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PROGRESS ON MACHINE LEARNING FOR THE SNS HIGH VOLTAGE CONVERTER MODULATORS

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Abstract

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 due to reliability issues in the past and the availability of large sets of archived waveforms. Progress in the past two years has resulted in generating a significant amount of simulated and measured data for training neural network models such as recurrent neural networks, convolutional neural networks, and variational autoencoders. Applications in anomaly detection, fault classification, and prognostics of capacitor degradation were pursued in collaboration with the Jefferson Laboratory, and early promising results were achieved. This paper will discuss the progress to date and present results from these efforts.

INTRODUCTION

The SNS uses a linac to accelerate protons to an energy of 1 GeV using high power RF delivered from klystrons. The klystrons are in turn power by HVCMs which convert 13.8 kVAC to up to 130 kV, 1.3 ms long pulses at 60 Hz [1]. A simplified schematic of a HVCM is shown in Fig. 1 . Figure 2 shows the layout of the SNS RF systems with 15 HVCMs, each driving multiple klystrons with the exception of the Coupled Cavity Linac (CCL) section where each HVCM drives a single klystron. The transformer T1, rectifier (Rec) and filter capacitors C1 and C2 convert the 13.8 kVAC to ±1300 VDC. Insulated-gate bipolar transistor (IGBT) switches Qa1 to Qc4 switch at a nominal frequency of 20 kHz into pulse transformers which step the pulses up to high voltage. The high voltage pulses are then combined in parallel, rectified and filtered to produce the 1.3 ms, 60 Hz pulse train with an apparent switching frequency of 120 kHz. HVCMs have historically been a source of significant machine downtime at SNS, and still represent a significant percentage of lost user time. The HVCMs use a PXI based controller which digitizes up to 32 waveform channels at 50 MHz. Waveform and settings files are saved whenever there is a fault, and decimated to 2.5 MS/s and saved approximately 30 minutes after turn on or after HVCM settings have changed. We recently opened-source the normal and fault data from the 15 HVCM powering the SNS, which are described in this paper [2] and can be downloaded from this Mendeley repository [3].

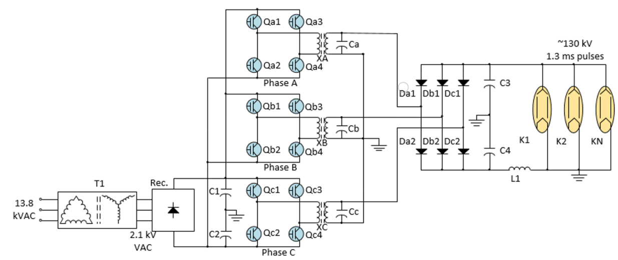

Figure 1: Simplified schematic of a HVCM.

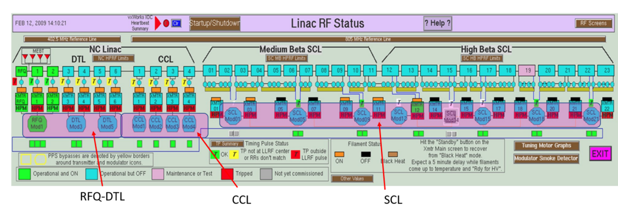

Figure 2: Layout of SNS RF system.

In addition to the HVCM real waveforms, a LTspice model (based on the SPICE circuit simulator) [4] of the HVCM circuit has been developed and validated, which we are using to generate a large amount of simulated data to model changes in values of circuit components and certain operating conditions such as IGBT switching frequency. To enable frequency modulation in the simulation, LTspice was coupled with MATLAB/SIMULINK. MATLAB is also being used for automation of LTspice execution to sweep ranges of component values. This helps generating LTspice simulations to model degradation of components such as plastic film capacitors. Thirteen of the waveforms related to the DC capacitor voltage, IGBT current, pulse transformer flux, and klystron voltage and current have been identified for the machine learning (ML) effort, since those have been the most useful in troubleshooting past failures. Figure 3 shows a comparison between the LTspice simulated waveform and a measured one for the magnetic flux in the A phase (A-flux).

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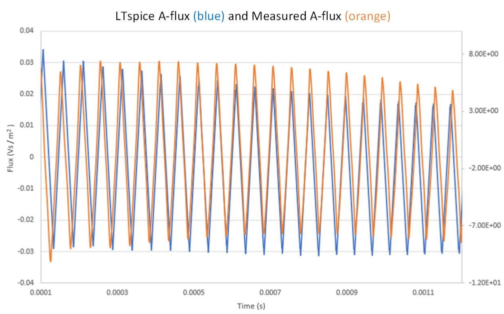

Figure 3: Simulated (LTspice) vs. measured waveform.

METHODS

We have tested variety of ML methods in this work, but the ones that have shown best results belong to (1) recurrent neural networks (RNN), (2) convolutional neural networks (CNN), and (3) autoencoders (AE).

RNNs are adapted to work for time series or sequential data. Given that we use signal data, RNNs are a good fit due to their temporal nature. We have used different types of RNN cells such as long short-term memory (LSTM) and gated recurrent unit (GRU) [5]. We have also used bi-directional layers to improve the performance, which train two RNN simultaneously, the first is trained on the forward time sequence as is, and the second on the reversed copy of the time sequence; providing additional context.

AE are unsupervised neural networks used to learn data representations. AE consists of encoder, bottleneck, and decoder, where the bottleneck contains a compressed knowledge representation of the original input. The input and output layers of the AE are identical, and the quality of the AE in reconstructing its input is assessed. In Fig. 4 (bottom), we have developed a variational AE for anomaly detection, which consists of five Conv1D (1D convolutional) layers for the encoder and the decoder. Instead of encoding the input space as a single point like classical AE, we encode the input space as a distribution over the latent space, where the input to the decoder is sampled from a normal distribution $\mathcal{N}(\mu, \sigma)$.

We have also 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. ConvLSTM resolves the drawback of the fully-connected LSTM by retaining spatial information using the convolutional layers. Figure 4 (top) shows our ConvLSTM AE architecture for anomaly detection, which consists of Conv1D layers followed by ConvLSTM layers.

RESULTS

Fault Detection

The ConvLSTM is used for anomaly detection on the HVCM system powering the RFQ section (radio-frequency quadrupole). The ConvLSTM is trained to learn how to accurately reproduce the normal waveforms (e.g. C-flux). Now the difference between model prediction (reconstructed waveform) and the original waveform is called reconstruction error, which helps the analyst to determine an error threshold for the AE. When feeding an anomaly waveform to the AE, the AE struggles in reconstructing that waveform since it deviates from the normal training data. As a result, a larger reconstruction error is observed that exceeds the threshold, leading to anomaly detection. The confusion matrix results based on the test set are shown in Fig. 5. This shows a very good performance by the ConvLSTM AE, as the system was able to identify 39 out of the 50 faults, while keeping the false positive events low (8 out of 81 are false positive). The model can be improved by collecting more data from the RFQ module.

Similarly, we applied the variational AE in Fig. 4 (bottom) to detect the anomalies in the measured waveforms by accounting for the system and operational differences between the modules. In this application, all modulators that belong to RFQ, DTL (drift-tube linac), CCL, and SCL (super-conducting linac) have been included through a one-hot encoding input to the decoder (see Fig. 4). The concept of training the variational AE is similar to ConvLSTM. The receiver operating characteristic (ROC) curve, which describes the relationship between the true positive and false positive rates, is shown in Fig. 6. A perfect model would have a 1.0 true positive rate at zero false positive rate. 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 with this model. The performance challenges for the variational AE originate from both the data limitation for certain modules, and the differences in their operating conditions, which are reflected in their waveform topology. The data used in this analysis can be found here [2, 3].

Prognostics of Capacitor Degradation

We have produced LTspice simulations for the CCL system. The CCL was arbitrarily chosen as a representative module and was used to match the parameters of (e.g. frequency modulation, voltages, inductances, etc) in LTspice; only the three capacitor values (Ca, Cb, Cc) in Fig. 1 were varied. The final candidate model was obtained after Hyperband optimization and contains four Conv1D layers, which extract salient features from the waveforms. The output of these four layers is flattened and fed into three independent branches each containing a short fully-connected layer composed of 16 nodes feeding into one node. These outputs are then concatenated to form an output vector containing the three predicted capacitances. The input to the model features 10 different simulated waveform types, namely, IGBT current in the 3 phases (6), magnetic flux (3), and modulator voltage (1). A five-fold cross validation was employed to produce a trained network with 676 samples withheld as a test set, and the remaining 2704 samples are used for training. The resulting predictions on all capacitance values can be found in Fig. 7, showing very small percent error on both the training and testing sets. Samples of real pulses from the CCL - collected close to when the capacitances

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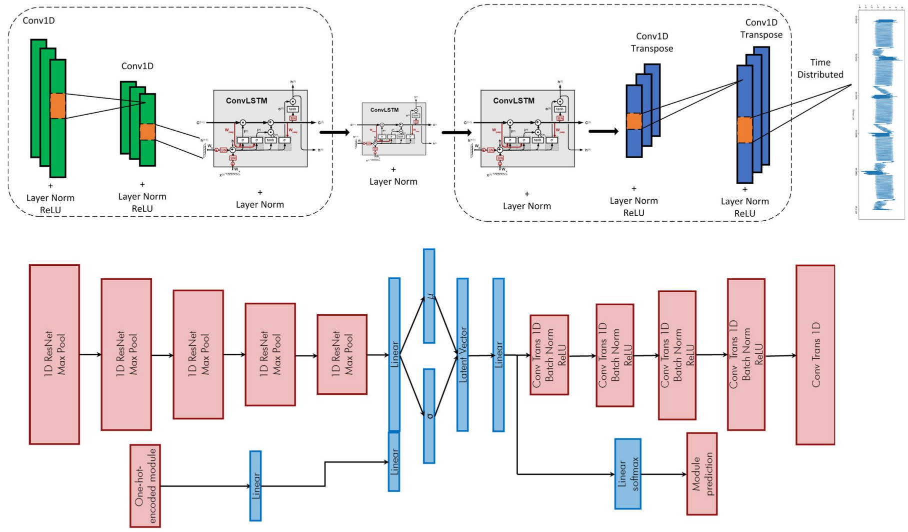

Figure 4: Autoencoder architectures used for anomaly detection: ConvLSTM (top) variational convolutional (bottom).

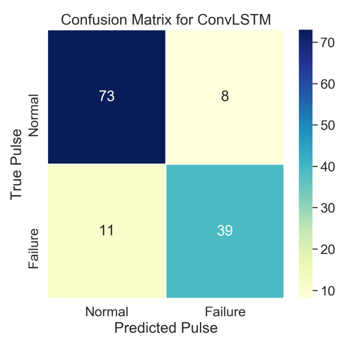

Figure 5: Confusion matrix for ConvLSTM for RFQ system.

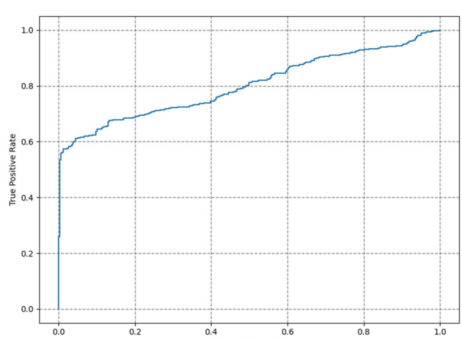

Figure 6: ROC curve for the variational AE for multiple systems.

were measured - were truncated and aligned to match the simulation and then fed through the resulting network. Preliminary results in Table 1 show between a 1 and 7 percent error on predicting the capacitances of Ca, Cb, and Cc using the proposed model. For reference, the manufacturer's tolerance is approximately 10%. These promising results show that a well-trained ML model can be used to predict the capacitance value, which is essential to model the capacitor degradation; enabling accurate prognostics.

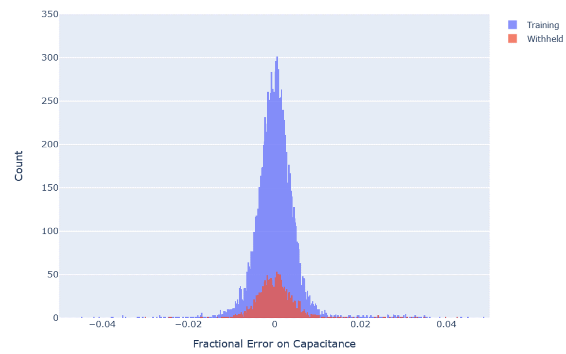

Figure 7: Capacitance prediction error on training and testing (withheld) datasets by CNN.

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 goal for the team will focus on leveraging ML models such as generative adversarial networks (GAN) for fault classification to be able to identify the fault type (e.g. multi-class classification). In addition, 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, and the ML model will be tested in predicting those measurements.

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