Beamline Steering Using Machine Learning

SLAC NATIONAL ACCELERATOR LABORATORY

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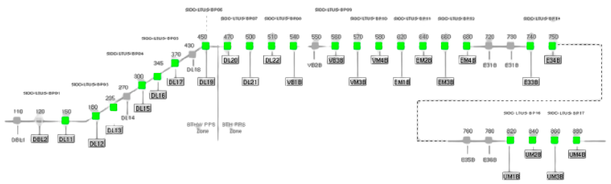
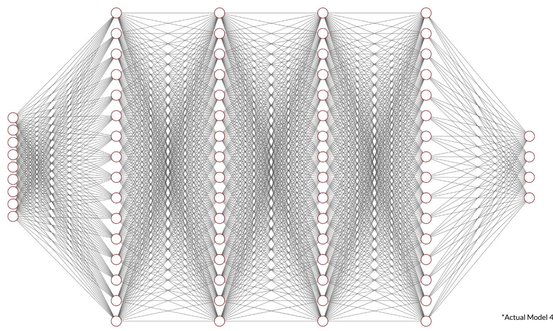
Overview
The Journey To The Undulator:

The LTU (LINAC To Undulator) is notoriously difficult to aim. Each subsequent use of the accelerator requires recalibrating the magnets in this section. My project decreases the time it takes to steer the beam and provides a framework for the creation of future machine learning tools.

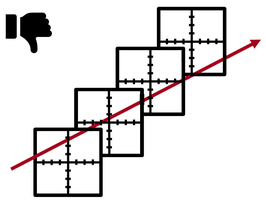


Developing a Machine Learning Model:

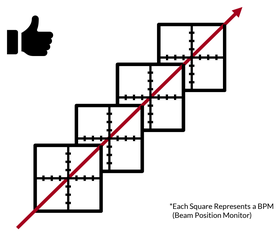


*Actual Model 4x Bigger Than Diagram

Feed Forward Neural Network
8 hidden layers: 64 Nodes each
Trained on 75 million data points



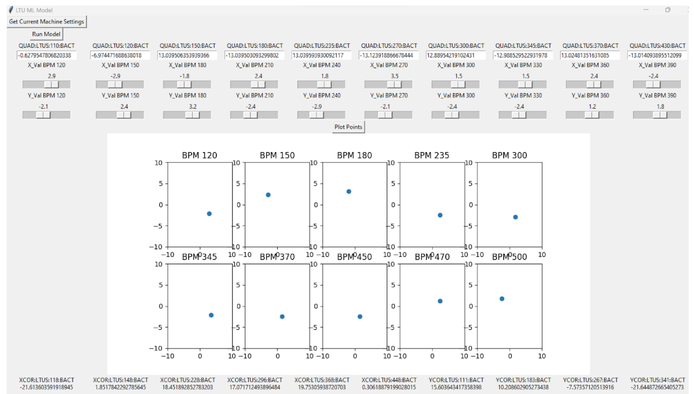
- Current method's RMSE(Root Mean Squared Error) can range from 0.016 to 0 .008
- Can take hours to aim

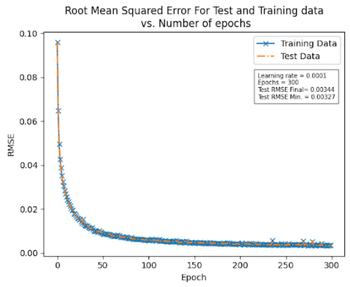


*Each Square Represents a BPM (Beam Position Monitor)

- Current machine learning model has RMSE of 0.0034
- The model can decrease steering time by half

GUI For Beamline Operators:

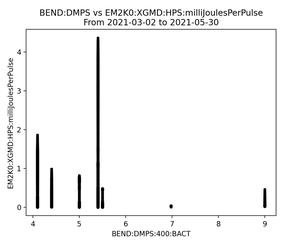


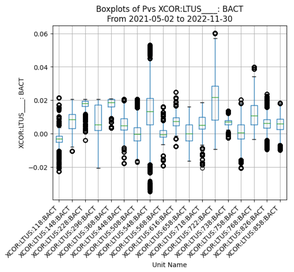


*Graph Shows The Process of Training The ML Model

The GUI (Graphical User Interface) takes in 33 inputs: The desired X and Y Coordinates of the beam along its length and Quadrupole magnet settings. These inputs are run through my model, and the GUI then displays the necessary corrector magnet settings to steer the beam in the desired direction. The GUI can also display the current machine settings and past machine settings.

Data Analysis:





To train the model, we looked at the top 25% of runs from March 2021 to November 2022. This analysis resulted in 200 million datapoints. We then gathered relevant data at the LTU during these times, giving us 75 million data points to train the model with.

Framework For Future Models:

Find times when the beam is most efficient

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Pull relevant PV data for the gathered times

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Train machine learning model on PV data

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Create model GUI for use by relevant parties

Modular code for each step of the framework will allow engineers and physicists to repeat this process for any section of the beamline.

Conclusion And Next Steps:

Machine learning has proven a valuable tool for helping aim the beamline. Initial models have already decreased error by more than half. Modular code will allow easy replication of this process for other areas of the LINAC.

Future models will be able to decrease error even further by utilizing more complex neural networks and larger data sets with a greater spread of values.

Acknowledgments:

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