ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-MOPAB289

MACHINE LEARNING TRAINING FOR HOM REDUCTION AND EMITTANCE PRESERVATION IN A TESLA-TYPE CRYOMODULE AT FAST*

J. Diaz Cruz[1†], A. Edelen, J.P. Sikora, B. Jacobson, SLAC, Menlo Park, CA 94720, USA
A. Lumpkin, D. Edstrom, R. Thurman-Keup, FNAL, Batavia, IL 60510, USA
[1]also at University of New Mexico, Albuquerque, NM 87131, USA

Abstract

Low emittance electron beams are of high importance at facilities like the Linac Coherent Light Source II (LCLS-II) at SLAC. Emittance dilution effects due to off-axis beam transport for a TESLA-type cryomodule (CM) have been shown at the Fermilab Accelerator Science and Technology (FAST) facility. The results showed the correlation between the electron beam-induced cavity high-order modes (HOMs) and bunch-by-bunch centroid slewing and oscillation downstream of the CM. Mitigation of emittance dilution can be achieved by reducing the HOM signals and the standard deviation in the bunch-by-bunch beam positions downstream of the CM. Here we present a Machine Learning (ML) based optimization and model construction for HOM signal level reduction using Neural Networks (NN). To gather training data we performed experiments using 50 bunch electron beams with charges up to 600 pC/b. We measured HOM signals of all cavities and beam position with a set of BPMs downstream of the CM. The beam trajectory was changed using V/H125 corrector set located upstream of the CM. The preliminary results presented here will inform the LCLS-II injector commissioning and will serve as a prototype for HOM reduction and emittance preservation.

INTRODUCTION

Low emittance electron beams are of high importance in accelerating structures at large facilities like the LCLS-II at SLAC. With a set of experiments performed at FAST, it was shown that off-axis beam transport may result in emittance dilution due to transverse long-range (LRW) and short-range wakefields (SRW) [1, 2]. A set of LRWs known as Higher-Order Modes (HOM), which are cavity resonant frequencies higher than the fundamental 1.3 GHz, have amplitudes that are proportional to beam offset, charge and coupling impedance (R/Q). Therefore, reducing HOM signals may help to mitigate emittance dilution effects.

In order to further investigate the relation between emittance dilution, HOMs and beam offset, and to inform the LCLS-II injector commissioning plans, a new set of experiments were performed at FAST. This time, two 4-channel HOM detectors were used to measure signals at the upstream (US) and downstream (DS) couplers of 8 superconducting RF (SRF) cavities inside a Tesla-type CM [3]. The new results showed a correlation between the electron beam-induced cavity HOM signal levels and bunch-by-bunch centroid slewing and oscillation at 11 BPMS located downstream of the CM [4]. Thus, by reducing HOM signals and bunch-by-bunch centroid slewing downstream of the CM, one can mitigate emittance dilution. In principle, a NN control policy could be used for this purpose.

ML is undergoing a renaissance in a wide variety of applications due to larger computational resources, advanced theoretical models, and successful practical applications during the last years. Particle accelerators are part of this resurgence of ML by developing new system modelling techniques, virtual instrumentation and diagnostics, tuning and control schemes, surrogate models, among others [5]. In this paper, we evaluate a NN model for bunch-by-bunch centroid slewing prediction, and its application in a ML based optimization and model construction for HOM signal level reduction and emittance preservation.

EXPERIMENTAL SETUP AND DATA ACQUISITION

The Hardware

The Integrable Optics Test Accelerator (IOTA) at the FAST facility has a unique configuration of two TESLA-type SRF cavities after a photocatode RF gun, followed by an 8-cavity CM, like the ones used for LCLS-II at SLAC. Four meters upstream the CM, there is a set of horizontal and vertical correctors (H/V125) used to steer the electron beam and there are 11 BPMs downstream the CM over a 80 m length (Fig. 1).

Two 4-channel chassis were built to detect the magnitude of the HOMs at the US and DS couplers of each SRF cavity. Each channel has a 1.3 GHz notch filter to reduce the nominal resonant frequency, a bandpass filter centered at 1.75 GHz with 300 MHz bandwidth to emphasize the main TE111 HOM dipole modes, and a Schottky diode for HOM detection. More details are found in [3].

The Experiment

An electron beam of 50 bunches and 3 MHz bunch repetition rate is produced at the RF gun with an energy <5 MeV. This bunch pattern repeats at 1 Hz; each repetition is called a ”shot”. After the two capture cavities (CC1 and CC2), the 25 MeV beam is transported to and through the CM with an exit energy of 100 MeV. HOM waveforms and BPM data

* Work supported under contract DE-AC02-76SF00515 with the U.S. Department of Energy.
Work supported by Fermi Research Alliance, LLC under Contract No. DE-AC02-07CH11359 with the U.S. Department of Energy
† dejorge@slac.stanford.edu

ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-MOPAB289

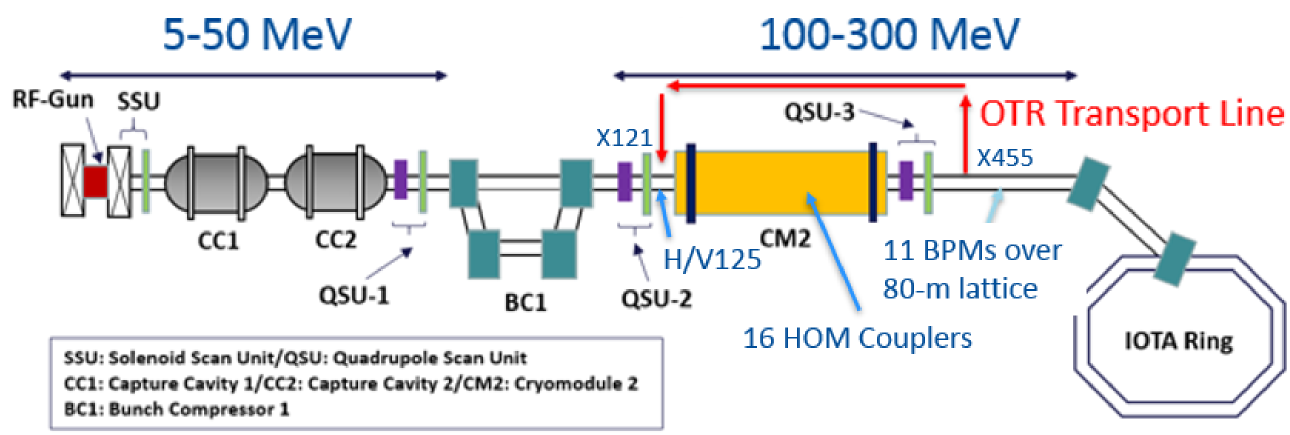

Figure 1: Schematic of the FAST/IOTA beamline layout.

are capture while steering the beam using the H/V125 corrector currents, for different values of bunch charge. First, a "reference" trajectory is found by minimizing as many US HOM signals as possible by steering the beam. Then, we capture HOM and BPM data for this reference trajectory and for several values of bunch charge. We then repeat the previous measurements for values of the corrector currents from -1 A to 1 A in 0.5 A steps.

The Data

An US HOM waveform example for all 8 cavities is shown in Fig. 2. Although several features can be extracted from each of these waveforms (rising time, oscillation frequency, decaying time), we decided to use the peak value as a representative number. Averaging the peak value over 300 shots, the relation between V125 corrector current and HOM signal peaks at 400 pC/b and 50 bunches is shown in Fig. 3.

The evolution of the relative beam centroid position as measured by B441PV (a BPM located DS the CM) over a 250 pC/b beam with 50 bunches is shown in Fig. 4 for multiple values of V125 corrector current and H125 at reference. A clear slew is present in the centroid position measurements, which is proportional to the V125 corrector current offset. With these results we can see how both HOM signal peaks and centroid slews are proportional to the corrector current offset (i.e. beam off-axis). In principle, we can train a NN to predict the centroid slew based on the HOM signal peaks.

NEURAL NETWORK MODEL

A NN was trained to predict the centroid motion's standard deviation as measured by multiple BPMs (B440PV/PH and B441PV/PH) over beams of 50 bunches, for several values of bunch charge and H/V125 corrector currents. The inputs to the NN are the US and DS HOM signal peaks as measured by the SLAC HOM detectors. The training data includes measurements for beam charges of 200 and 100 pC/b, H/V125 corrector currents from -1.0 A to +1.0 A from the reference current, with 0.5 A current steps. At each beam configuration, signals for 300 shots were captured.

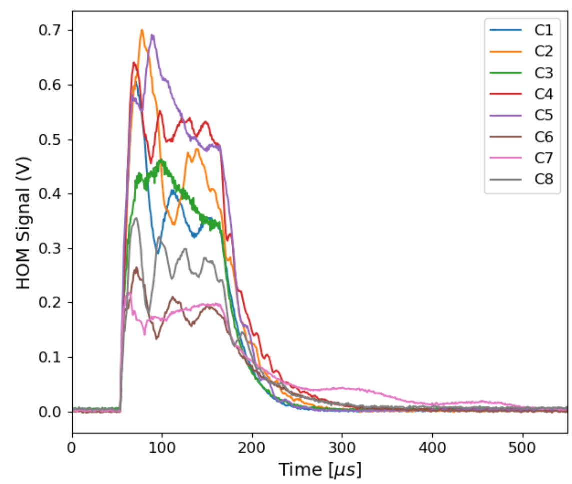

Figure 2: US HOM waveforms with 125 pC/b, 50 bunches, V125=+1.0 A and H125 at reference value.

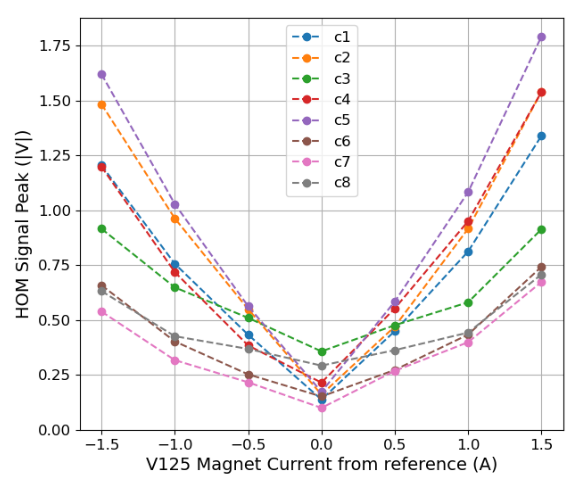

Figure 3: HOM peak signals vs V125 corrector current values for different values of V125 with 400 pC/b, 50 b and H125 at reference value.

The NN architecture consists of a normalization layer followed by 6 hidden layers (four layers of 100 nodes followed

ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-MOPAB289

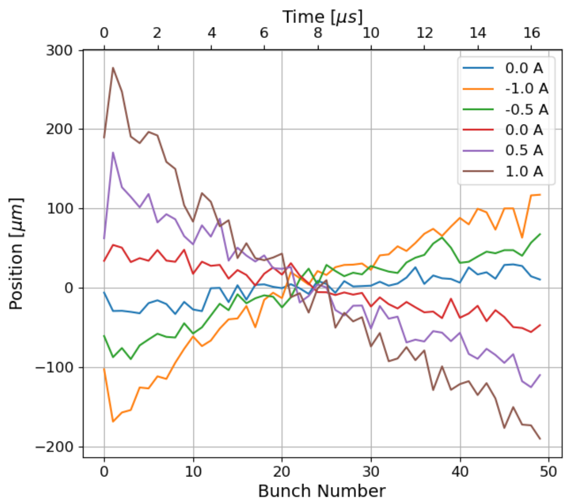

Figure 4: Bunch by bunch centroid slew in B441PV for different values of V125 corrector current offset, with 125 pC/b, 50 bunches and H125 at reference value.

by two layers of 64 nodes). Each hidden layer uses the hyperbolic tangent activation function. A 80-20 split was used for the training and test datasets. From the training dateset, 20% was used for validation. Early stop was implemented.

TRAINING RESULTS

The performance of the model was evaluated in terms of the mean absolute error (MAE) and the mean absolute percentage error (MAPE). Computing resources of the SLAC Shared Scientific Data Facility (SDF) were used to perform the NN training [6]. The results are shown in Table 1. The accuracy of the prediction of the standard deviation of the bunch by bunch centroid slew is about 8% for all BPMs. A representative histogram of the test dataset MAPE for B441PV is shown in Fig. 5. The performance of the NN model for predictions of B441PV standard deviation over the test dataset is shown in Fig. 6.

The groups in Fig. 5 represent BPM measurements over the same beam and corrector configuration (i.e. fixed bunch charge and H/V125 corrector currents). The NN model is capable of predicting the average bunch by bunch centroid slew's standard deviation for a given beam and corrector configuration. However, it is not accurate when predicting the exact value. This may be related to the noise on the BPM measurements and the low charge. Having the average bunch by bunch centroid slew's standard deviation might be enough when designing a controller based on this predictions.

CONCLUSIONS AND FUTURE WORK

Data with the unprecedented correlation between beam steering, US and DS HOM signals and BPM measurements showing bunch by bunch centroid slew after a Tesla-type CM at FAST has been used to train a NN model. Results show that the NN model is capable of predicting centroid slew's standard deviation with about 8% accuracy. These are encouraging results towards developing a ML-based controller for HOM reduction and emittance preservation for the LCLS-II project at SLAC. Our next steps include the development of the controller using an inverse model of the NN developed in this research, i.e. a NN that can predict HOM signals for a given beam offset. We also plan to explore adaptive learning, Gaussian Processes and Gaussian Process based Bayesian optimization.

Table 1: NN Performance Results

BPM	Train MAE	Val MAE	Test MAE	Test MAPE
B440PV	41.42	41.98	42.82	9.76
B440PH	29.82	30.46	30.54	8.2
B441PV	18.98	19.26	19.5	8.4
B441PH	20.89	21.43	21.62	8.44

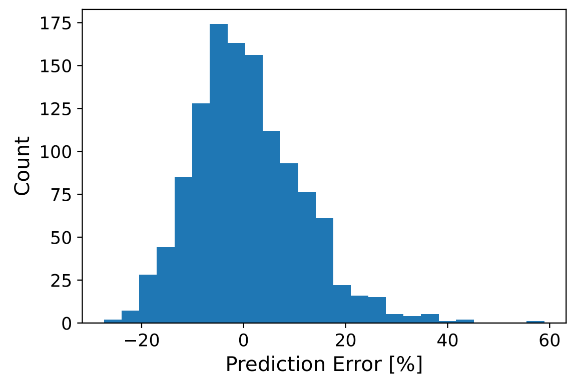

Figure 5: Histogram of prediction errors.

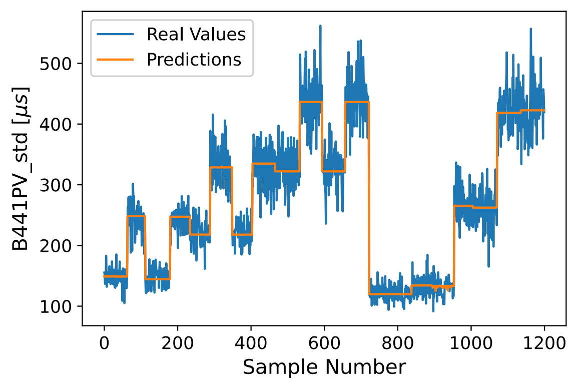

Figure 6: NN model predictions and real values for B441PV.

ACKNOWLEDGEMENTS

The Fermilab authors acknowledge the support of C. Drennan, A. Valishev, D. Broemmelsiek, G. Stancari, and M. Lindgren, all in the Accelerator Division at Fermilab. The SLAC/FNAL authors acknowledge the support of J. Schmerge (Superconducting Linac Division, SLAC).

ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-MOPAB289

REFERENCES

[1] A. H. Lumpkin *et al.*, "Submacropulse electron-beam dynamics correlated with higher-order modes in Tesla-type superconducting rf cavities", *Phys. Rev. Accel. Beams*, vol. 21, no. 6, p. 064401, 2018. doi:10.1103/PhysRevAccelBeams.21.064401

[2] A. H. Lumpkin *et al.*, "Submicropulse electron-beam dynamics correlated with short-range wakefields in Tesla-type superconducting rf cavities", *Phys. Rev. Accel. Beams*, vol. 23, no. 5, p. 054401, 2020. doi:10.1103/PhysRevAccelBeams.23.054401

[3] J. P. Sikora *et al.*, "Commissioning of the LCLS-II Prototype HOM Detectors with Tesla-Type Cavities at Fast", presented at the 12th Int. Particle Accelerator Conf. (IPAC'21), Campinas, Brazil, May 2021, paper MOPAB323, this conference.

[4] A. H. Lumpkin *et al.*, "Investigations of Long-Range Wakefield Effects in a TESLA-type Cryomodule at FAST", presented at the 12th Int. Particle Accelerator Conf. (IPAC'21), Campinas, Brazil, May 2021, paper TUPAB274, this conference.

[5] A. Edelen *et al.*, "Opportunities in Machine Learning for Particle Accelerators", FERMILAB, Batavia, Illinois, United States, Rep. FERMILAB-PUB-19-017-AD, Nov. 2018.

[6] SLAC Shared Scientific Data Facility, https://ondemand-dev.slac.stanford.edu/.