C4, L1) and applied to the cathode of the klystrons [2].

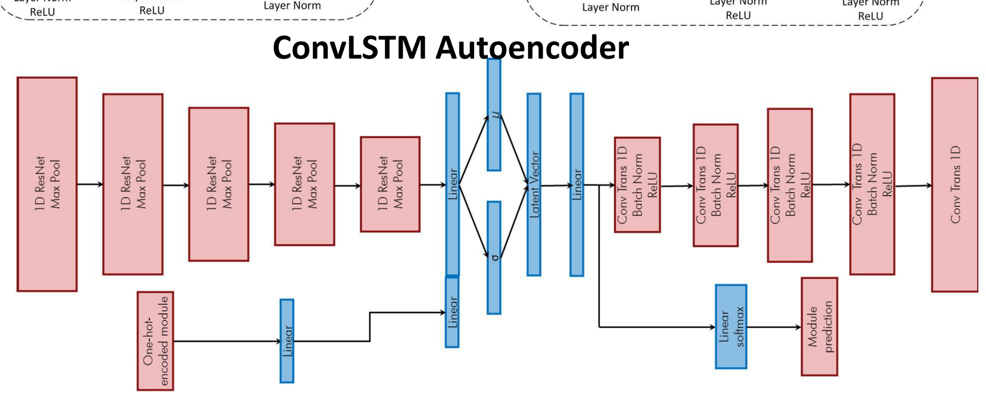
(a) 13.8 kVAC switch gear and magnetics, (b) six pulse-controlled rectifier unit, (c) high voltage enclosure and tank with a klystron (red) in background, (d) HVCM controller rack [3].

- **Machine Learning Modeling**

- Recurrent neural networks (RNN) are adapted to work for HVCM signal data. We tested hybrid layers such as ConvLSTM, which is a type of RNN for spatio-temporal prediction that has convolutional structures in both the input-to-state and state-to-state transitions.
- We also developed a variational autoencoder (VAE) for anomaly detection, which consists of Conv1D layers. Instead of encoding the input space as a single point like ConvLSTM, it is sampled from a normal distribution.



ConvLSTM Autoencoder

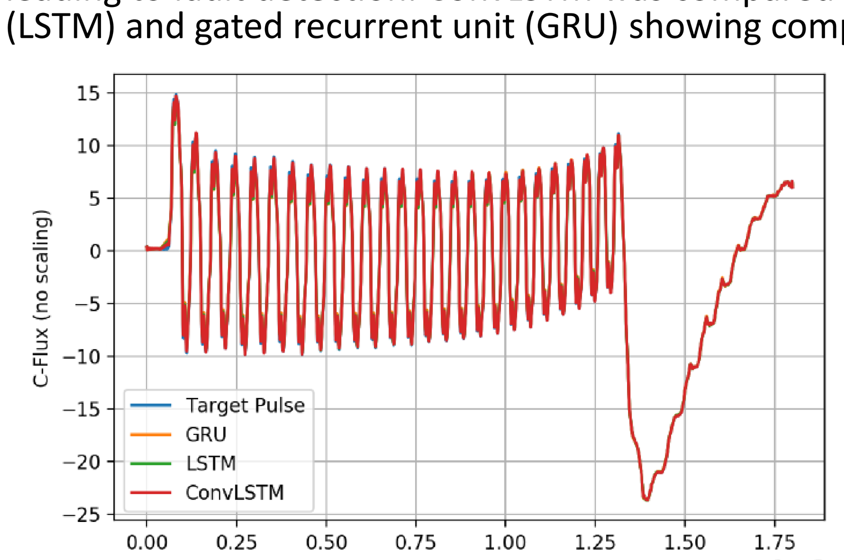


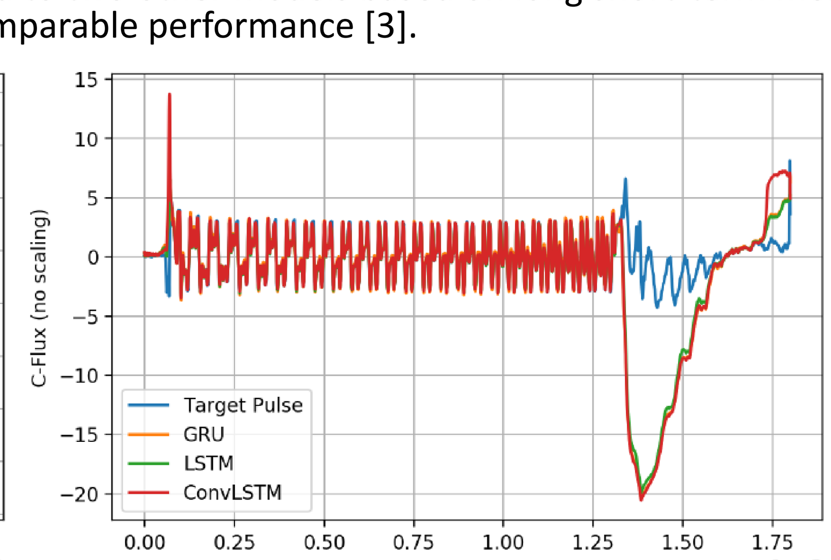
Variational Autoencoder (VAE)

Results

- **AutoEncoder Reconstruction Loss**

The ConvLSTM is trained to learn how to reproduce the normal waveforms (e.g., C-flux) as in the **left Figure below**. The difference between model prediction (reconstructed waveform) and the original waveform is called reconstruction error, which is used to determine the error threshold. When feeding an anomaly waveform as in the **right Figure below**, ConvLSTM struggles in reconstructing that waveform such as in the time range 1.25-1.5 ms. As a result, a large reconstruction error is observed that exceeds the threshold; leading to fault detection. ConvLSTM was compared to two other models based on long short-term memory (LSTM) and gated recurrent unit (GRU) showing comparable performance [3].

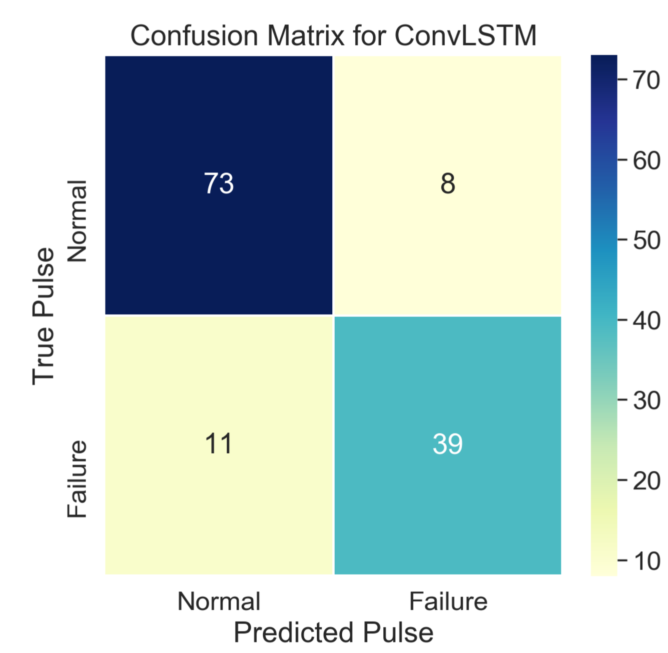




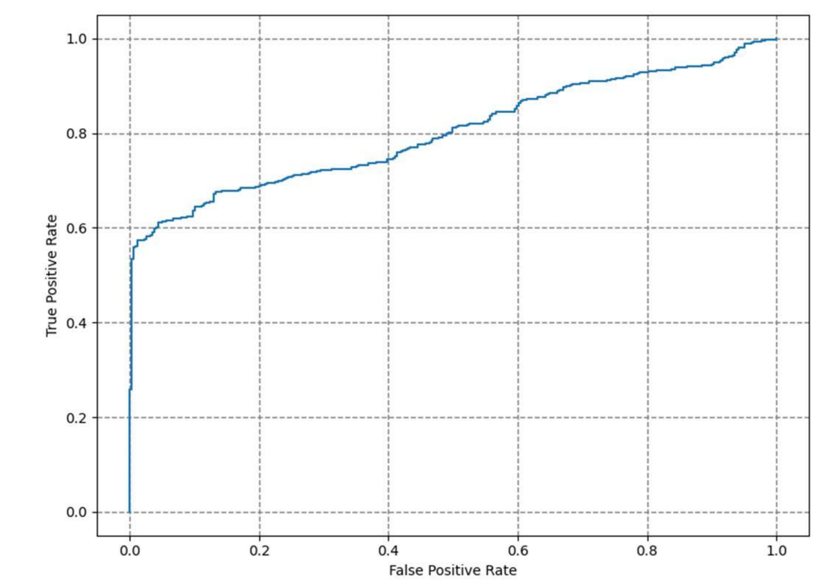
Results – continued

- **Anomaly Detection with Autoencoders**
- The ConvLSTM is applied to the HVCM system powering the RFQ (radio-frequency quadrupole) section. The confusion matrix is shown in the **left Figure below**. A very good performance is observed, as the model identifies 39/50 faults, while keeping low false positive rate (8/81 are false positive) [3].
- Similarly, we applied the VAE to detect the anomalies by accounting for the system and operational differences between the modules (RFQ, DTL, CCL, SCL) through a one-hot encoding input to the decoder [1]. The receiver operating characteristic (ROC) curve, which describes the relationship between the true positive and false positive rates, is shown in the **right Figure below**. Although our model is not perfect, it still provides up to 60% true positive rate for false positive rate within 10%, implying we can detect 60% of the anomalies in the HVCM modules with VAE.

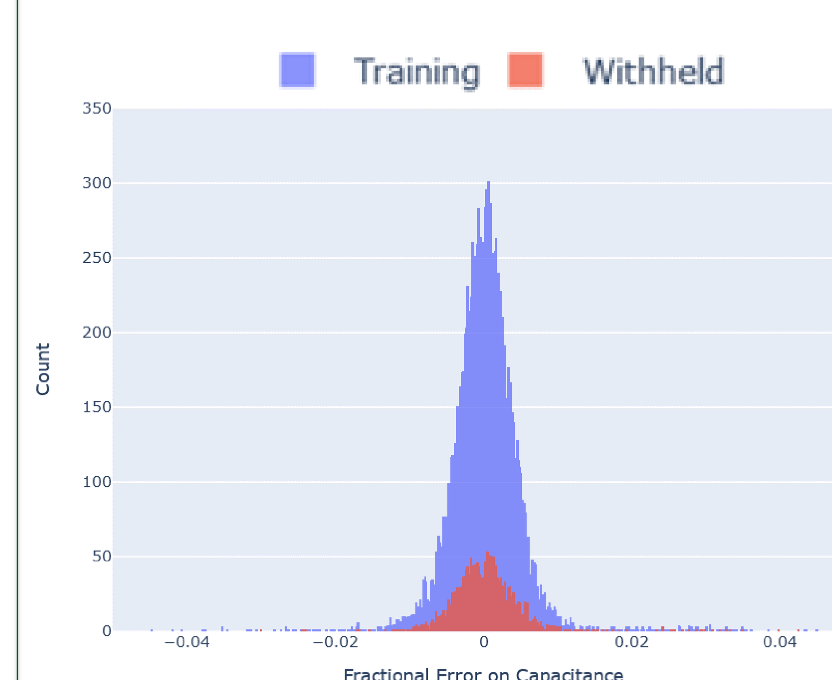
Single-module results using ConvLSTM (RFQ)



Multi-module results using VAE (RFQ, DTL,CCL, SCL)



- **Prognostics of Capacitor Degradation**
- We have produced LTspice simulations for the CCL system, which agrees well with the measured waveforms. A CNN model that contains 4 Conv1D layers is used for capacitor prediction. The output of these 4 layers is flattened and fed into 3 independent branches, each is a fully-connected layer with 16 nodes feeding into one node. These 3 branches predict the 3 capacitances: Ca, Cb, Cc.
- The predictions on all capacitance values can be found in the Histogram below, showing very small percent error on both the training and testing sets. The results in the table show 1%-7% errors on predicting the capacitances, which are below the manufacturer's tolerance (10%). These promising results show that a well-trained ML model can be used to predict a degraded capacitance value, which is essential for accurate prognostics.



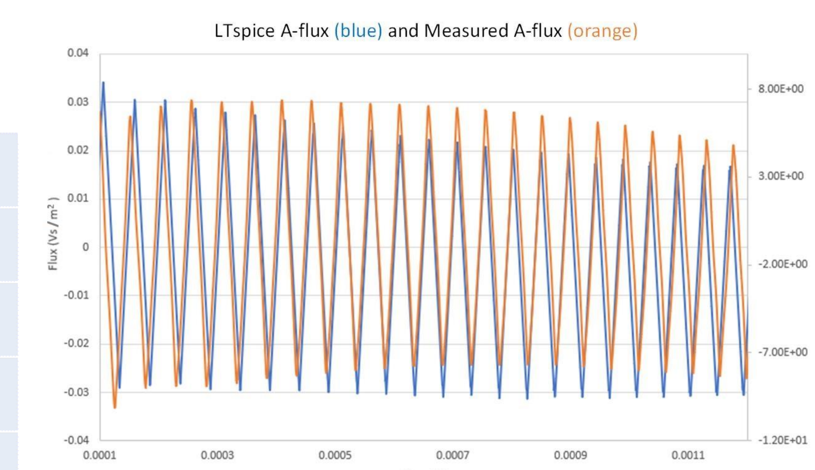


Table 1: Prediction of measured capacitor values by CNN

Item	Ca (pF)	Cb (pF)	Cc (pF)
CNN	3135.8	3369.6	3419.5
Measured	3170	3160	3220
Relative Diff. (%)	**1.1**	**6.6**	**6.2**

Conclusions

Significant research progress has been done in developing and exploring ML models to improve the reliability of the HVCM at the SNS. The next goals for the team will focus on:

1- Extending the fault detection methods to fault prognosis, where fault scenarios will be modeled in the lab, and ML will be tested in discovering them as early as possible.

2- Leveraging ML models such as generative adversarial networks for fault classification to be able to identify the fault type.

3- We will extend the capacitor degradation prognostics to cover real dynamic measurements. This will involve a designed experiment setup at which the degraded capacitor values will be measured at different times.

References

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