USING AI FOR MANAGEMENT OF FIELD EMISSION IN SRF LINACS

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Abstract

Field emission control, mitigation, and reduction is critical for reliable operation of high gradient superconducting radio-frequency (SRF) accelerators. With the SRF cavities at high gradients, the field emission of electrons from cavity walls can occur and will impact the operational gradient, radiological environment via activated components, and reliability of CEBAF's two linacs. A new effort has started to minimize field emission in the CEBAF linacs by re-distributing cavity gradients. To measure radiation levels, newly designed neutron and gamma radiation dose rate monitors have been installed in both linacs. Artificial intelligence (AI) techniques will be used to identify cavities with high levels of field emission based on control system data such as radiation levels, cryogenic readbacks, and vacuum loads. The gradients on the most offending cavities will be reduced and compensated for by increasing the gradients on least offensive cavities. Training data will be collected during this year's operational program and initial implementation of AI models will be deployed. Preliminary results and future plans are presented.

INTRODUCTION

The Continuous Electron Beam Accelerator Facility (CEBAF) at Jefferson Lab is a high power, continuous wave recirculating linac that completed an energy enhancing upgrade to 12 GeV in 2017 [1]. This upgrade included the installation of 11 additional higher gradient cryomodules, named C100s for their capability of producing a 100 MeV energy gain. Field emission (FE) is a well-known phenomenon in superconducting radiofrequency (SRF) cavities that can have deleterious impact on accelerator hardware, cryogenic heat loads, and machine operations. Field emitted electrons can be accelerated similarly to CEBAF's electron beam and can generate neutron and gamma radiation on impact. Managing FE in CEBAF's C100 cryomodules has emerged as an on-going operational challenge since the 12 GeV upgrade (Fig. 1).

CEBAF recently designed, built, calibrated, and installed neutron dose rate meters (NDX) [2]. The NDX monitors are deployed around CEBAF with a majority of detectors placed near the newer higher gradient cryomodules. This new system allows for more detailed measurements to be made of the radiation response to RF

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configurations and is currently being used to minimize the FE-based radiation through manual gradient optimizations.



Figure 1: CEBAF schematic denoting the location of C100 cryomodules. One north linac C100 was removed for refurbishment during the time of this study.

Several beam studies were conducted during CEBAF restoration that leveraged the NDX system to measure FE-related radiation response to changes in cavity RF gradients. This data provides an ample training set for the development of artificial intelligence (AI) models to aid operations in maintaining a lower radiation environment. Preliminary attempts at modeling radiation as a function of gradient appear successful.

NDX SYSTEM

Installation and commissioning of the NDX system was completed in August 2021. The system has 21 detectors positioned at strategic locations in the CEBAF tunnel. The majority of these detectors are positioned around the newer higher gradient cryomodules with names corresponding to the adjacent downstream cryomodule. These detectors are primarily designed to measure neutron radiation, but as an ancillary and necessary feature, they also provide measurements of gamma radiation dose rates. The NDX system is now the primary tool for measuring FE-related radiation at CEBAF.

Electrometers associated with the detectors measure the current signal over a variable integration time period, typically set to one second. These signals are converted to

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dose rates, presented over CEBAF's standard EPICS control system, and stored in the control system archiver.

PROBLEM OF FIELD EMISSION

SRF cavity walls may emit electrons when exposed to a sufficiently high RF gradient, which are subsequently accelerated by the same RF field. Electrons are emitted with an exponential response to increases beyond this onset threshold. Many of these electrons quickly impact the cavity and are reabsorbed, potentially causing increased cryogenic heat load or radiation. However, some FE electrons are captured by RF fields and transported long distances (>100 m) through adjacent cavities and cryomodules either upstream or downstream [3]. These electrons eventually collide with accelerator hardware producing much higher radiation levels at the new location.

This radiation has several deleterious effects on CEBAF operations. For example, hardware can be damaged requiring early replacement, components can become activated which present hazards for nearby work, and the increased radiation and field emission can increase the number of machine trips or lower the maximum operational gradient ("operational drive high") that can be achieved. These issues all contribute to increased CEBAF downtime and lowered energy reach. Field emission control, reduction, and management is critical for reliable, high gradient operation at CEBAF.

Field emission during CEBAF operations is largely impacted by contamination on the cavity wall surface. SRF cavity fabrication uses state-of-the-art surface processing and assembly techniques to control FE, however, particulates may be introduced through activities such as vacuum valve operations or installation work [4, 5]. Trace gasses may freeze on to cavity wall surfaces and activate or degrade existing field emitters [5]. These gasses may also be removed during warm-up events or over time during RF operations.

Ideally, all cavities could be run below the FE onset gradient. However, CEBAF's experimental requirements demand that many cavities are set beyond this threshold in order to meet the target energy of experimenters. Thus the question becomes how to best distribute gradient in order to reduce FE across a linac. CEBAF operations staff already have tools available for automatic gradient distribution to optimize for common cavity faults and other operational criteria. Our goal is to first develop AI tools to help operators better leverage the existing toolkit, rather than replace the existing automated gradient distribution process.

During summer 2021, operations staff used manual investigations of FE-related radiation response to changes in gradient to achieve large-scale reductions in radiation while maintaining linac energy gain. Use of machine learning (ML) models and advanced optimization techniques may be able to surpass these manually found settings. Additionally, operational conditions evolve and change during an experimental run. Existing field emitters may degrade or new ones appear. Operational limits on cavity gradients change as hardware fails or is repaired. As such operations would need to continue fine tuning this optimization throughout a run as time and manpower allow. AI may be able to provide similar functionality without the need for time consuming manual efforts.

These operational characteristics raise interesting , questions regarding the management of FE:

- 1. Given a machine configuration, can the cavities that are the leading contributors to FE-radiation be identified? This would allow for off-line optimization work to be performed without interrupting beam delivery.
- 2. Can changes in existing field emitters be detected and localized? This would allow degraded or improved field emitters to be identified for manual operator intervention or possibly to inform updates to existing ML model regarding the previous question.
- 3. Can the appearance or elimination of field emitters be detected and localized? Completely new field emitters would likely pose a challenge for ML models trained on old data. Quickly identifying these would alert users that the model needs to be re-trained, and improve the rapidity of manual interventions.

Currently, these questions can be answered manually by invasively adjusting cavity gradients to explore the machine response. However, this process can take hours. This level of effort and beam studies time is difficult to obtain during experimental runs. Providing non-invasive AI methods to replace or enhance existing manual optimizations could enable CEBAF to maintain a lower level of FE during operations.

DATA COLLECTION METHODS

Our initial approach to these problems is to focus on the response of the C100 cryomodules at the end of the north linac. Two types of data were collected during beam studies, the radiation onset for C100 cavities, and radiation responses to a range of operational C100 gradient settings. First, the radiation onsets of C100 cavities were determined under pseudo-operational conditions. This is subtly different, but closely related to, a cavity's FE onset. The radiation onset measurements determine the highest gradient a cavity can achieve before the NDX system can definitively detect an increase above background radiation in a configuration approximating normal beam operations. Secondly, we measured the radiation response across the linac using the NDX system while scanning a range of gradients consistent with normal operations.

Radiation Onset

Automated radiation onset measurements were performed via software on one cryomodule at a time. First we turn off RF in at least the adjacent four cryomodules on either side to remove radiation generated by other cavities. Then all cavity gradients in the cryomodule of interest were increased as much as possible without causing a noticeable rise in radiation. 18th Int. Conf. on Acc. and Large Exp. Physics Control SystemsISBN: 978-3-95450-221-9ISSN: 2226-0358

Once this elevated baseline was achieved, each cavity was individually walked up in 0.125 MV/m steps until a significant increase in radiation was observed. Determining if radiation levels exceeded background was done using a statistical comparison. Unconverted NDX detector current signals were sampled for ten seconds at the start of the scan to establish the background. Then similar samples were taken after each step. A difference in average currents of ten standard errors was considered statistically Our statistical approach significant. typically corresponded to a dose rate increase on the order of 1-10 mrem/h. This automated onset scanning procedure requires approximately one hour to find the radiation onsets for the eight cavities in a cryomodule. However, we believe there is opportunity for considerable speed enhancements.

Gradient Scan

A gradient scan was conducted by setting the entire linac to RF settings consistent with an energy gain used during experimental runs. This process sets all C100 cavities to their operational maximum gradients (drive high limits). From this starting point, we systematically stepped all of the C100 cavities' gradients down.

Each stage of a gradient scan consisted of stepping down individual cavity gradients in identical step sizes and in a randomized order. After turning down a cavity, we waited several seconds for the cryogenic system to settle, then allowed several seconds for dedicated radiation measurements. Data was collected for both the settle and dedicated measurement periods as radiation responses appear to be similar during both phases.

Aggregated Per-C100 Gradient 160 140 120 100 80 2021-08-23 2021-08-23 2021-08-23 2021-08-23 **Neutron Dose Rate** 10 7.5 5 2.5 2021-08-23 2021-08-23 2021-08-23 2021-08-23 15:00:00.00 14:40:00.00 14:50:00.00 15:10:00.00 Gamma Dose Rate 125 100 75 50 25 0 2021-08-2

Figure 2: A single gradient scan using three 1 MV/m steps (top). The measured neutron (middle) and gamma (bottom) dose rates (rem/h) show the reduction in radiation as cavity gradients are lowered.

Figure 2 shows a single gradient scan and its radiation response. Notice that the reduction in radiation is a mix of plateaus and steep declines. This likely indicates that specific cavities were the primary field emitters as THPV043

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radiation levels dropped with small changes to gradient. In this example, radiation is practically eliminated while gradients have been indiscriminately reduced 15-20% below their standard operational settings. A more optimal approach could likely achieve similar radiation reductions while sparing much of the gradient losses.

A single gradient scan consisted of several such identical stages. A typical scan with three stages could be completed in approximately 20 minutes. As was the case with onset scans, there are opportunities to speed up the process by either collecting fewer samples per step, requiring less wait time after gradient change to collect data, or by algorithmic enhancements.

Multiple scans were performed at various step sizes ranging from 0.1 MV/m to 1 MV/m, and were performed starting at various offsets from the C100 cavities' maximum gradients. This allowed for a range of gradient combinations covering the highest 3 MV/m range of each cavity to be explored. All gradient scan data collection was managed by CEBAF's EPICS control system archiver, with the data collection software maintaining an index file for later retrieval.

DATA EXPLORATION

The gradient scans produced 17,940 samples (10 samples for each of the 1,794 gradient combinations explored during the scans). After data cleaning, 17,610 samples remained. The gradient scans produced a broad range in radiation mimicking dose rates that will be seen during operations (Fig. 3). Higher dose rates are possible but not achievable during beam studies without exceeding the current operational limits.



Figure 3: Radiation dose rate measured by NDX detectors during gradient scan studies. Each dot represents a single one-second integrated measurement. Six detectors (1L22-1L27) are positioned near C100s in the north linac.

C100 gradient settings were very positively correlated with individual radiation readings and radiation readings

were highly correlated amongst detectors near the C100 cryomodules (Fig. 4). Positive correlations were expected between gradients and detector readings given that, in general, higher gradients lead to higher radiation. Readings between detectors were also expected to be positively correlated as they occupy the same linac tunnel. However, it is possible that the structure of the gradient scans, where all C100 cavity gradients were stepped down in stages, exaggerated the correlations between detectors. Future gradients scans should keep this concern under consideration and allow additional randomness in the scanning procedure.



Figure 4: Dose rates were very positively correlated among the C100-adjacent NDX detectors. Correlations between other detectors were likely due to changes in non-C100 configurations between beam studies. Note that the same cryomodules are listed twice, once for gamma radiation and once for neutron.

MODELING RESULTS

We developed a preliminary model to address the first operational FE problem, i.e., identifying cavities that are leading offenders. Our initial approach is to directly model the radiation produced at all C100-adjacent detectors as a function of C100 cavity gradients and radiation onset values. Given a sufficient model, standard "black box" optimization techniques can be used to optimize the gradient settings, or an automated procedure can check which gradients will have the most anticipated impact on radiation production.

Preliminary attempts at modeling the radiation readings as a function of cavity gradients and radiation onset values used a multi-output random forest regressor [6] trained on 12,302 examples and tested on 5,308 examples for a 70/30 split. Examples taken from repeated measurements of a gradient configuration were grouped exclusively into the training or testing set to ensure the test data was unseen during training. Model development was performed using the scikit-learn python package [7].

Early attempts to model radiation using solely untransformed cavity gradients were unsuccessful.

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δ However, providing a feature set that more closely mimics attribution to the author(s), title of the work, publisher, the described physical process proved effective [3]. For this model, the following five features per cavity were Surface FE: $g_i = 2^{max(gmes_i - rad_onset_i, 0)}$ $u_i = \sum_i (gmes_i)$ energy gain: where cavity j is upstream of cavity i $d_i = \sum_i (gmes_i)$ Downstream energy gain: where cavity j is downstream of cavity i Upstream interactions: $u_i g_i$ Downstream interaction: $d_i q_i$ Where *gmes*_i is the measured cavity gradient of cavity *i*, and *rad_onset*_{*i*} is the radiation onset gradient of cavity *i* found during beam studies. These features, while crude approximations of the physical processes, are sufficient as the model achieved an R-Squared score of 0.978 using these features. Figure 5 shows the difference in observed and predicted neutron dose rates detected upstream of 1L25 as the aggregate C100 gradient changed. Table 1 gives additional metrics for model performance. under the terms of the CC BY 3.0 licence (© 2022). Any distribution of this work must 1L25 Neutron Radiation vs Aggregate C100 Gradient Observed Predicted Error 420 440 460 480 500 C100 Gradient (MV/m) Total

Figure 5: Testing results of the random forest model predicting neutron dose rates at detector 1L25. The model maintains small errors across the range of gradients.

A significant drawback of this approach is that the model will need to be retrained on new data when there are changes to active field emitters (i.e. if they are processed away or their onset changes). Additional work will investigate alternative modeling approaches or mitigations of this shortcoming, such as developing procedures for rapid or non-invasive data collection.

The initial modeling results provide confidence that the data from the NDX detectors, along with machine learning

be used

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techniques, can be leveraged to address the three operational questions highlighted earlier.

Table 1: Performance Metrics of the Multi-Output Random Forest Regressor

Metric	Training	Testing
R-Squared	0.999	0.978
MSE	0.001	0.052
MAE	0.013	0.115

SUMMARY

We have begun leveraging the NDX system to develop AI models capable of enhancing the management of field emission during CEBAF operations. Initial data collection and modeling efforts show promising signs that this is an effective tool to apply for that purpose. Our future work aims to refine this work with more advanced deep learning techniques and to expand the scope of the problems investigated.

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