BPM measurement prediction based on HOM signals using Machine Learning*

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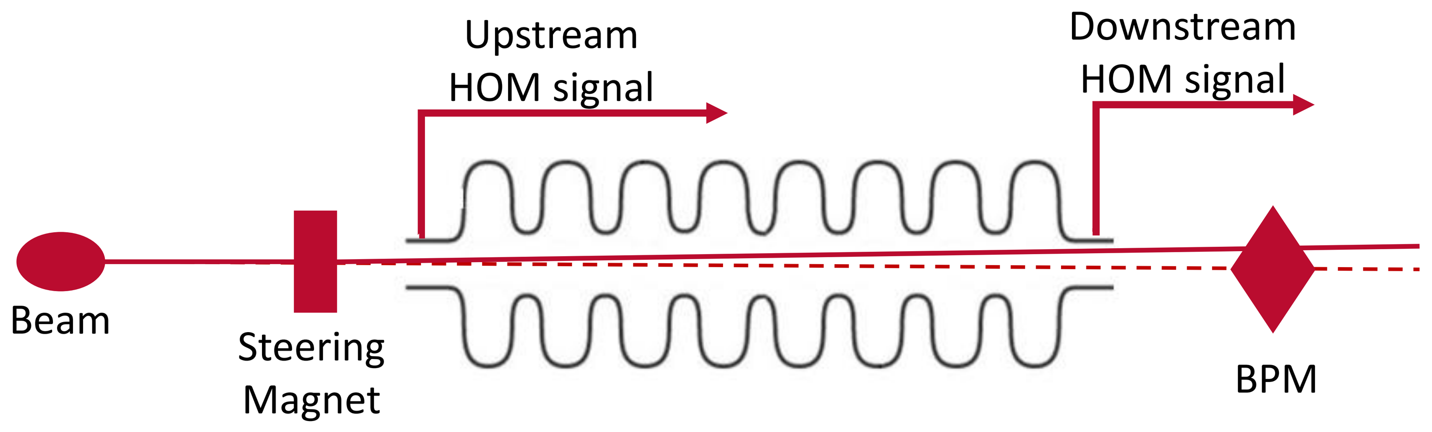
ABSTRACT

Emittance dilution effects due to off-axis beam transport affect the beam quality at facilities like the Linac Coherent Light Source II (LCLS-II) at SLAC, where a low emittance electron beam is desired at the first cryomodule (CM). Transverse offset of the beam as measured by Beam Position Monitors (BPMs) downstream a CM has shown correlation with the beam-induced higher-order modes (HOMs) signals of superconducting RF cavities. Experiments performed at the Fermilab Accelerator Science and Technology (FAST) facility collected HOM signals and BPM measurements for various beam offsets, using a set of vertical and horizontal corrector magnets to change the transverse position of the beam. Here, we present the collected data, and a couple of Neural Networks for bunch-by-bunch mean and standard deviation prediction for BPMs based on HOM measurements.

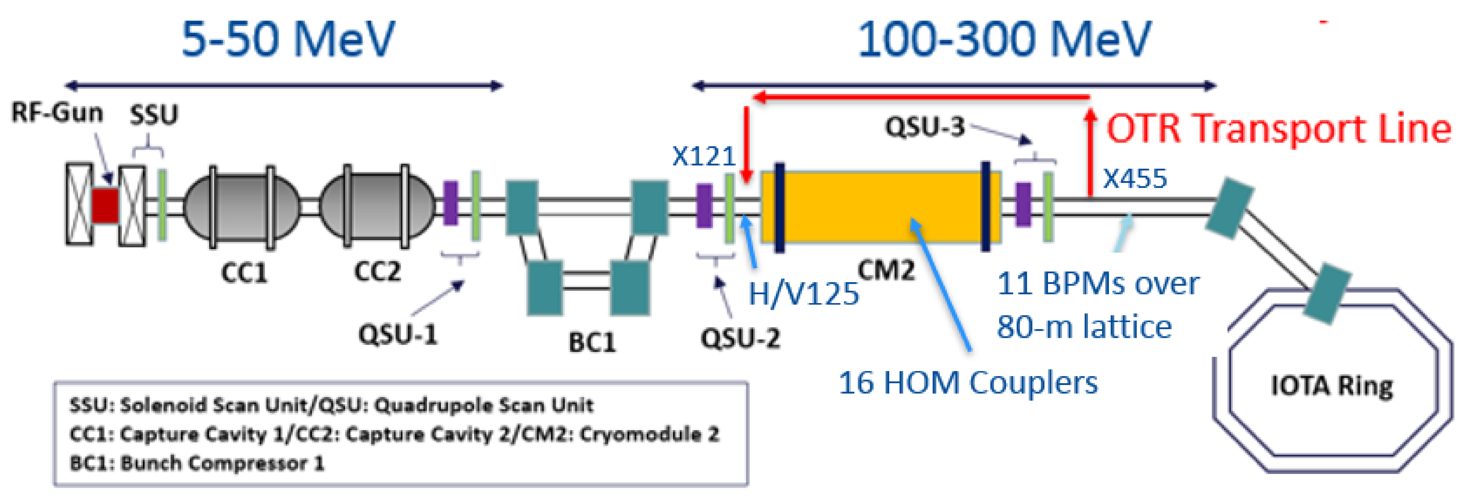
BACKGROUND AND MOTIVATION

- Off-axis beam transport may result in emittance dilution due to transverse long-range (**LRW**) and short-range wakefields (**SRW**).
- A set of LRWs known as High Order Modes (**HOMs**) are proportional to beam offset in SRF cavities.
- Reducing HOMs may help to mitigate emittance dilution effects.
- Low emittance electron beams are of high importance in accelerating structures at large facilities like the LCLS-II at SLAC.



EXPERIMENT & DATA

The FAST Facility at Fermilab

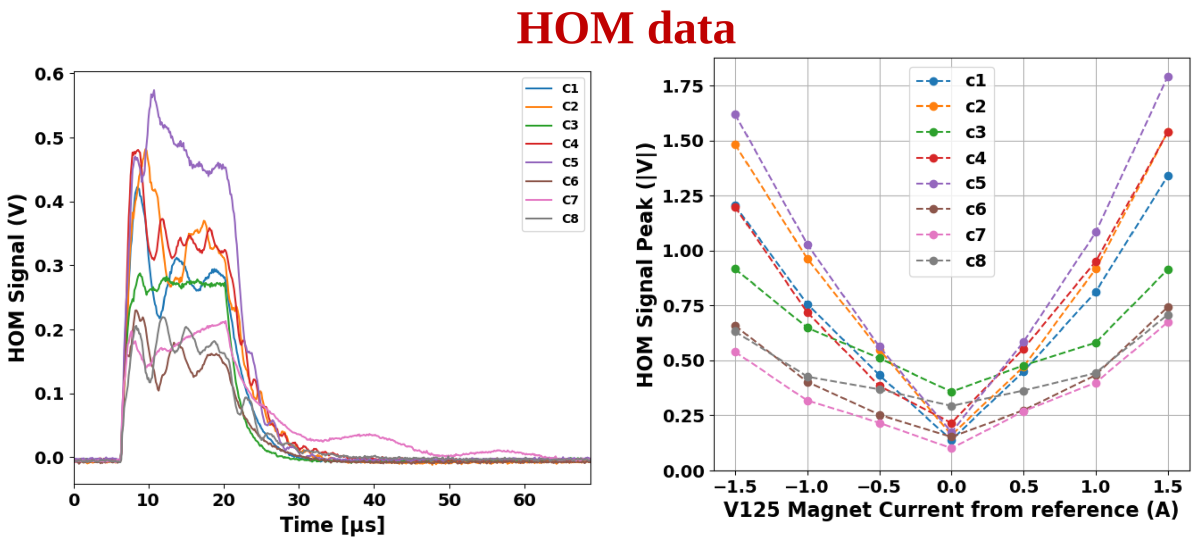


The Beam: electron beam of 50 bunches and 3 MHz bunch repetition rate. Bunch pattern repeats at 1 Hz. Each repetition is called a "shot"

1. A "reference" trajectory was found by minimizing as many US HOM signals as possible by steering the beam.
2. We captured HOM and BPM data for this reference trajectory and for charges of 125, 250, 400 and 600 pC/b.
3. We then repeat the previous measurements for values of the corrector currents from -1.5 A to 1.5 A from the reference current, with 0.5 A steps.

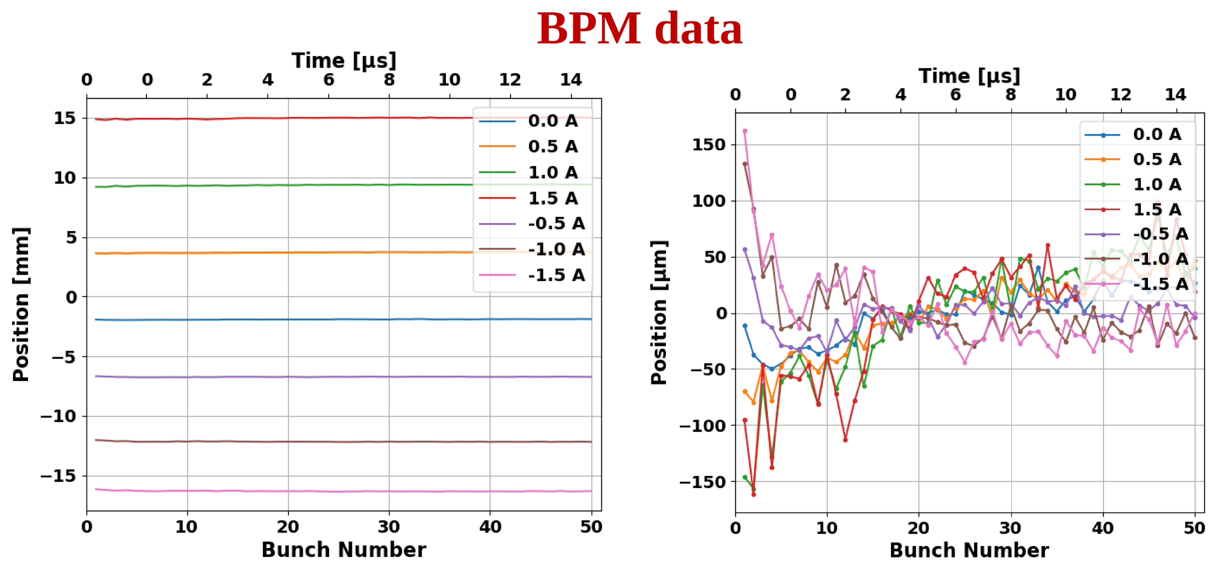
HOM data

Left: Upstream HOM waveforms for 8 cavities. Peak value as representative number
Right: Average US HOM peak value over 300 shots vs V125 corrector current offset at 400pC/b



BPM data

Vertical scan using V125
Left: BPM mean values over 300 shoots
Right: Evolution of relative beam centroid position.
Mean and standard deviation proportional to beam offset



NN MODEL AND RESULTS

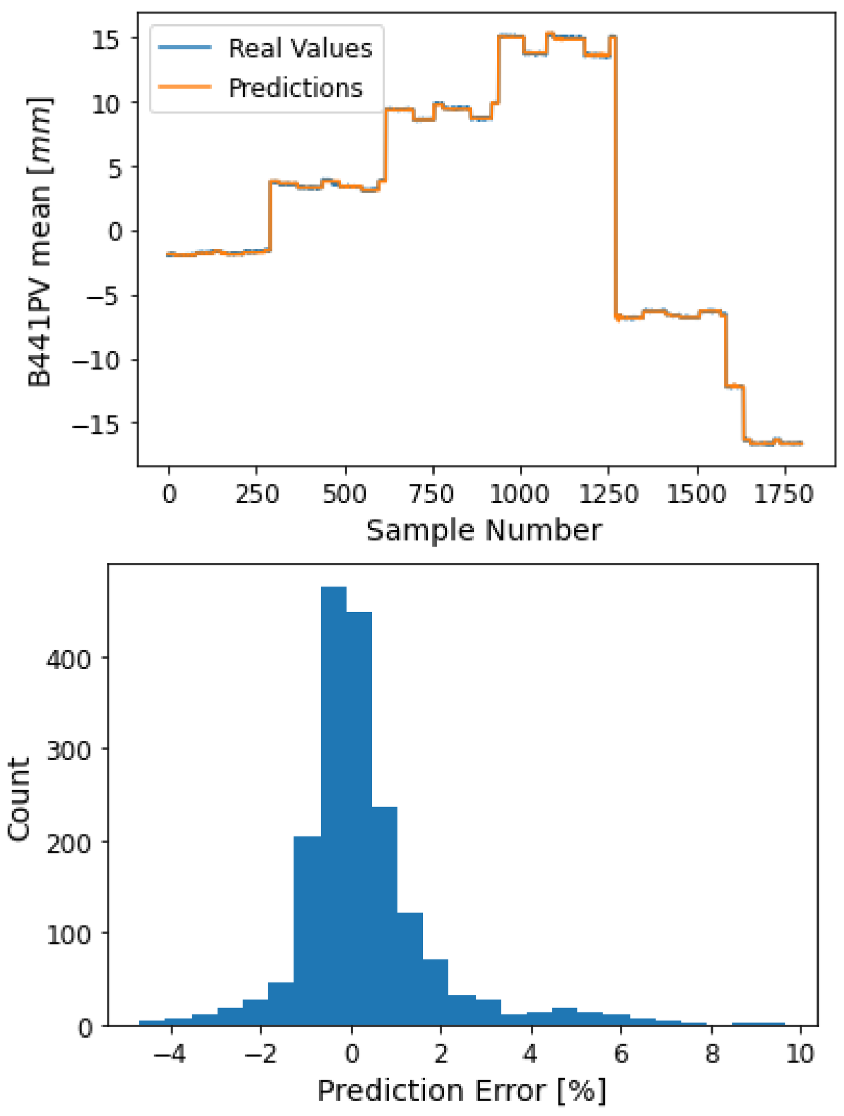
GOAL: Train a couple of NNs to predict BPM mean measurements and centroid motion's standard deviation using HOM signal peaks only

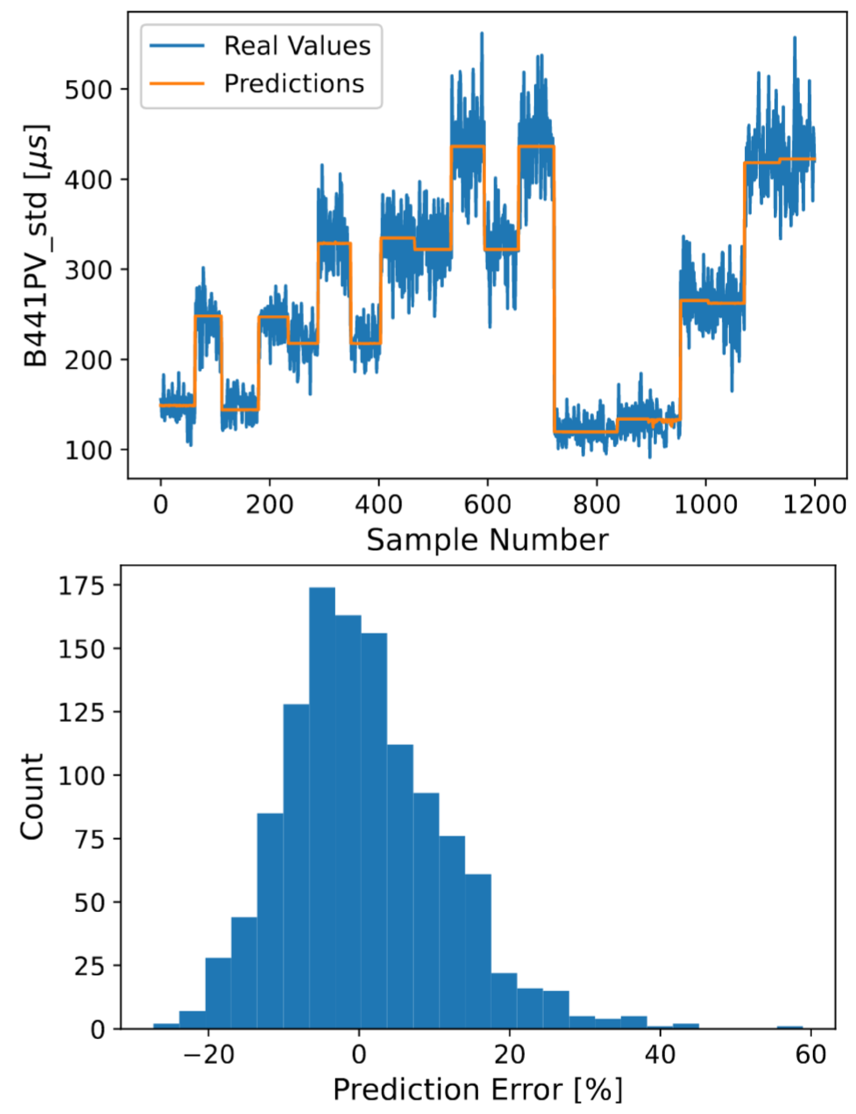
NN for mean prediction

- Normalization layer
- 2 hidden layers each one with 32 nodes
- Hyperbolic tangent activation function
- 80-20 split for the training and test datasets.
- From the training dataset, 20% was used for validation.
- Early stop was implemented

NN for std prediction

- Normalization layer
- 6 hidden layers (four layers of 100 nodes followed by two layers of 64 nodes)
- Hyperbolic tangent activation function
- 80-20 split for the training and test datasets.
- From the training dataset, 20% was used for validation.
- Early stop was implemented





NN results for BPM mean prediction

BPM	Train MAE [µ m]	Val MAE [µm]	Test MAE [µm]	Test MAPE [%]
B418PV	41.05	40.75	41.03	0.61
B441PV	44.25	42.94	46.69	0.91

NN results for BPM std prediction

BPM	Train MAE [µm]	Val MAE [µm]	Test MAE [µm]	Test MAPE [%]
B440PV	41.42	41.98	42.82	9.76
B440PH	29.82	30.46	30.54	8.20
B441PV	18.98	19.26	19.50	8.40
B441PH	20.89	21.43	21.62	8.44

Conclusions and Future Work

- Data with the correlation between beam steering, HOM signals and BPM measurements has been used to train a NN model.
- A NN model is capable of predicting BPM mean value over a train of bunches with less than 1% error.
- A NN model is capable of predicting the centroid slew's standard deviation with less than 10% error.
- 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 (GP) and GP optimizers.

References

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