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FIELD EMISSION MITIGATION IN CEBAF SRF CAVITIES USING DEEP LEARNING *

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Abstract

The Continuous Electron Beam Accelerator Facility (CEBAF) operates hundreds of superconducting radio frequency (SRF) cavities in its two main linear accelerators. Field emission can occur when the cavities are set to high operating RF gradients and is an ongoing operational challenge. This is especially true in higher gradient SRF cavities. Field emission results in damage to accelerator hardware, generates high levels of neutron and gamma radiation, and has deleterious effects on CEBAF operations. Therefore, field emission reduction is imperative for the reliable, high gradient operation of CEBAF that is required by experimenters. In this paper, we explore the use of deep learning architectures via multilayer perceptron and the use of tree-based models to simultaneously model radiation measurements at multiple detectors in response to arbitrary gradient distributions. These models are trained on collected data and could be used to minimize the radiation production through gradient redistribution. This work builds on previous efforts in developing machine learning (ML) models, and is able to produce similar model performance as our previous ML model without requiring knowledge of the field emission onset for each cavity.

INTRODUCTION

CEBAF is a high energy, recirculating continuous wave linear accelerator (linac) that delivers accelerated electron beams for experimental research in nuclear physics [1, 2]. Field emission is an ongoing operational challenge in CEBAF superconducting radio frequency (SRF) cavities. When SRF cavities are exposed to high operating RF gradient, electrons are emitted from the walls of the SRF cavities resulting in field emission [3, 4]. As the field emission has deleterious effect overall on CEBAF operation, it is mandatory to mitigate field emission for the reliable operation of CEBAF.

One of the primary negative effects of field emission is radiation production caused when field emitted electrons are accelerated and collide with another material. Each cavity has a unique gradient threshold over which field electrons are emitted, and these threshold values change over time. Measuring these thresholds requires an invasive procedure that disrupts beam delivery.

CEBAF is equipped with a purpose built neutron detection system, the NDX system. NDX detectors are capable of detecting both neutron and gamma radiation, and represent our best means of measuring the radiation produced by field emission throughout a linac during radio frequency (RF) system operation.

In this paper, we use a multilayer perceptron (MLP) based artificial neural network (ANN) architecture and the tree-based XGBoost (Extreme Gradient Boosting) model [5] to model the gamma and neutron radiation measured at six NDX detectors at the end of the North Linac based on nearby cavity RF gradients. The above mentioned models may support radiation minimization through gradient redistribution. The purpose of this work is to find a best model capable of modeling the radiation readings at NDX detectors given a set of nearby cavity gradients.

MATERIALS AND METHOD

Experimental Set Up and Data Collection

Jefferson Lab installed the new NDX detectors around the CEBAF in the summer of 2021. In August 2021, we measured the gamma and neutron radiation response of four C100 cryomodules (1L22-1L25) at the end of the CEBAF's north linac after NDX commissioning completed. We chose this small section of linac due to its high density of nearby NDX detectors and those cryomodules' history of field emission. We recorded the NDX measured dose rates as we stepped cavity gradients downward from their operation maximums in a process we refer to as a gradient scan. Gradient scans occurred in the absence of the electron beam, but with the RF system powered on. All cavities in the linac were set to their expected operational settings, but only the cavities in the four chosen C100s were changed during the study. We took multiple readings at each gradient configuration. Control system data from the collection process is shown in Fig. 1. More details on the data collection process are given in a previous publication [1].

Dataset and Data Preprocessing

We focus on the gradient scan data of zones 1L22 through 1L25 taken during August 2021. Radiation measurements were used from the six NDX detectors at 1L22-1L27. Zone 1L26 was unpopulated at this time. This data includes 32 cavity gradients to be used as model inputs, and 12 radiation measurements (one gamma and one neutron reading from

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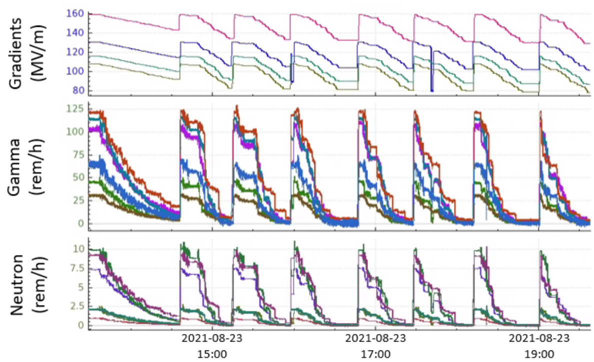

Figure 1: Time series waveform of Gradient (first plot), gamma (second plot) and neutron (third plot) measurement.

each of the six detectors) to be used as known model outputs. These values represent snapshots in time during the data collection process after RF gradients had stabilized at their new setpoint. Our data consists of three types, cavity gradients (MV/m, input), neutron radiation (rem/h, output), and gamma radiation (rem/h, output). Each class of data has measurements taken at multiple locations. These measurements differ in scale between and within data classes. Cavity gradients could range from 0-25 MV/m, but are less than 21.5 MV/m in practice. The NDX detectors have a very high dynamic range [6]. During our gradient scans, we found a max gamma dose rate of ~142 rem/h at a single detector and a max neutron dose rate of ~14.4 rem/h at a single detector.

The dataset used in this paper contains total 17610 data points measured from 1793 gradient combinations. We split the data into training, validation, and test sets using 64% in training, 16% in validation and 20% in testing. Examples from each gradient combination were grouped together and randomly assigned to one of the three sets. This group-based shuffling scheme prevents highly similar examples that are based on repeat measurements from appearing in both the training and testing sets. After data partitioning, we normalize both input and output using MinMaxScaler normalization technique. The whole data processing and model learning is illustrated in Fig. 2.

METHOD

We consider a basic deep learning model, the feed forward or multilayer perceptron (MLP) network and the XGBoost as a best model among tree-based models. We have designed various MLP models of two and three hidden layers. The diagram shown in Fig. 3 gives the baseline model architecture. The model inputs are cavity gradients, and its outputs are the predicted gamma and neutron radiation measurements at nearby NDX detectors. Using trial and error, we developed a two-layer MLP model that provides low loss across the multiple outputs. Additional details of the model are given in Fig. 3. We optimized the sum of mean squared error (MSE) losses across all normalized radiation signals using stochastic gradient descent (SGD). For XGBoost, we use the software library's default model hyperparameters (n_estimators=100, max_depth=6, max_leaves=0, min_child_weight=1), but found a learning rate of 0.2 to yield better performance. We score model performance using the R-squared, mean squared error (MSE), and mean absolute error (MAE) metrics.

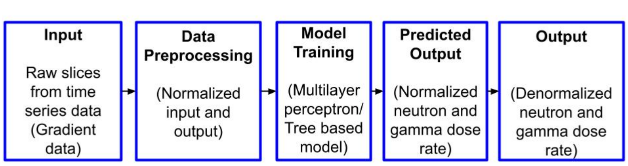

Figure 2: Data processing and model development pipeline.

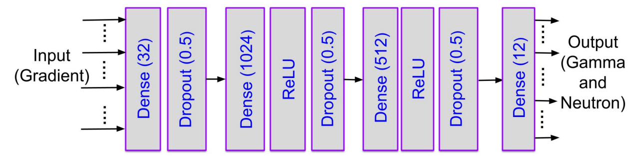

Figure 3: A baseline multilayer perceptron architecture with two hidden layers. Note: both inputs and outputs are individually normalized.

RESULTS AND DISCUSSION

As outlined above, we develop two models for predicting the radiation measurements in a portion of a linac based solely on cavity gradients. We find that both models perform extremely well on the collected data. This is demonstrated in the performance metrics given in Table 1 as well as the nearly on-diagonal nature of the observed vs predicted plots for both models (Figs. 4 and 5). While performance is generally similar, the XGBoost model appears to have a slight advantage. The MLP model, while requiring a large number of training epochs, shows model convergence around 1000 epochs and lack obvious signs of overfitting (Fig. 6). Validation error plateaus while training error continues to decrease, and the model's average loss is similar across both the validation and test sets.

Neither model requires feature engineering to achieve good performance. This is important as our previous model required explicit knowledge of each cavity's field emission

Table 1: Training, Validation and Test Results of MLP and XGBoost Model

Model	Metrics	Training	Validation	Test
	R^2	0.989	0.986	0.985
MLP	MSE	2.806	4.005	4.148
	MAE	0.853	1.015	0.985
	R^2	0.998	0.986	0.986
XGBoost	MSE	0.383	2.911	2.622
	MAE	0.345	0.853	0.794

R^2=Coefficient of determination, MSE=Mean squared error, MAE= Mean absolute error

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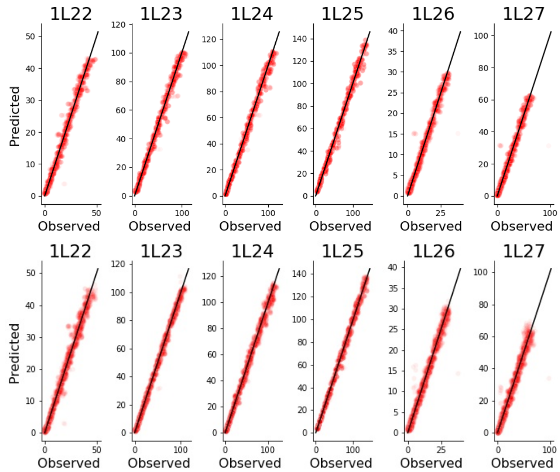

Figure 4: Observed vs predicted plots for gamma radiation (rem/h) by the MLP (top) and XGBoost (bottom) models for test dataset.

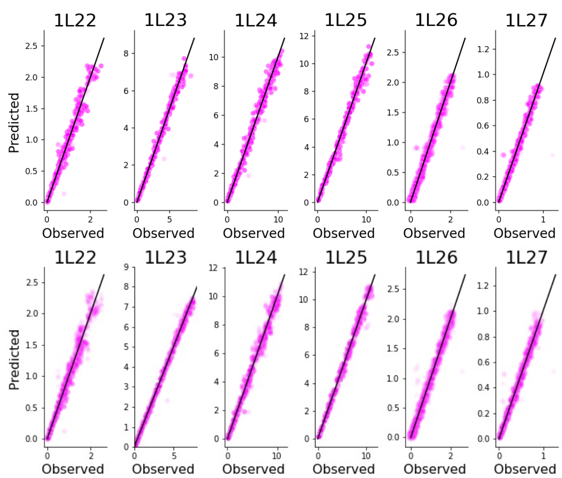

Figure 5: Observed vs predicted plots for neutron radiation (rem/h) by the MLP (top) and XGBoost (bottom) models for test dataset.

onset for use in calculating input features. Determining field emission onset requires an invasive measurement that interrupts beam delivery and is typically not performed. In spite of this simplification to the inputs, our model performance remains similar and may even have been slightly improved.

While these models both perform extremely well on the data collected within a narrow time window, we have discovered challenges in applying them to CEBAF during a run. The challenge largely relates to the constantly changing nature of CEBAF. Existing field emitters improve or degrade, new field emitters appear, and cavity gradients are adjusted as components break, problems fixed, or the linac energy changes due to experimental requirements. The challenges of data drift and concept drift are inherent to the online nature of a complex machine like CEBAF. This drift results in a dramatic decrease in model performance. We are currently investigating mitigation strategies using parasitic data collection during CEBAF operations that obviate the need

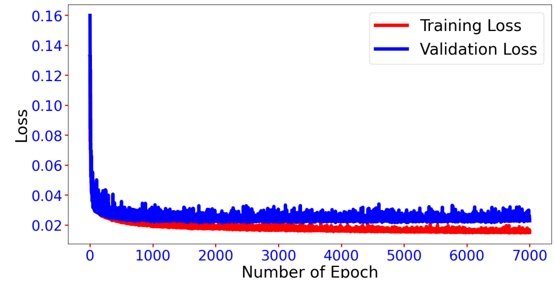

Figure 6: Training and Validation loss for MLP model.

for time intensive gradient scans and possible improvements to our gradient scan procedures.

CONCLUSION

In this paper, we apply MLP model and XGBoost model to effectively model the radiation measurement at the multiple detectors of NDX system based exclusively on RF cavity gradients. Both models perform very well on the given test set collected in August 2021 and neither require further feature engineering or other invasive measurements. While further work is required in order to keep these models performing well during the length of a run spanning few months in the face of changing operational conditions, we have demonstrated a basic model that is capable of predicting radiation on readily available machine data.

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