Understanding NuMI Beam Position with a ML Technique

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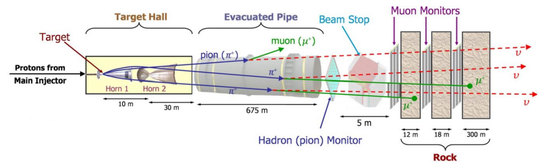
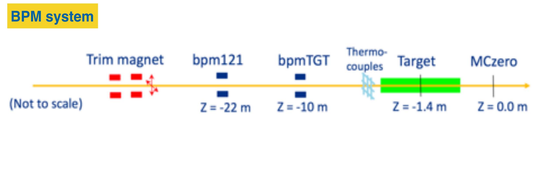
Background and Purpose

The NuMI beamline produces a beam of neutrinos by receiving the proton beam from the main injector, which collides with the target and produces pions. The pions then decay into muons, which also produces muon neutrinos. To measure the proton beam's performance, BPMs (Beam Position Monitors) are used to record the position of the beam, and muon monitors are used to measure the position and profile of the muon beam produced. The Multi-Wire sensor is used to record the position of the beam's centroid. This project uses data collected from the BPM and the Muon Monitor (MM) signals to develop two Machine Learning algorithms that each predict the horizontal and vertical position of the beam centroid.

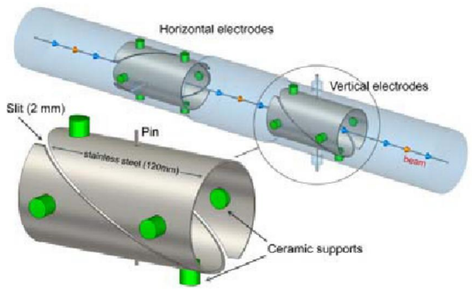


NuMI Beamline System. Protons exit the main injector and enter the target hall, where they collide with the target producing pions, which then decay into muons and muon neutrinos.



BPM system, displaying two of the bpms monitoring the position of the proton beam before it collides with the target.

Left Middle: The stripline bpm. The proton beam enters and passes through the stainless steel cylinder, causing electrons to congregate at the areas of highest positive charge density. The BPMs are fixed with ceramic supports, highlighted in green.



Left Below: Photograph of the muon monitors used in the NuMI Beamline system. The muon monitor is a capacitor filled with helium gas. As the charged muons pass through the capacitor, they interact with the helium atoms, resulting in the electrons being knocked out of the atom and collecting at the positively charged capacitor plate.

My models implement a neural network technique, in which there are several adjustable hyperparameters, including the number of hidden layers (layers of nodes between the input and output layers), the number of nodes per layer, the activation functions used by the nodes, the learning rate, and the number of epochs, or training iterations, the algorithm runs through. Each of these parameters were tested and tuned to produce effective models.

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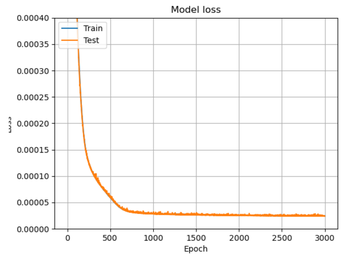
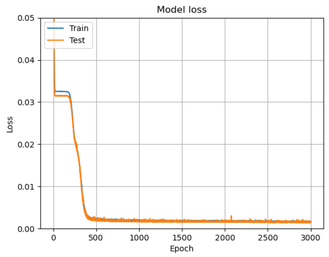
Model Development



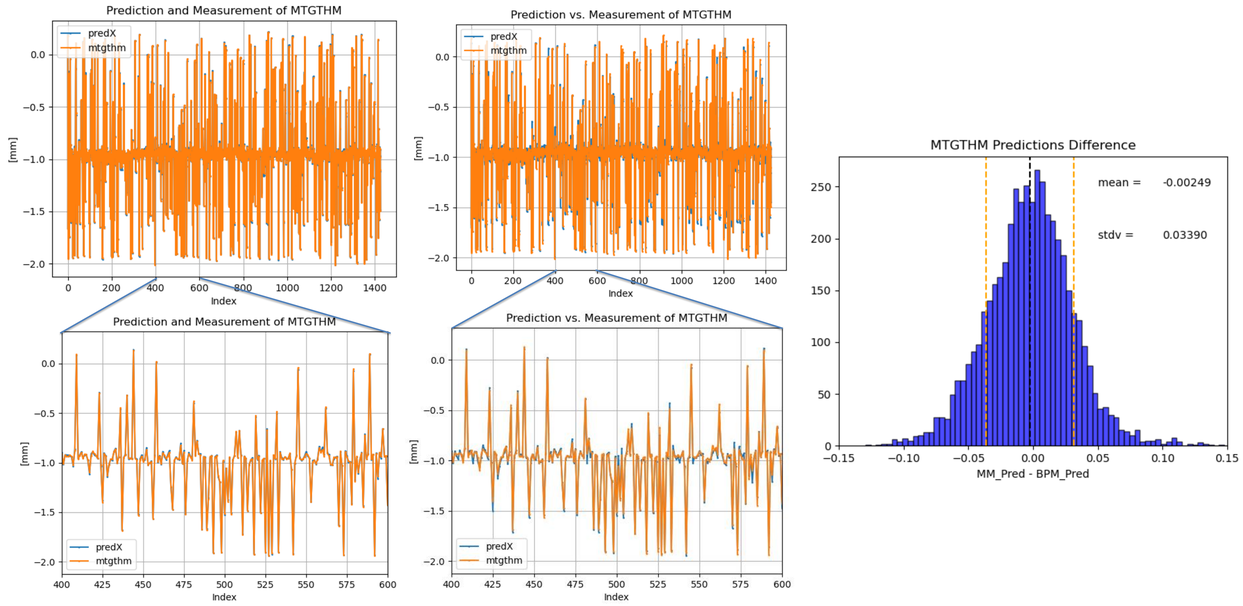


Plots of algorithm performance against training and test data samples over the number of epochs passed.

Left: Plot of performance of model using BPM data

Right: Plot of performance of model using MM data

Two models were developed, one using the BPM data and the other from the MM data, that each predict both the horizontal and vertical location of the beam's centroid. They use 4 hidden layers, with 480, 130, 135, and 11 nodes, and a learning rate of 0.00001. The models were run through 3,000 epochs and produced the predictions below.



Left: Prediction of horizontal position of centroid from BPM data, with close-up of plot pictured below

Middle: Prediction of horizontal position of centroid from MM data, with close-up of plot pictured below

Right: Histogram of the difference between the BPM and MM predictions for the horizontal position, including mean and std.

Remarks

Once implemented, my models will help Fermilab scientists detect BPM and Muon Monitor anomalies. Comparing the relative measurements of three independent beam positions can be used to understand the performance of each device, and if two of the values agree while the third differs, it will also help to understand which measurement is most reliable. Additionally, my project will help ensure the quality of the NuMI beamline.