Fermilab U.S. DEPARTMENT OF ENERGY Office of Science

Machine Learning Applications using NuMI Muon Monitor Data at Fermilab

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Topical Meeting

Feb 15, 2024

Outline

1. Motivation
2. Introduction to the muon monitors
3. Responses of Muon Monitors to the beam parameters
4. Machine Learning Applications

Motivation

Our goal is to improve and monitor the performance of delivering the neutrino beam for experiments by applying modern machine learning techniques.

AI helps to:

» **detect anomalies and developing trends such as target tilt/slip, density effects, horn tilt or slip, etc**

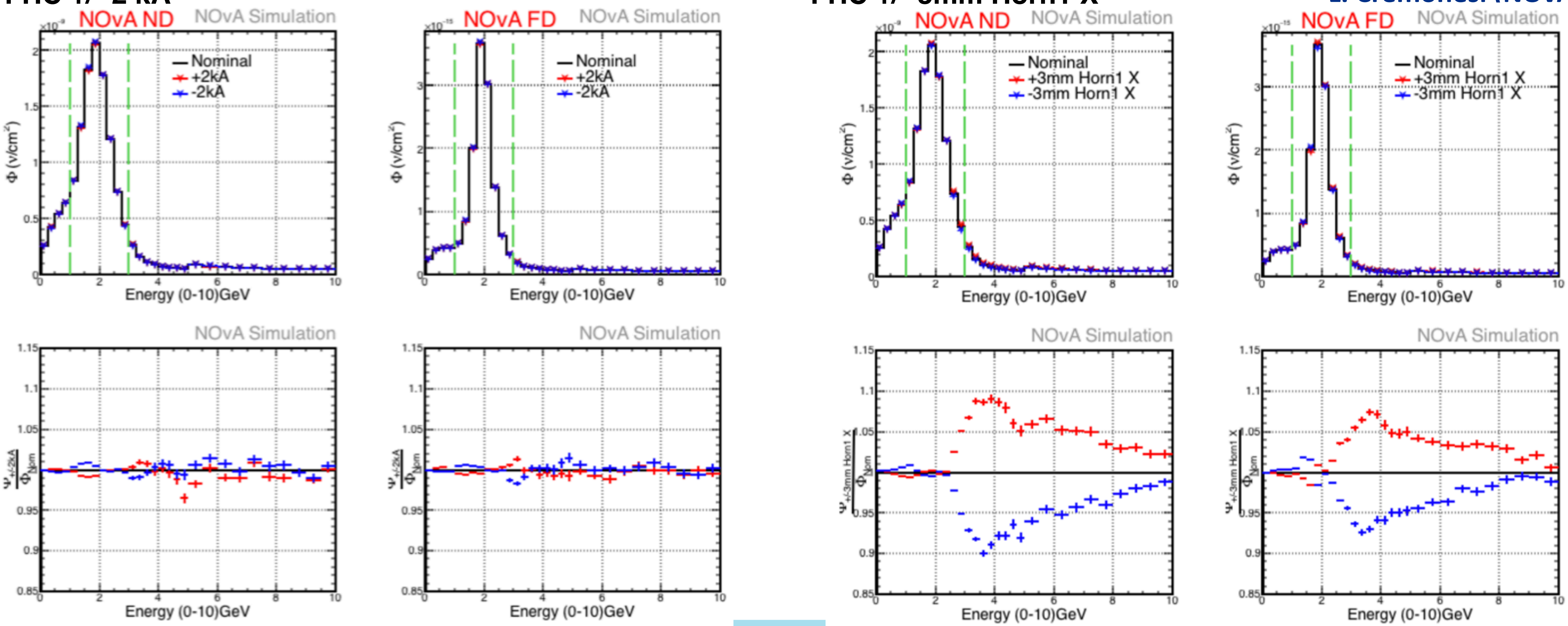
» **understand the physics tolerances in the real time operations**

» **make life easy for operators with ML predictions**

Physics Tolerances for Neutrino Flux Predictions

- **Physics tolerances: the acceptable limitations of possible upstream variables that have an effect on neutrino data quality**
- **Theses tolerances are set according to the simulation studies**
- **Flux systematic uncertainties are calculated according to the tolerances**
- **Any target change effects on neutrino measurements**
- **Changes on horn magnetic field has a significant impact on the neutrino beam**

FHC +/- 2 kA **FHC +/- 3mm Horn1 X** **L. Cremonesi (NOvA)**



Physics Tolerances for Neutrino Flux Predictions

Physics tolerance in NOvA

- Horn Current ±2 kA
- Horn1 position shifted by ±3 mm in X and Y separately
- Horn2 position shifted by ±3 mm in X and Y separately
- Beam position on the target shifted by ±1 mm in X and Y separately
- Beam spot size nominal ±0.2 mm both in X and Y
- Horn water layer ±1 mm
- Target position shifted in z by ±7 mm
- 54 μrad beam divergence

External detector like muon monitor can be used to build AI models to quantify these physics tolerances more precisely with real time beam operations

Quantity	1-sigma Shift	Notes	In TDR
Horn A Transverse Displacement	0.5 mm	X and Y shifted separately, added in quadrature	Y
Horn A Transverse Tilt	0.5 mm	X and Y shifted separately, added in quadrature; upstream and downstream ends shifted in different directions	N
Horn B Transverse Displacement	0.5 mm	X and Y shifted separately, added in quadrature	Y
Horn B Transverse Tilt	0.5 mm	X and Y shifted separately, added in quadrature; upstream and downstream ends shifted in different directions	N
Horn C Transverse Displacement	0.5 mm	X and Y shifted separately, added in quadrature	N
Horn C Transverse Tilt	0.5 mm	X and Y shifted separately, added in quadrature; upstream and downstream ends shifted in different directions	N
Target Transverse Displacement	0.5 mm	X and Y shifted separately, added in quadrature	N
Target Transverse Tilt	0.5 mm	X and Y shifted separately, added in quadrature; upstream and downstream ends shifted in different directions	N
Horn A Longitudinal Displacement	2 mm		N
Horn B Longitudinal Displacement	3 mm		N
Horn C Longitudinal Displacement	3 mm		N
Proton Beam Transverse Position	0.5 mm	X and Y shifted separately; added in quadrature	Y
Proton Beam Radius	10%	Updated from 0.1 mm for NuMI	Y
Proton angle on target	70μ rad	X and Y shifted separately; added in quadrature	Y
Decay Pipe Radius	0.1 m		Y
Horn Currents	1%	Changed in all three horns simultaneously	Y
Baffle Scraping	0.25%	To Be Updated	N
Bafflet Scraping	0.25%	To Be Updated	N
Target Density	2%		Y
Horn Water Layer Thickness	0.5 mm	Changed in all three horns simultaneously	Y
Upstream Target Degradation			N
# Protons on Target	2%		Y
Near Detector Position			N
Far Detector Position			N
Field in Horn Necks			N
Decay Pipe Position	20 mm		N

DUNE preliminary

Table 1: Sources of alignment and focusing uncertainties in the neutrino fluxes at DUNE. Sources that were considered in physics studies in the TDR are marked with a 'Y' in the 'In TDR' column.

DUNE-DocDB-19942

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2. **Introduction to the muon monitors**
3. Responses of Muon Monitors to the beam parameters
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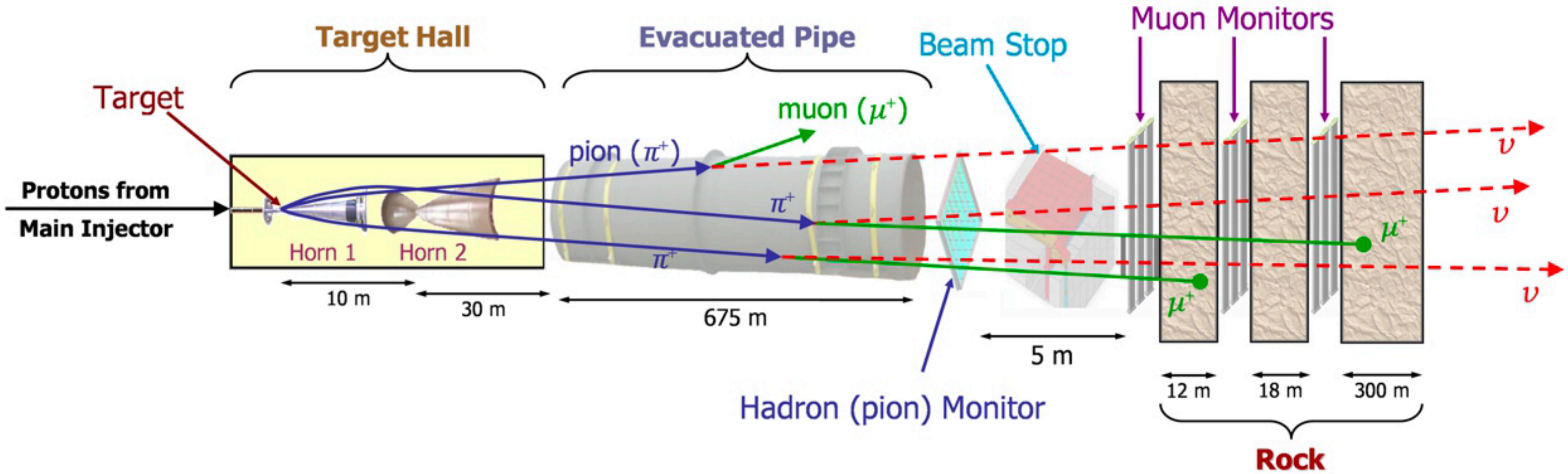
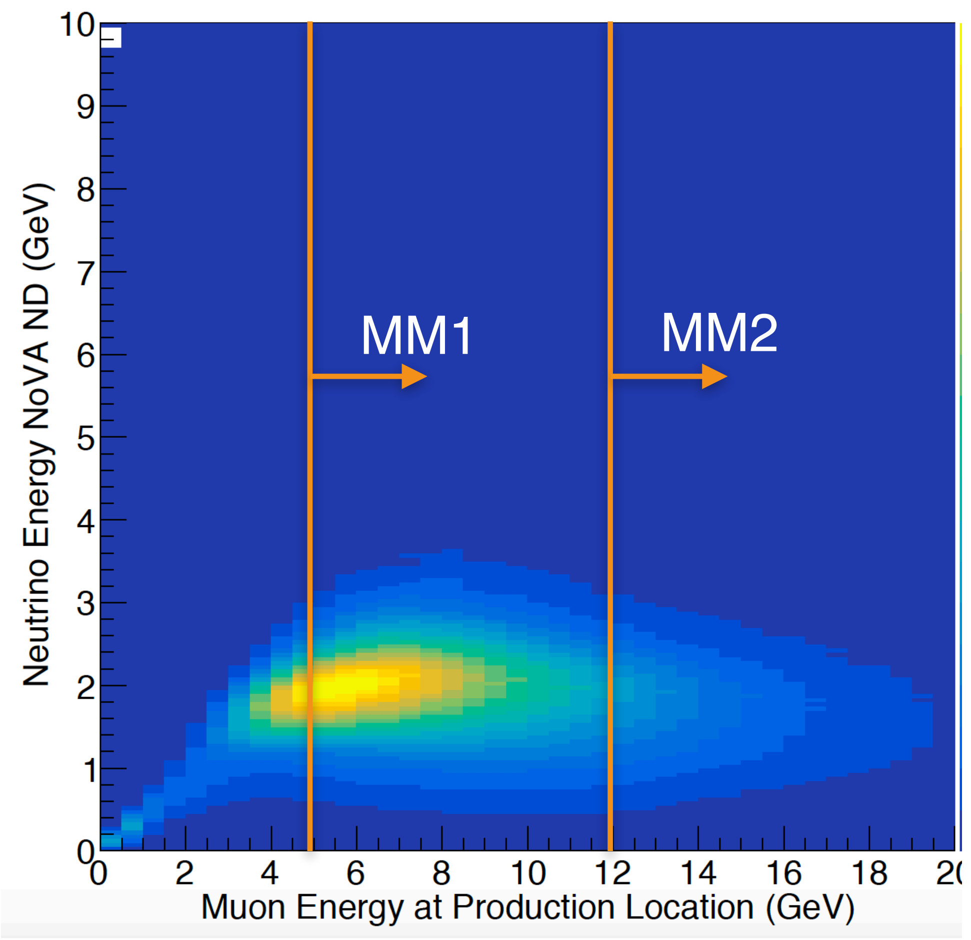
Introduction to Muon Monitors



- Three muon monitors are located in the downstream of the hadron absorber
- Each muon monitor consist of 9x9 arrays of ionization chambers
- Each ionization chamber consists of two ceramic parallel plates with the separation of 3 mm gap
- The chambers are filled with He gas



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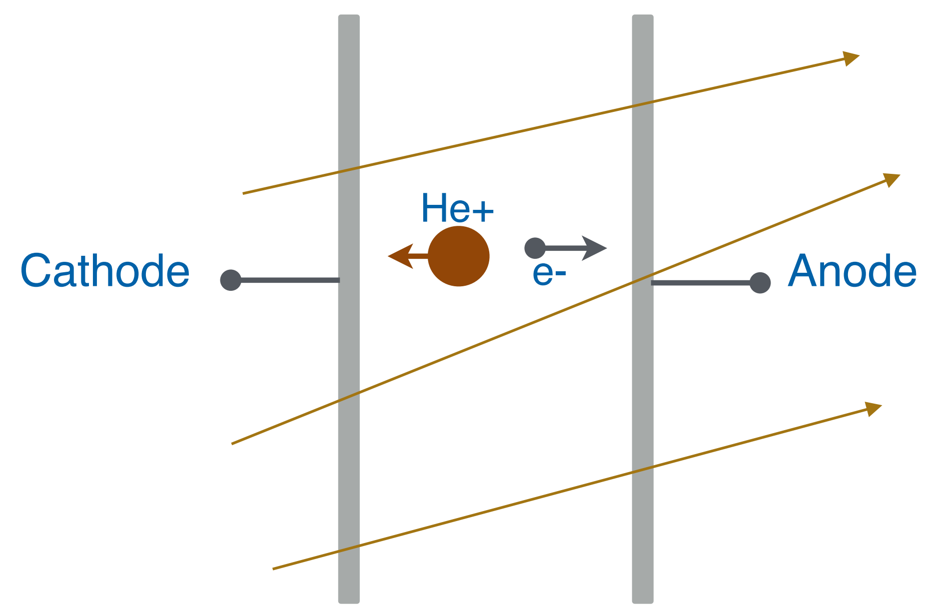
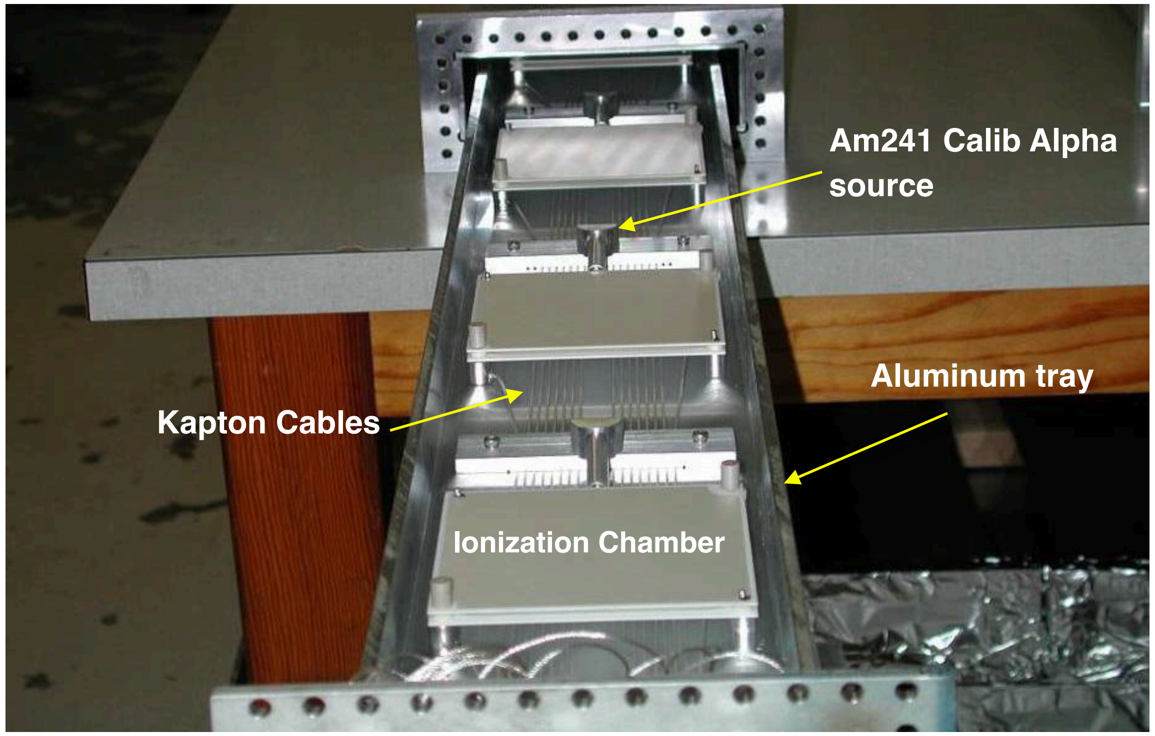
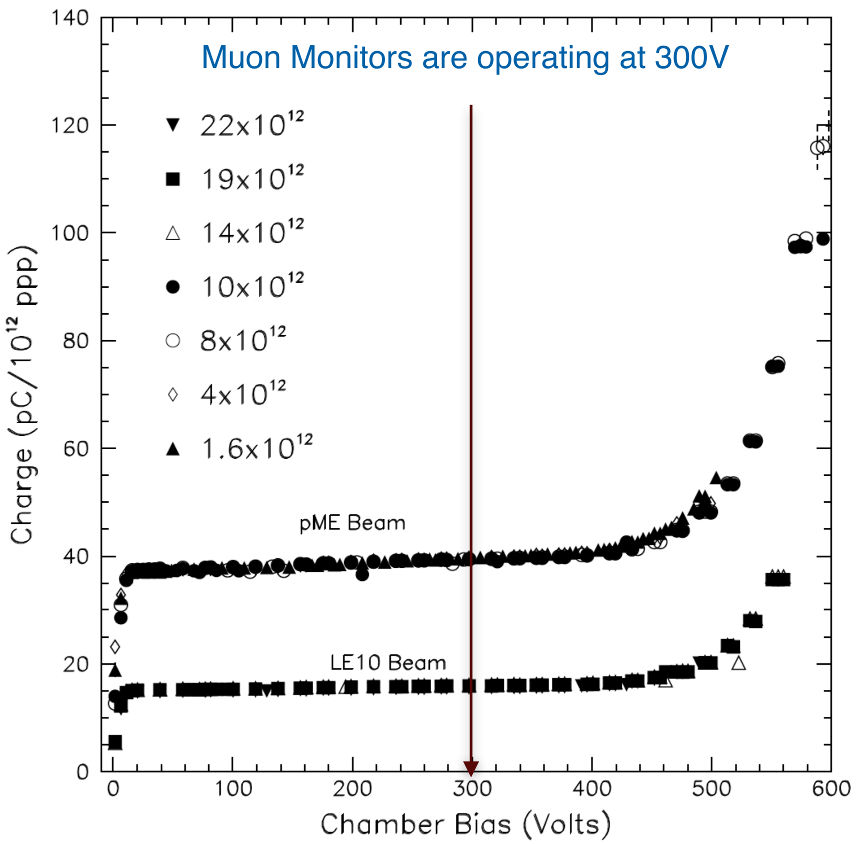
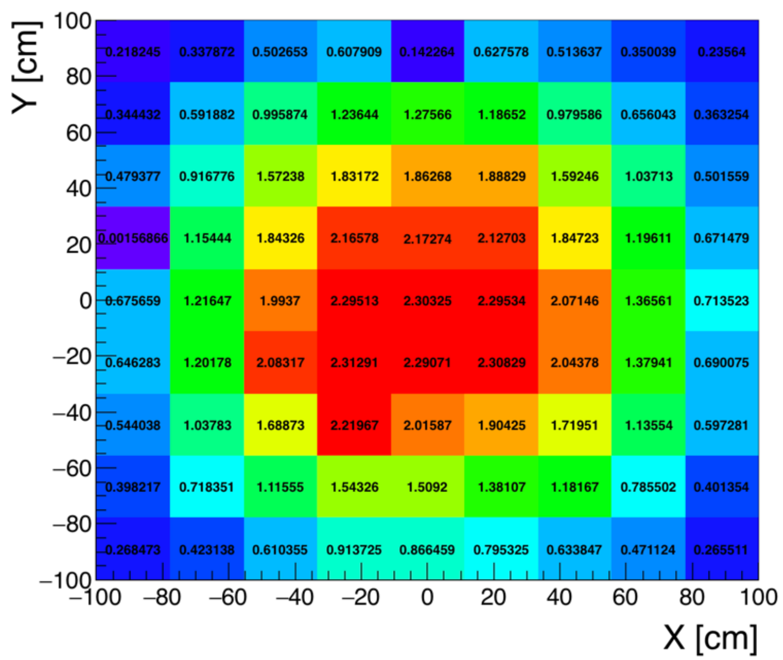
Introduction to Muon Monitors









- **Operational voltage has been selected to minimize the recombination effects and to avoid the signal issues with the proportional region**

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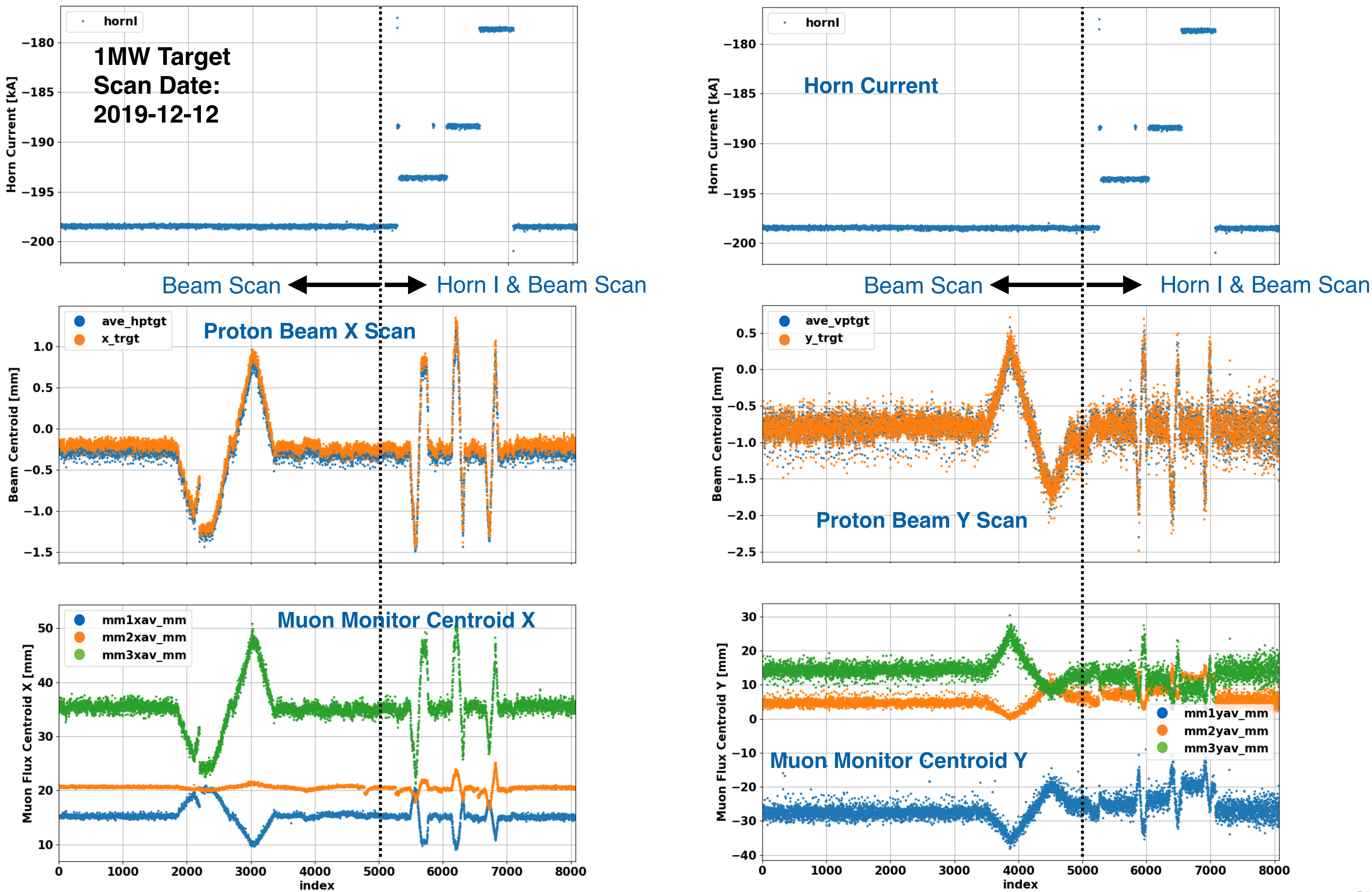
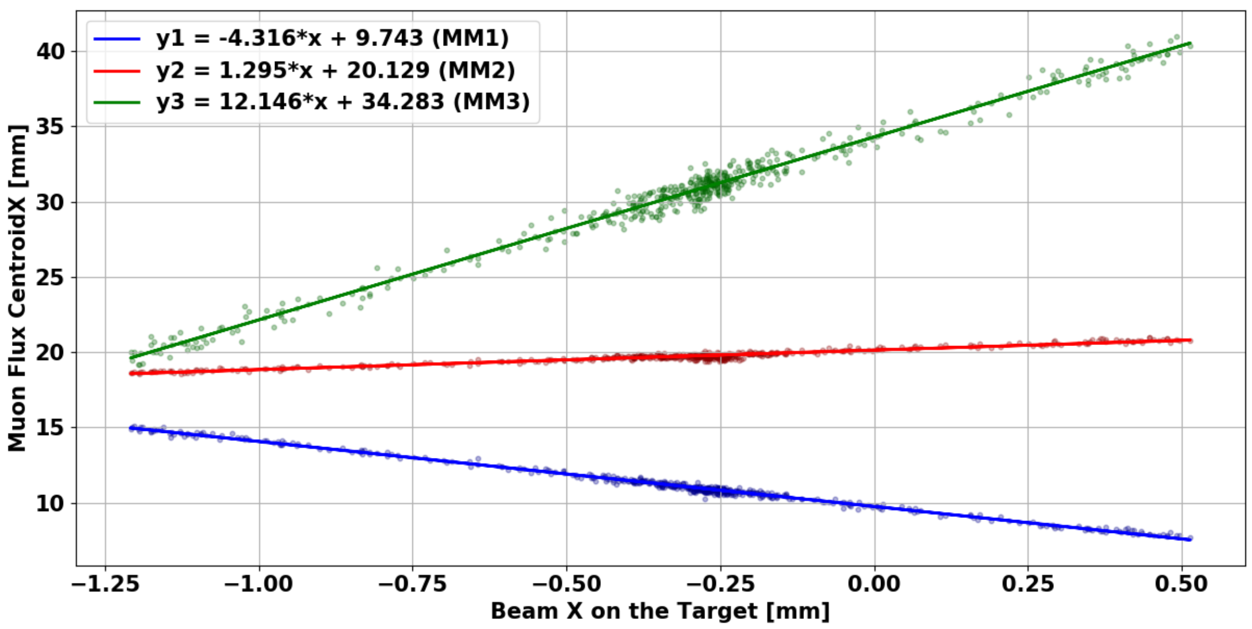
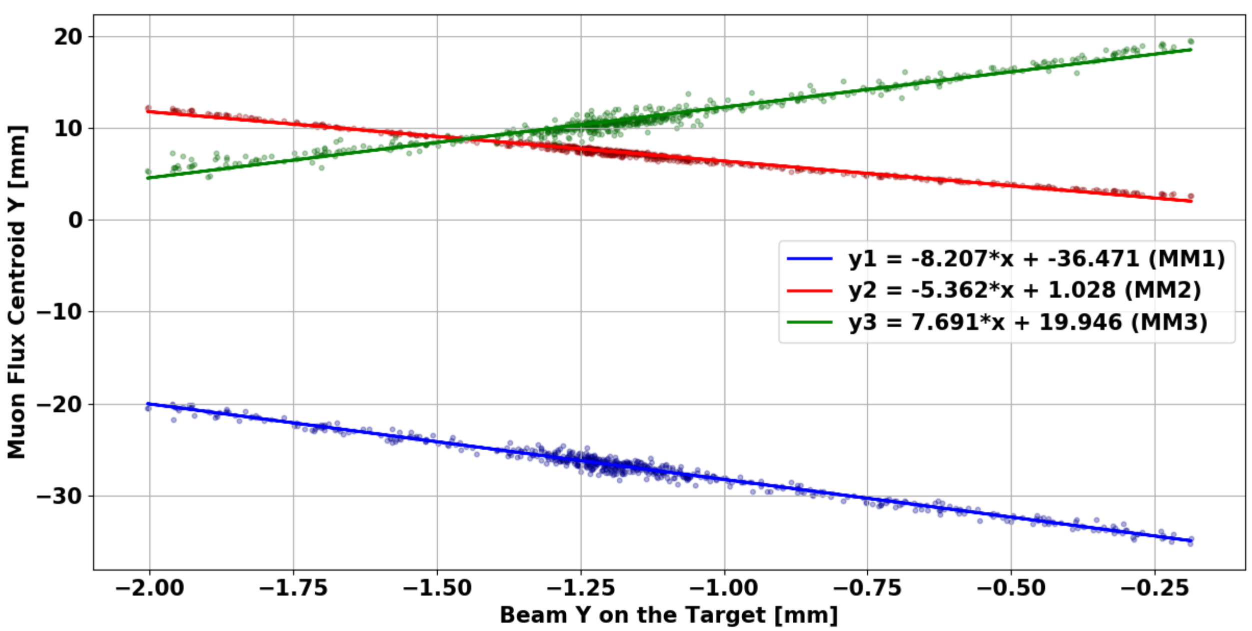
Horizontal and Vertical Scan



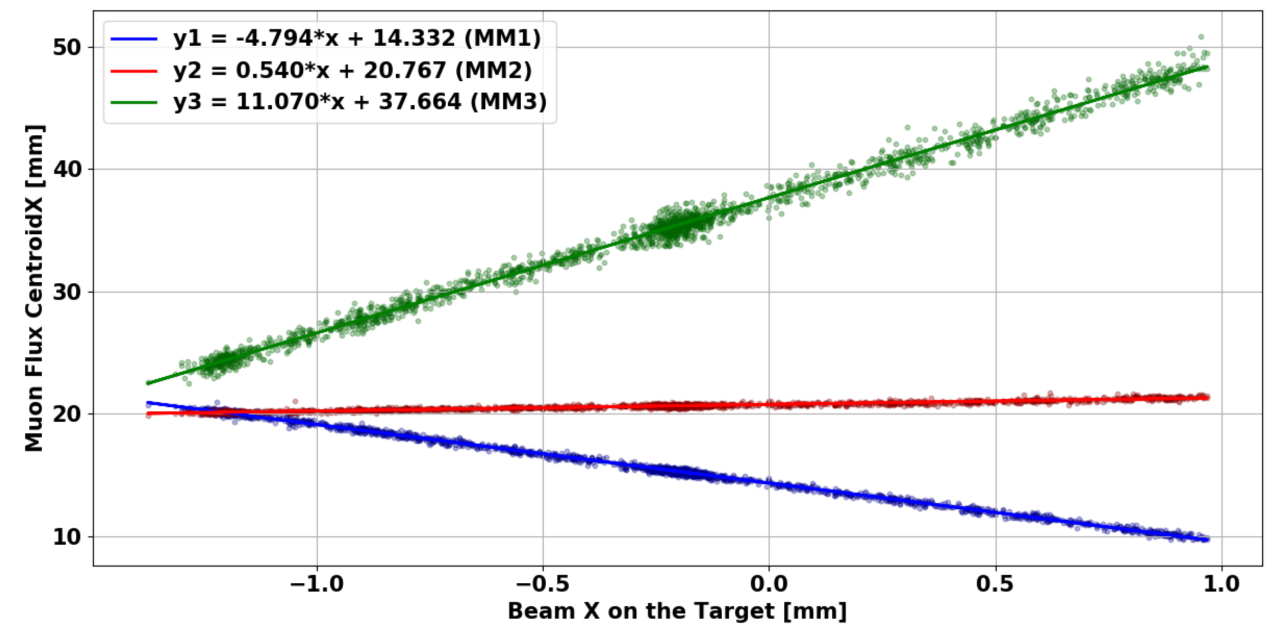
Correlations from beam scans

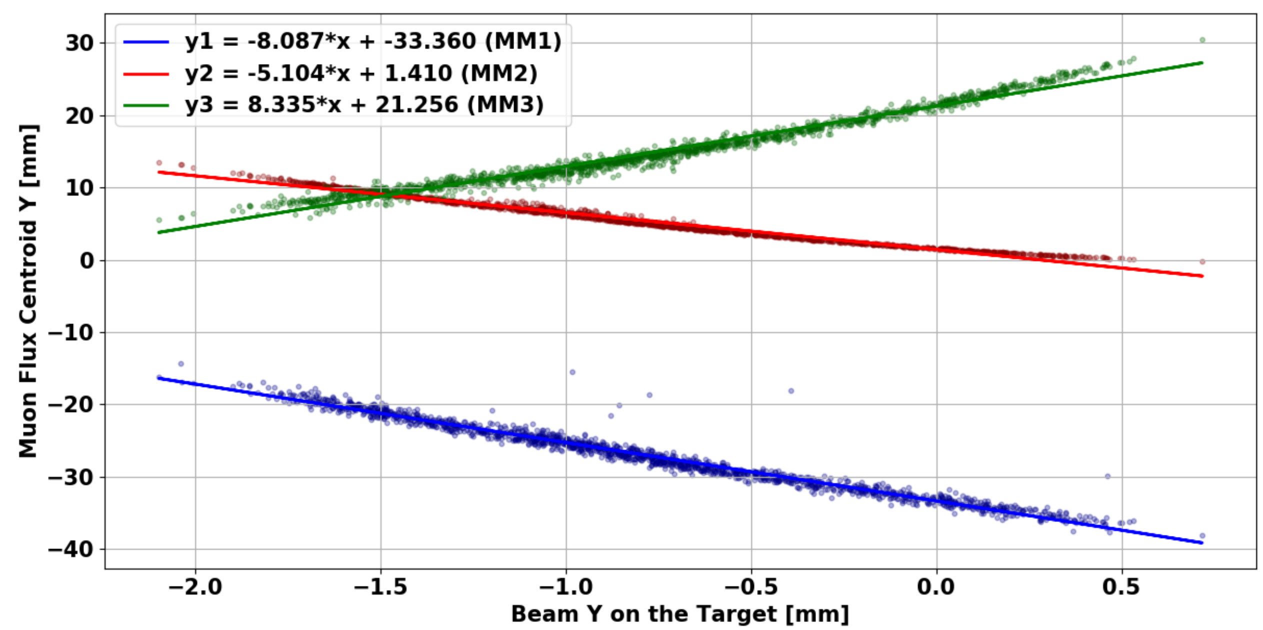
Scan data: 2019-07-03





Scan data: 2019-12-12





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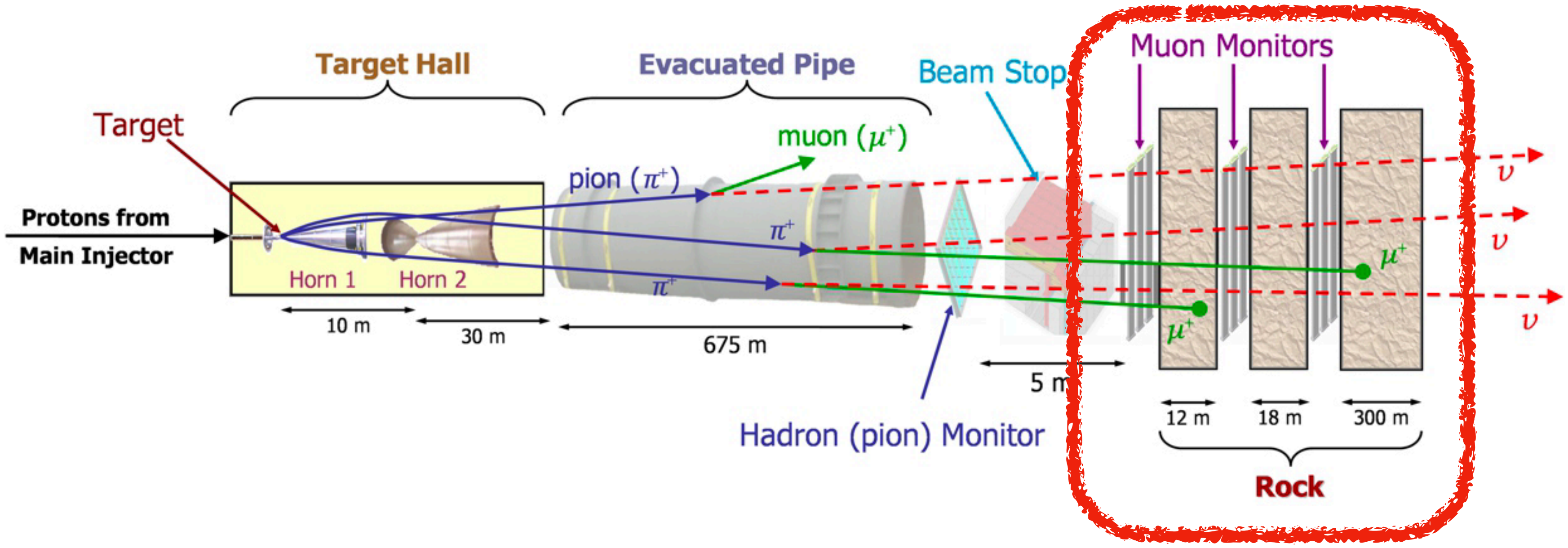
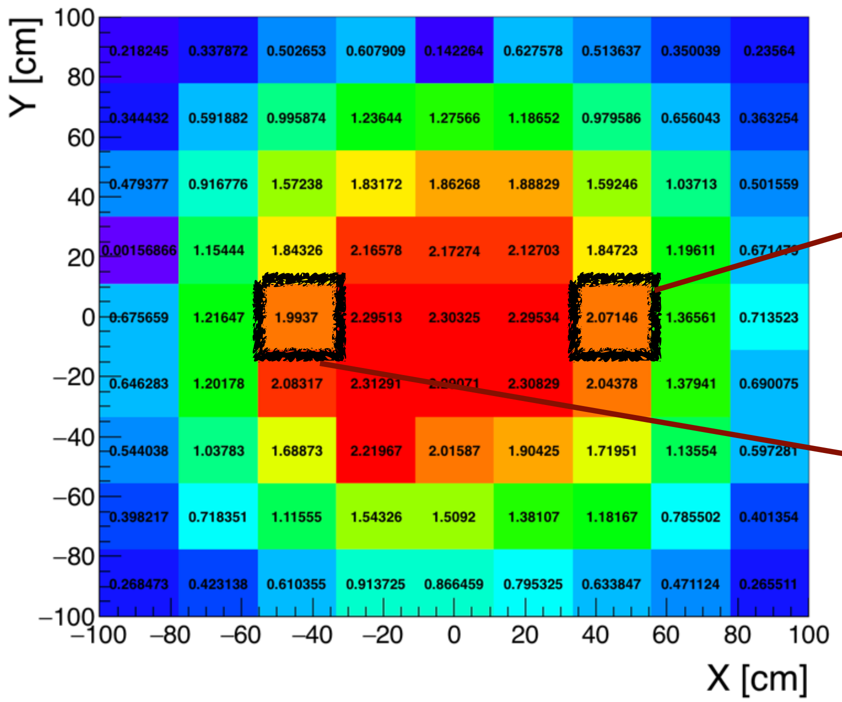
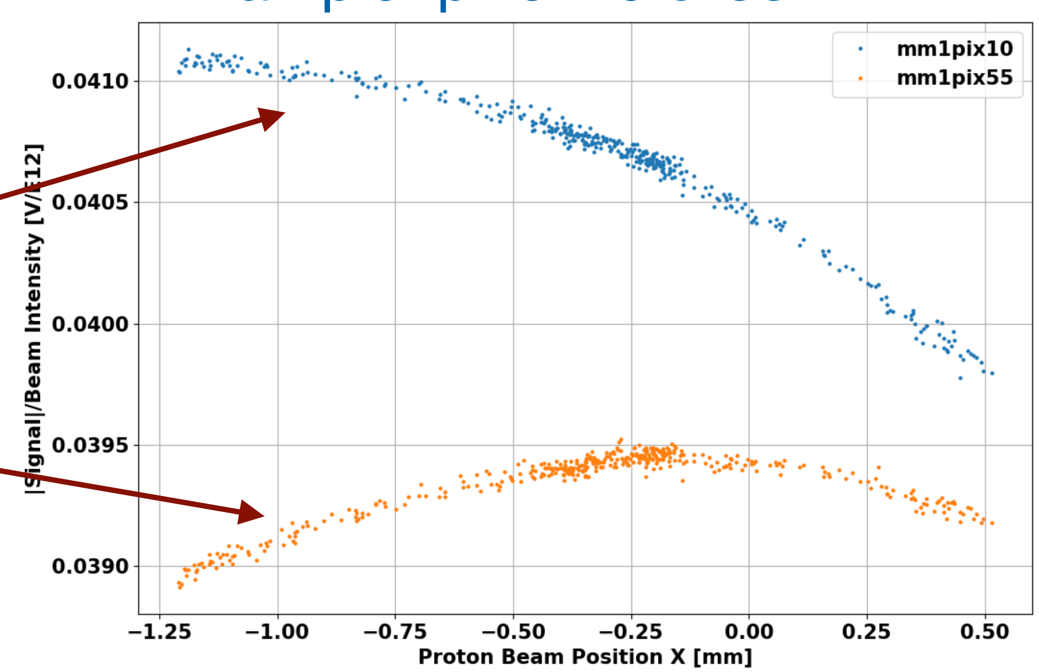
Pixels Responses



- Each muon monitor sensitive to different hadron momentum thresholds
- Focusing of muon flux at the monitors is unique
- Unique responses of individual pixels to the upstream beam, target and horn focusing changes



Example: pixel 10 & 55



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1. Motivation
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3. Responses of Muon Monitors to the beam and the horn current
4. **Machine Learning Applications**
   - **Predicting Beam Parameters**
   - **Identifying incidents / anomalies**

Next

Predicting Beam Parameters

MOTIVATION: Building a model to predict upstream beam variables by using downstream muon monitor data.

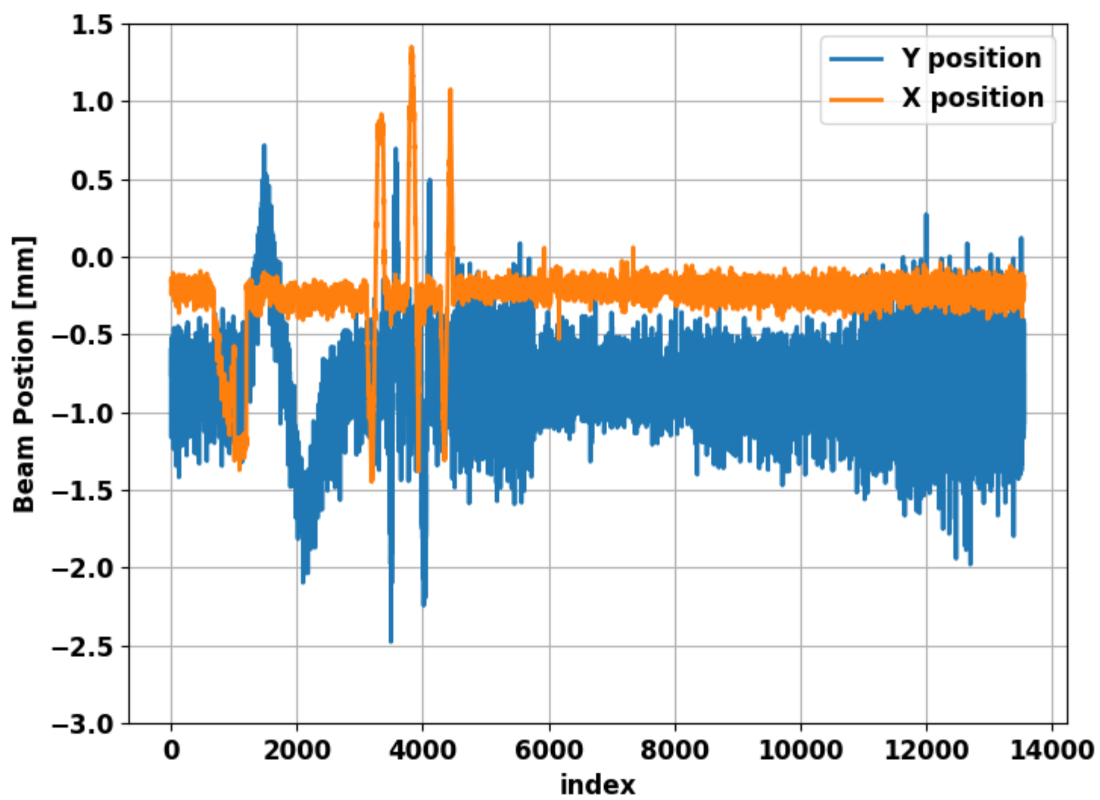
A Model to Predict Beam Variables and Horn Current

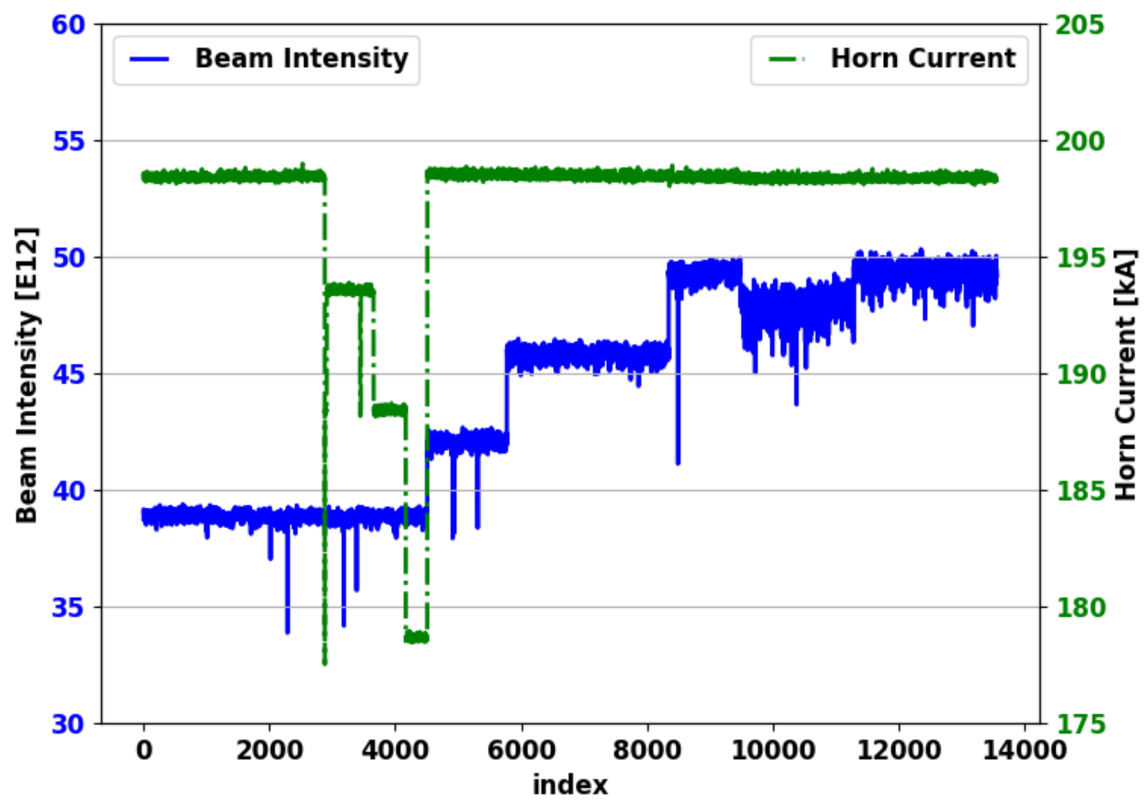
Data Preparation:

» **The data samples have been collected from the spill-by-spill time series measurements**

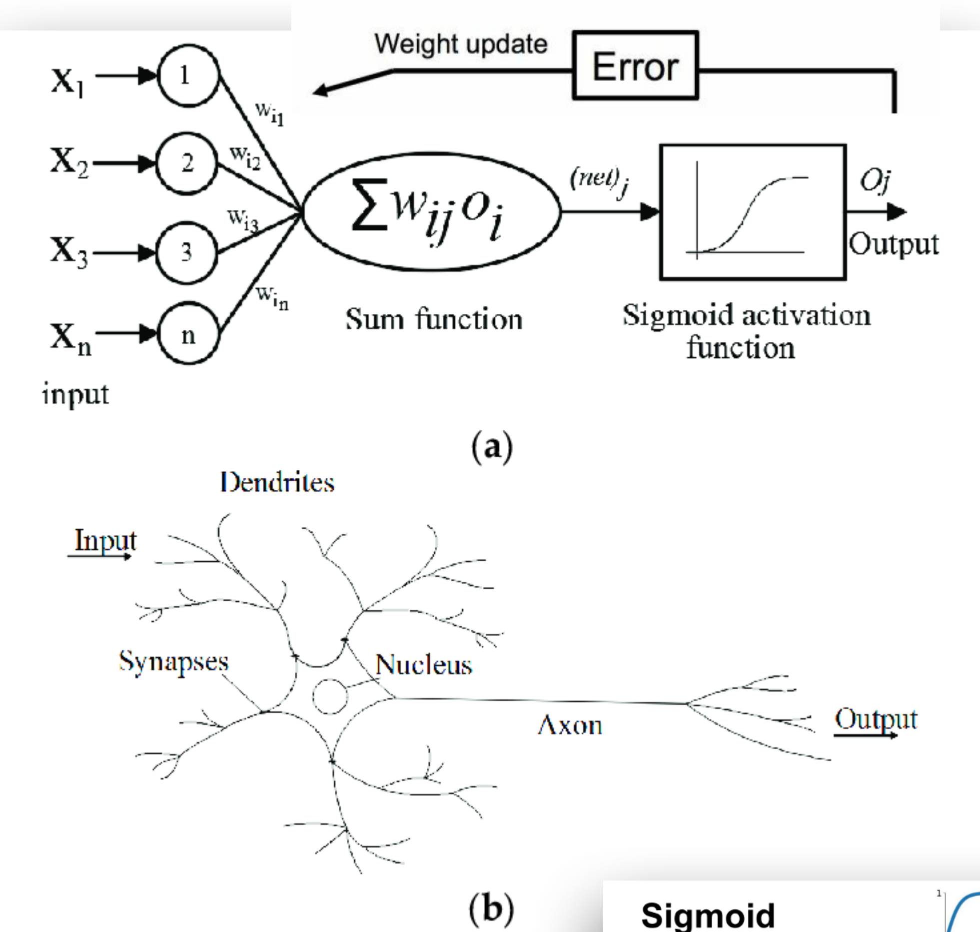
» **The randomly sampled training (70%) and validation (30%) data samples were selected from the target scans and normal operations**

» **A neural network has been trained by taking account 241 pixels as inputs**

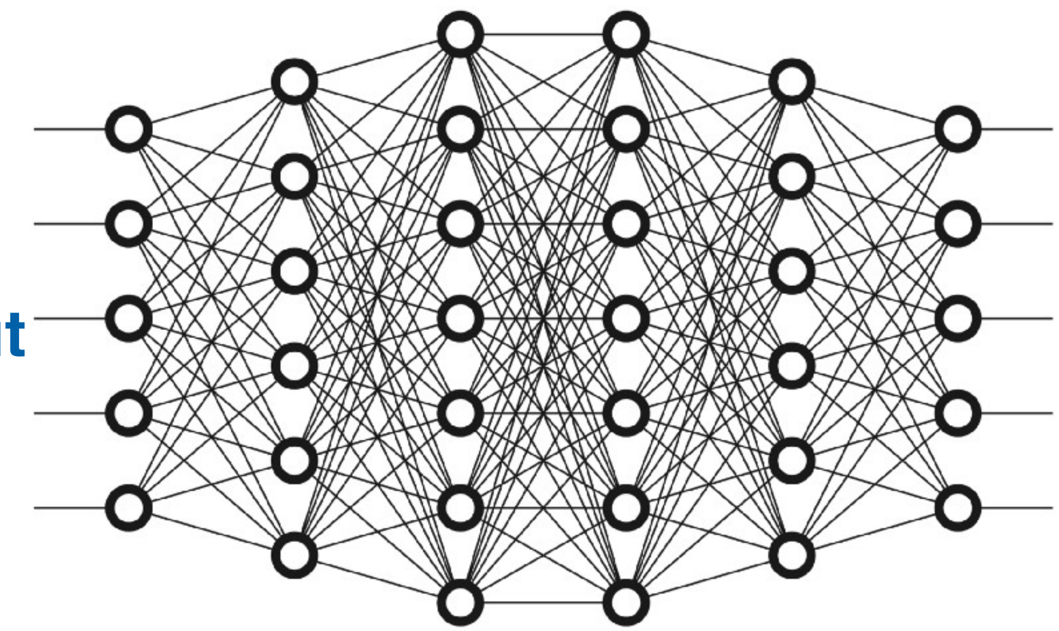




Neural Network Architecture



Input

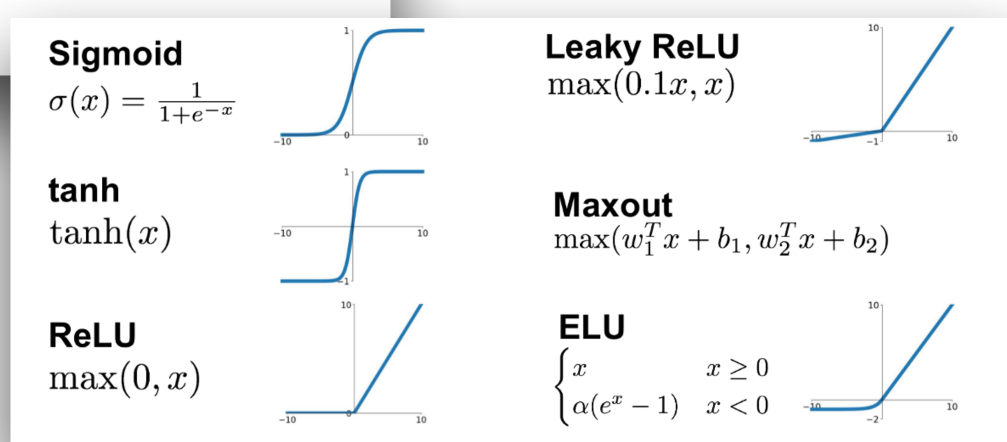


Output

Hidden Layers

$$\boxed{w_{new} = w_{old} + \eta \cdot \nabla Error}$$

Activation function



Weights are updated according to the back-propagation algorithm

Example of an activation function

$$\frac{1}{1 + \exp\left(-\sum_j w_j x_j - b\right)}.$$

Network tuning

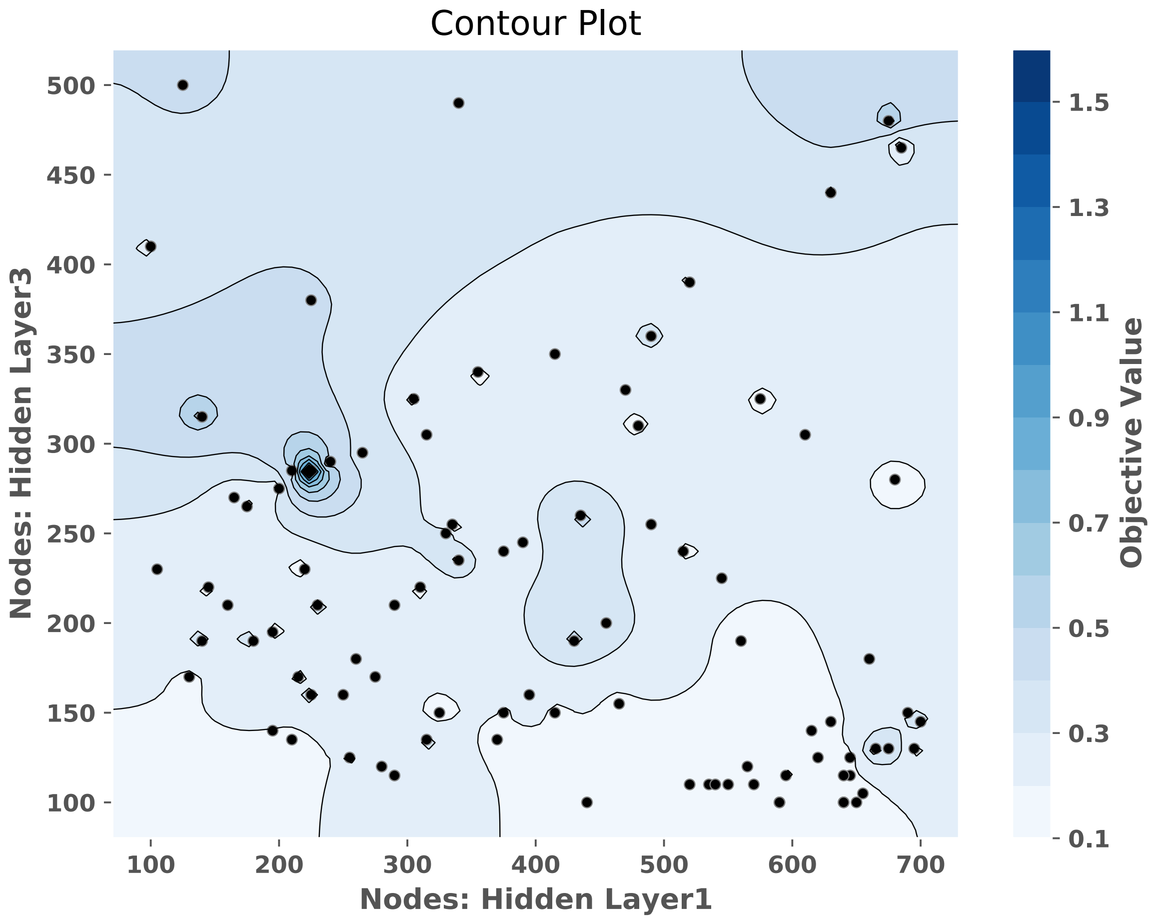
- » Learning rate
- » Number of nodes
- » Activation functions
- » Number of hidden layers
- » Batch size

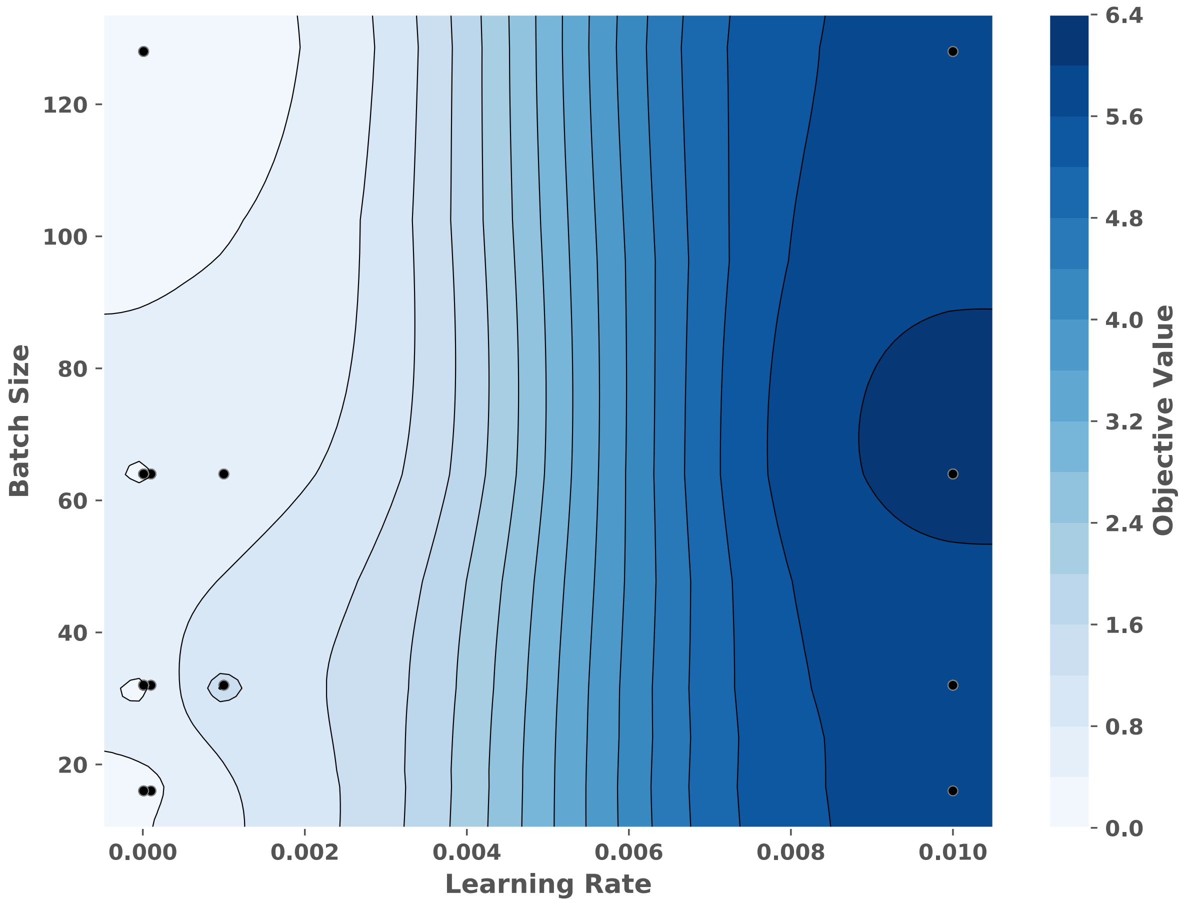
Hyperparameter Tuning

The process of searching for the best model architecture is referred to as hyperparameter tuning.

» **Tuning the model based on Bayesian Optimization Algorithm.**

» **Searching the optimal parameters minimizing the standard error on predictions.**





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Optimized Model Architecture

An example of optimized ANN architecture:

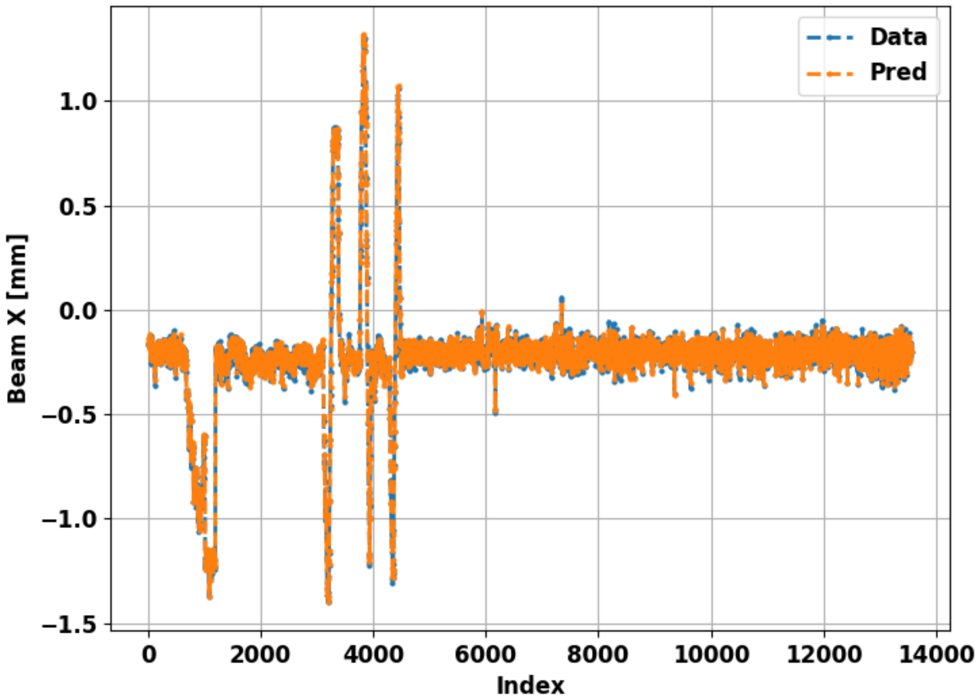
Input pixels = 241(removed 2 bad pixels)

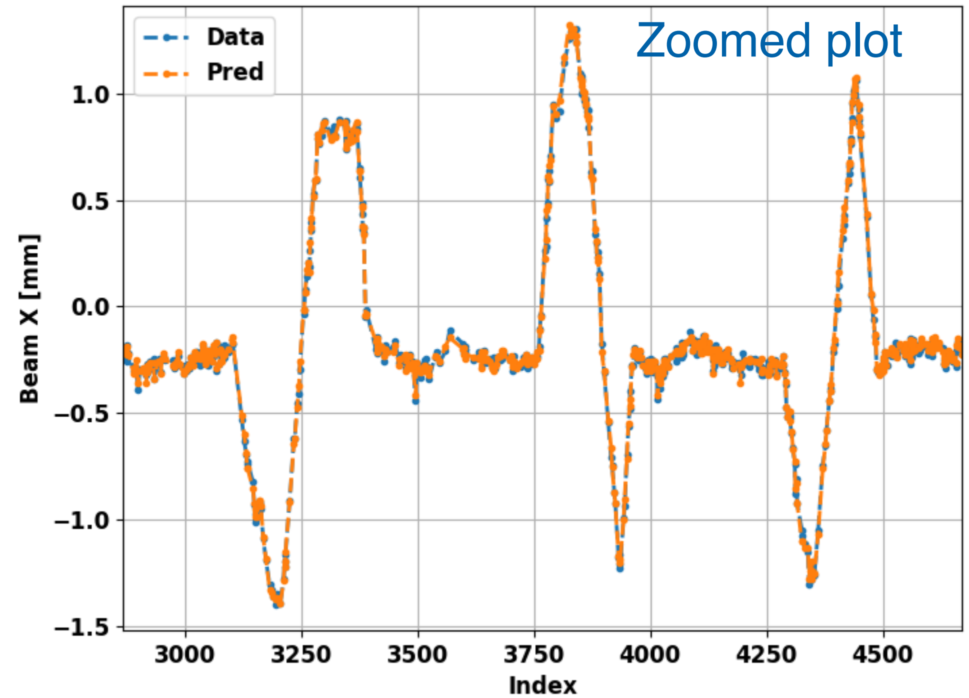
Batch size = 32

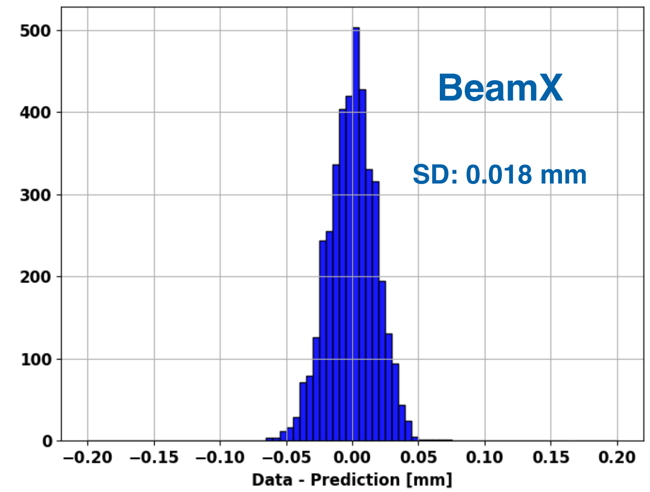
Learning rate = 1E-5

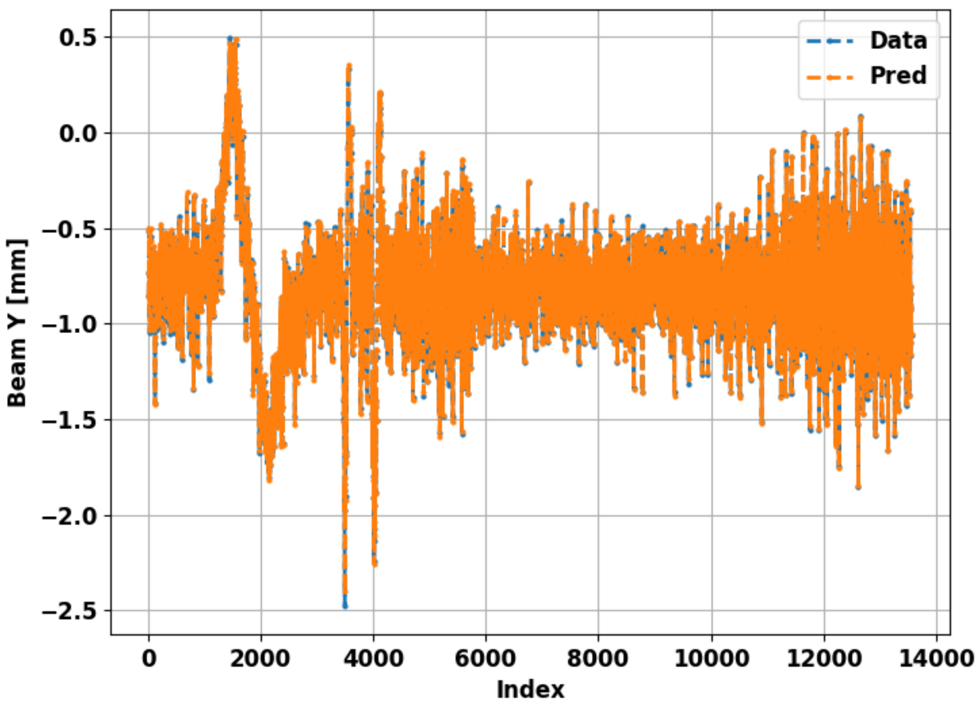
Layer (type)	Output Shape	Param #	**Activation**
dense (Dense)	(None, 480)	116160	Tanh
dense_1 (Dense)	(None, 130)	62530	Sigmoid
dense_2 (Dense)	(None, 135)	17685	Sigmoid
dense_3 (Dense)	(None, 11)	1496	Sigmoid
dense_4 (Dense)	(None, 4)	48	Linear

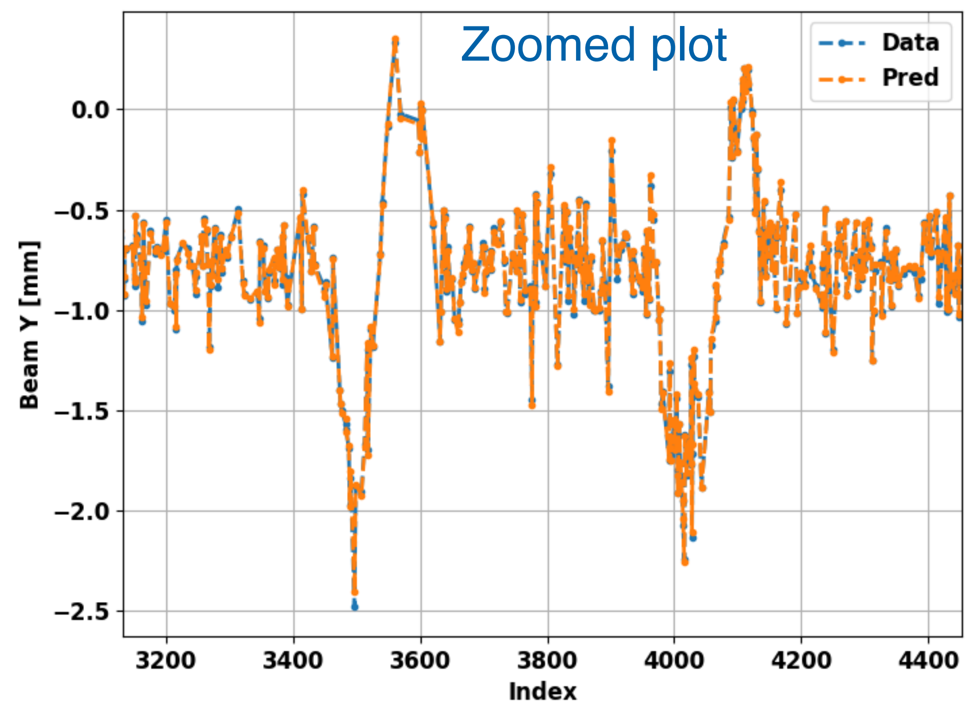
Predicting Proton Beam Positions

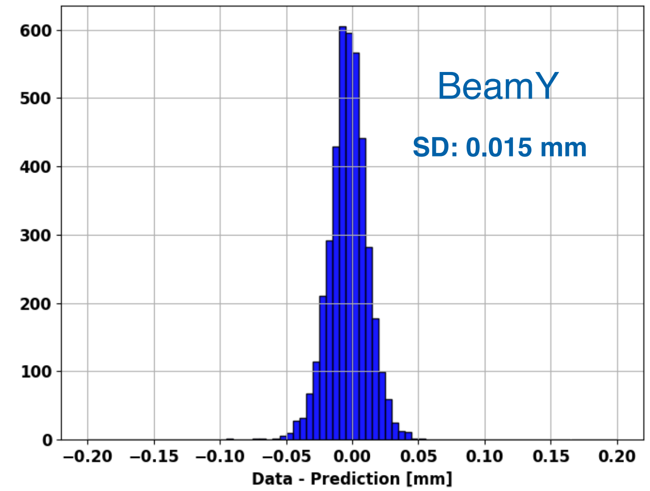




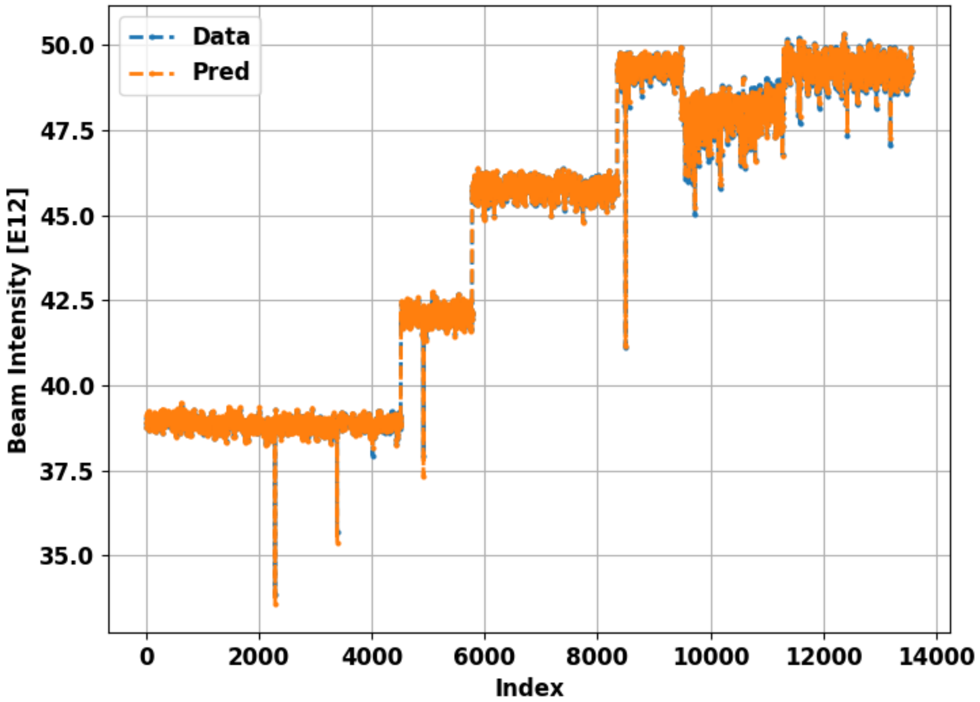


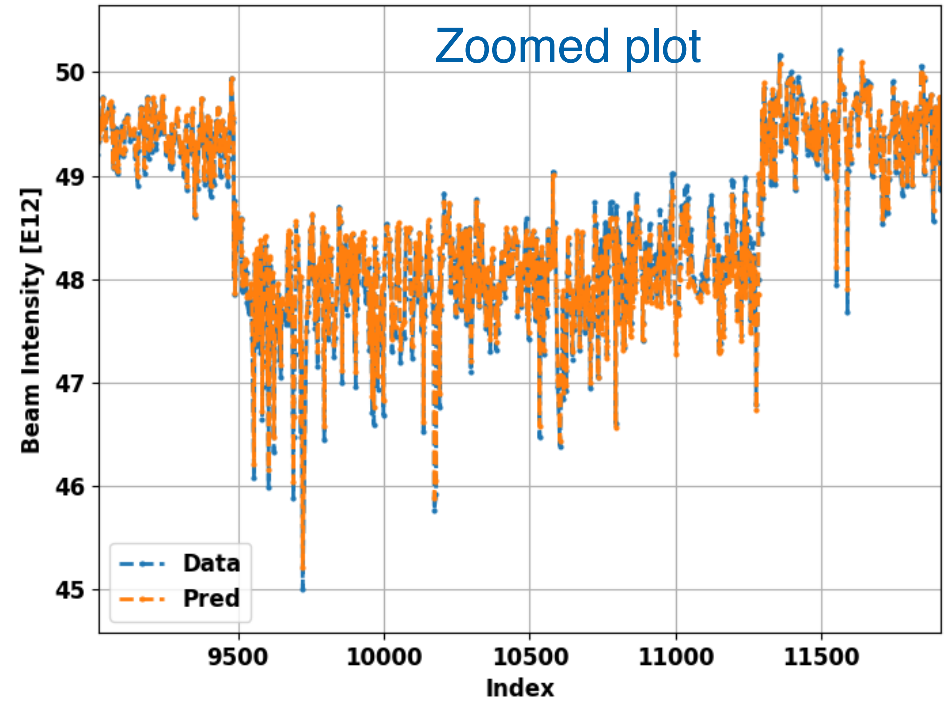


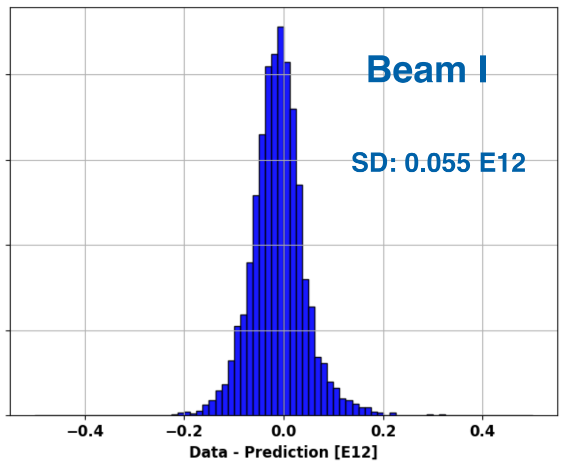


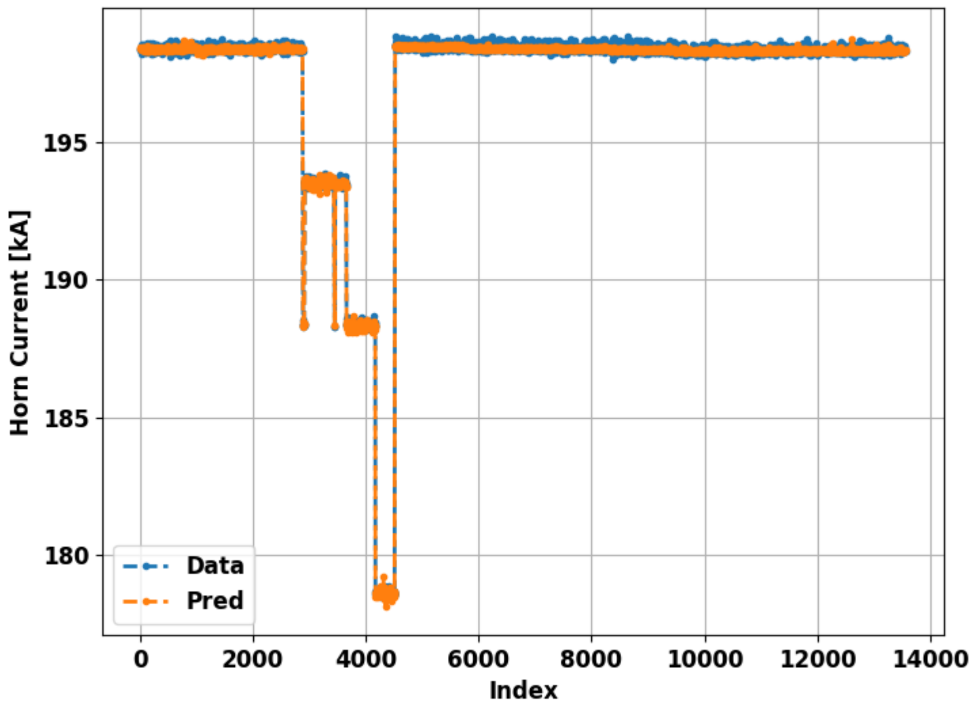


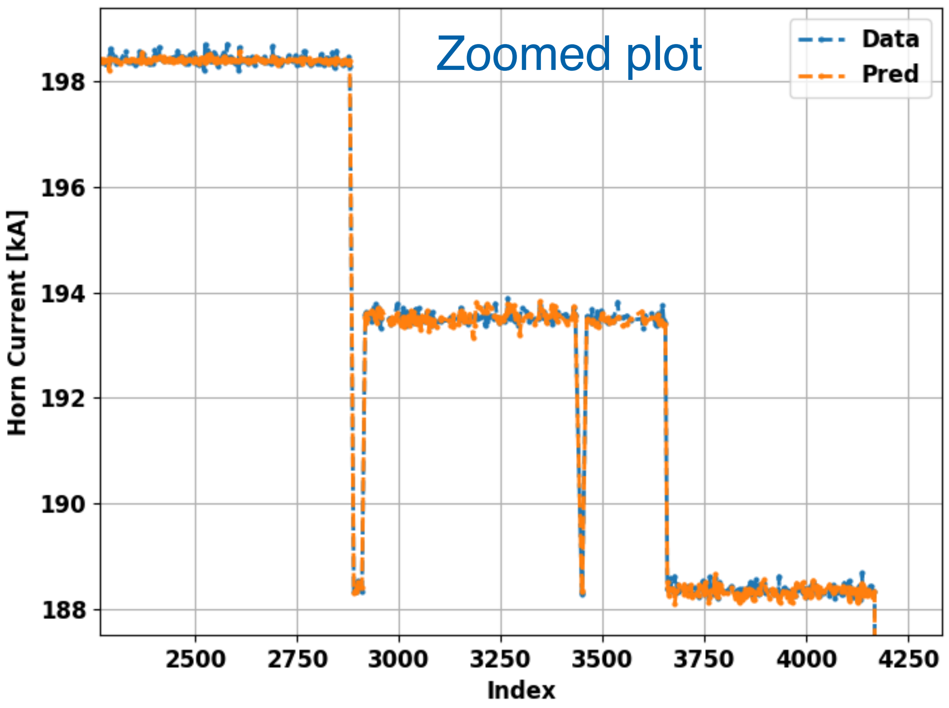
Predicting Beam Intensity and Horn Current

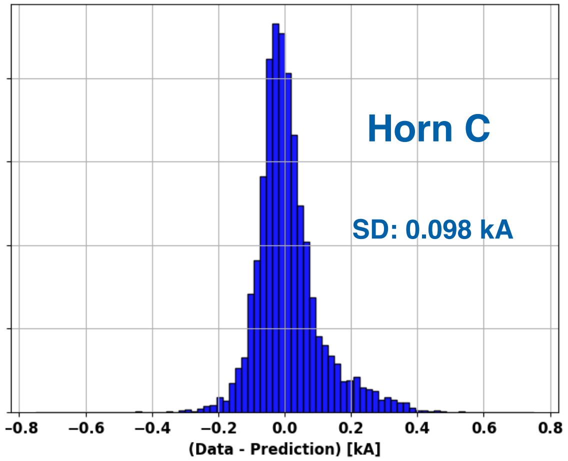






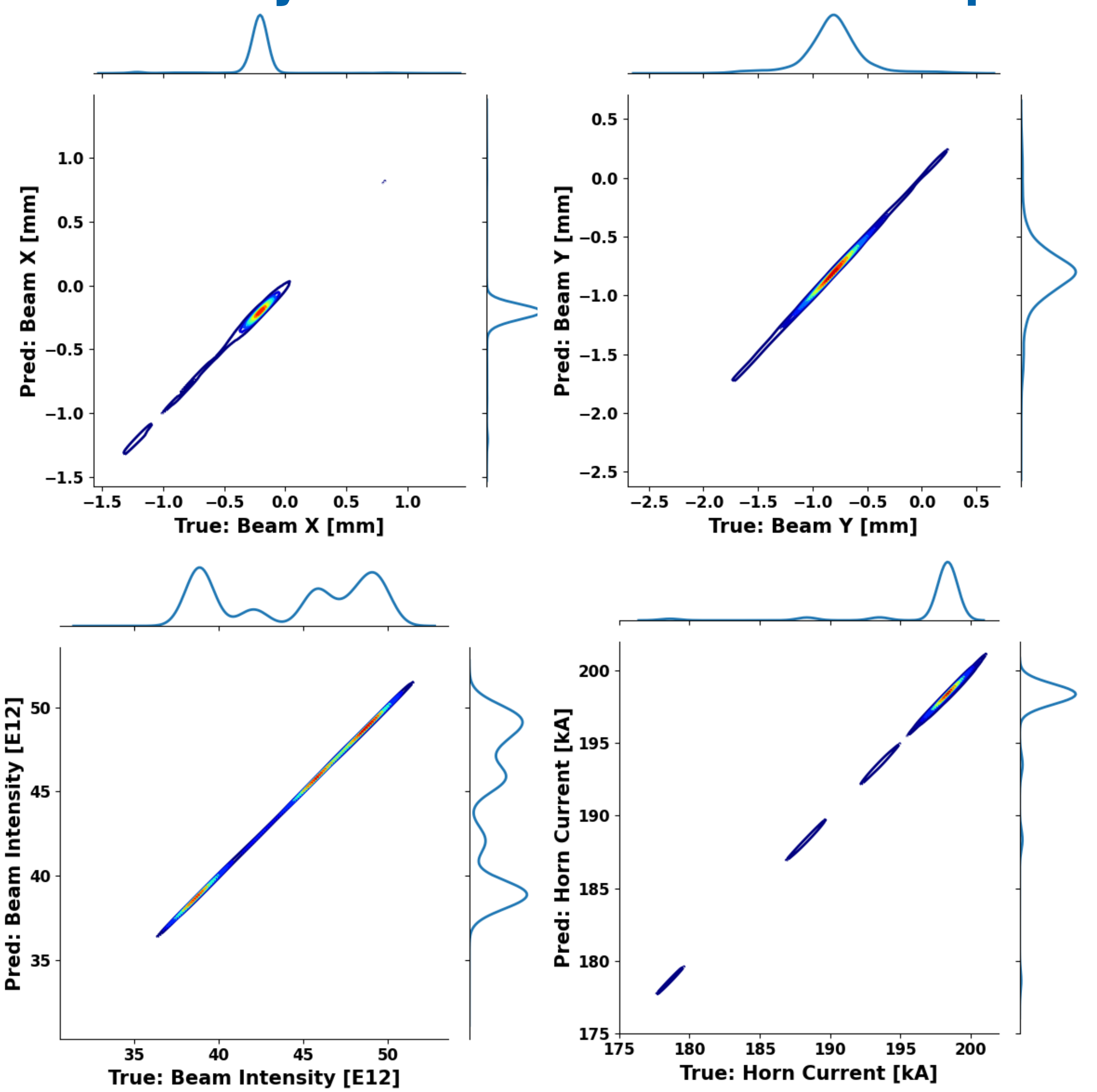






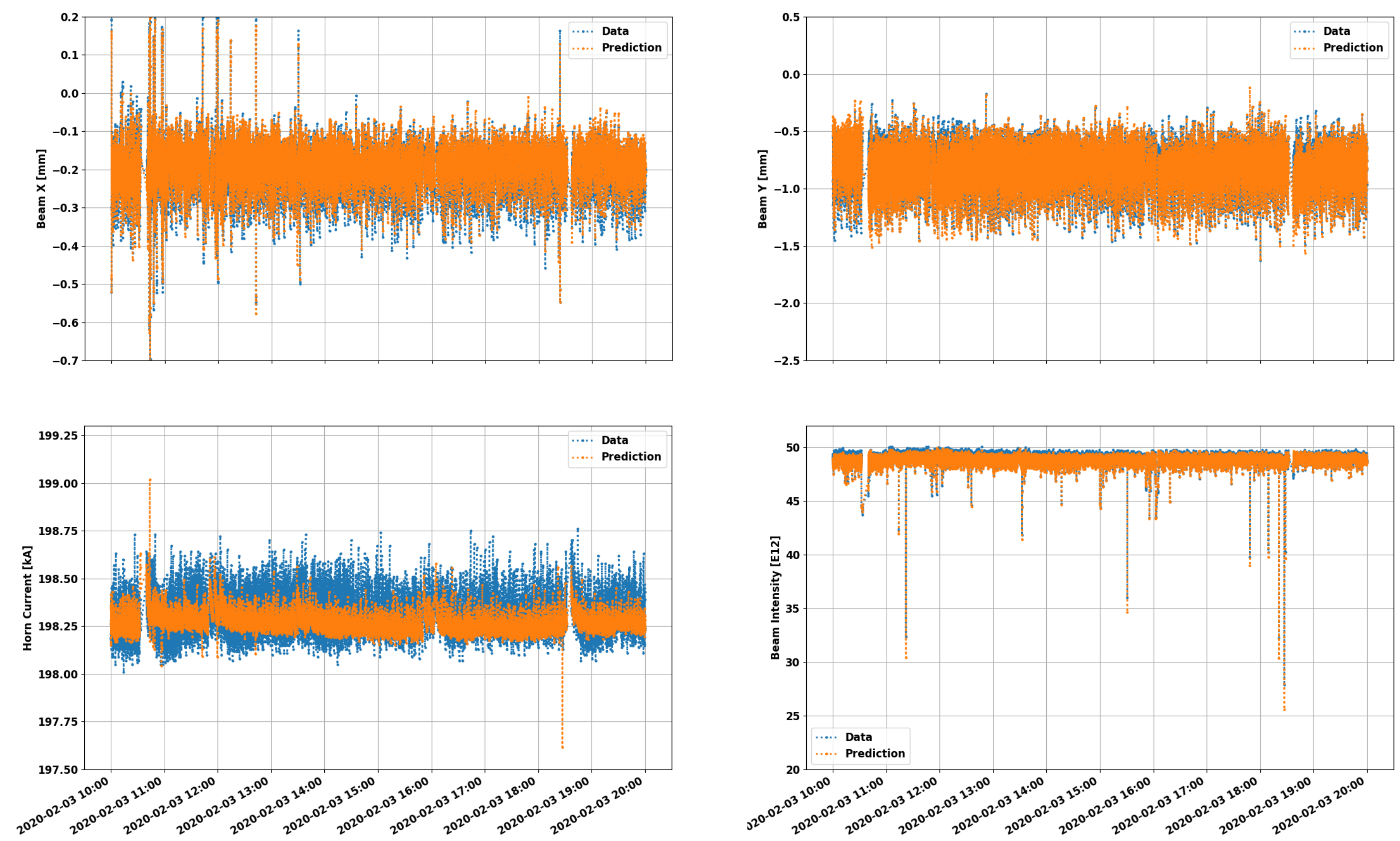
Validating and Testing

The model validation and performance testing have been done by using randomly selected validation sample.

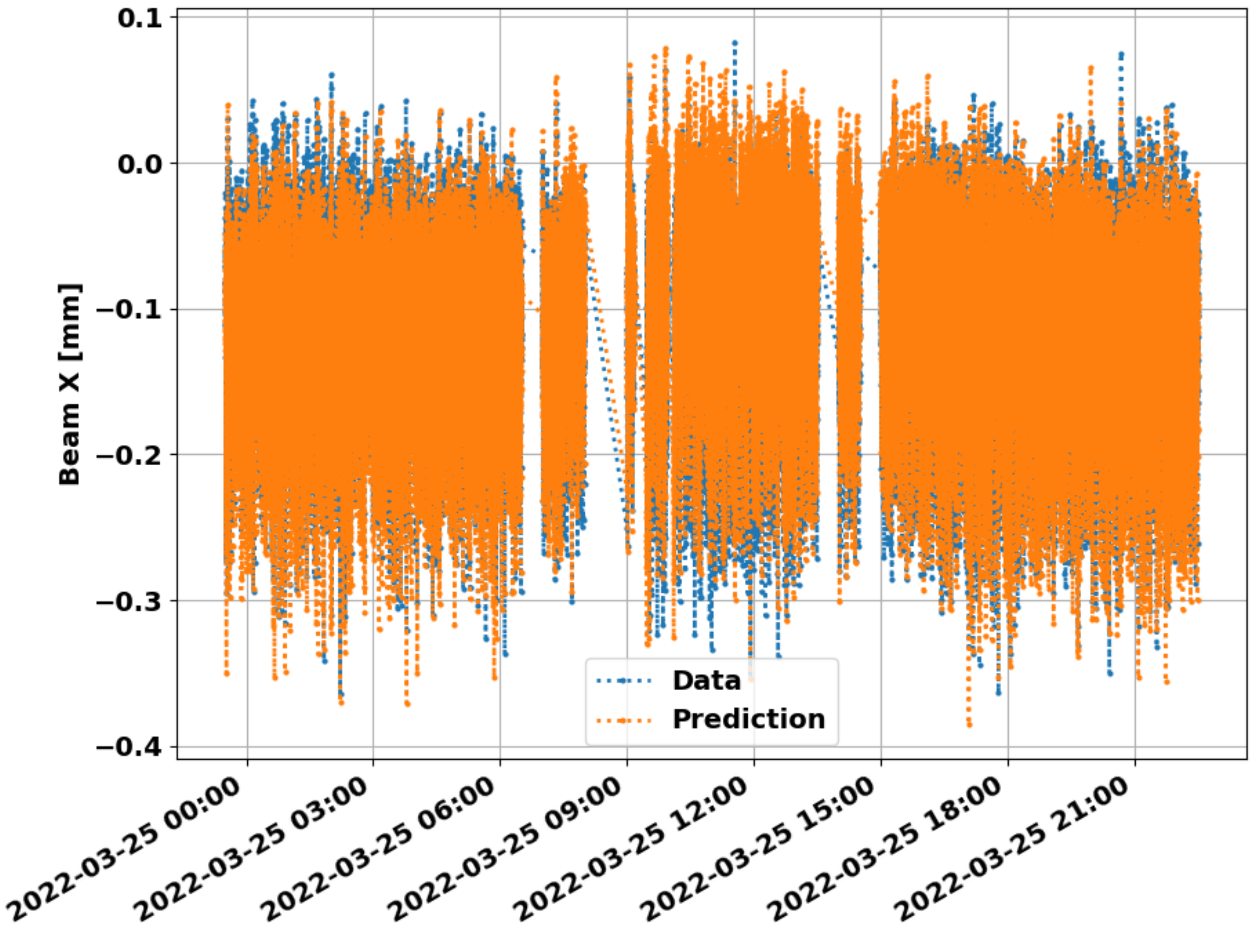


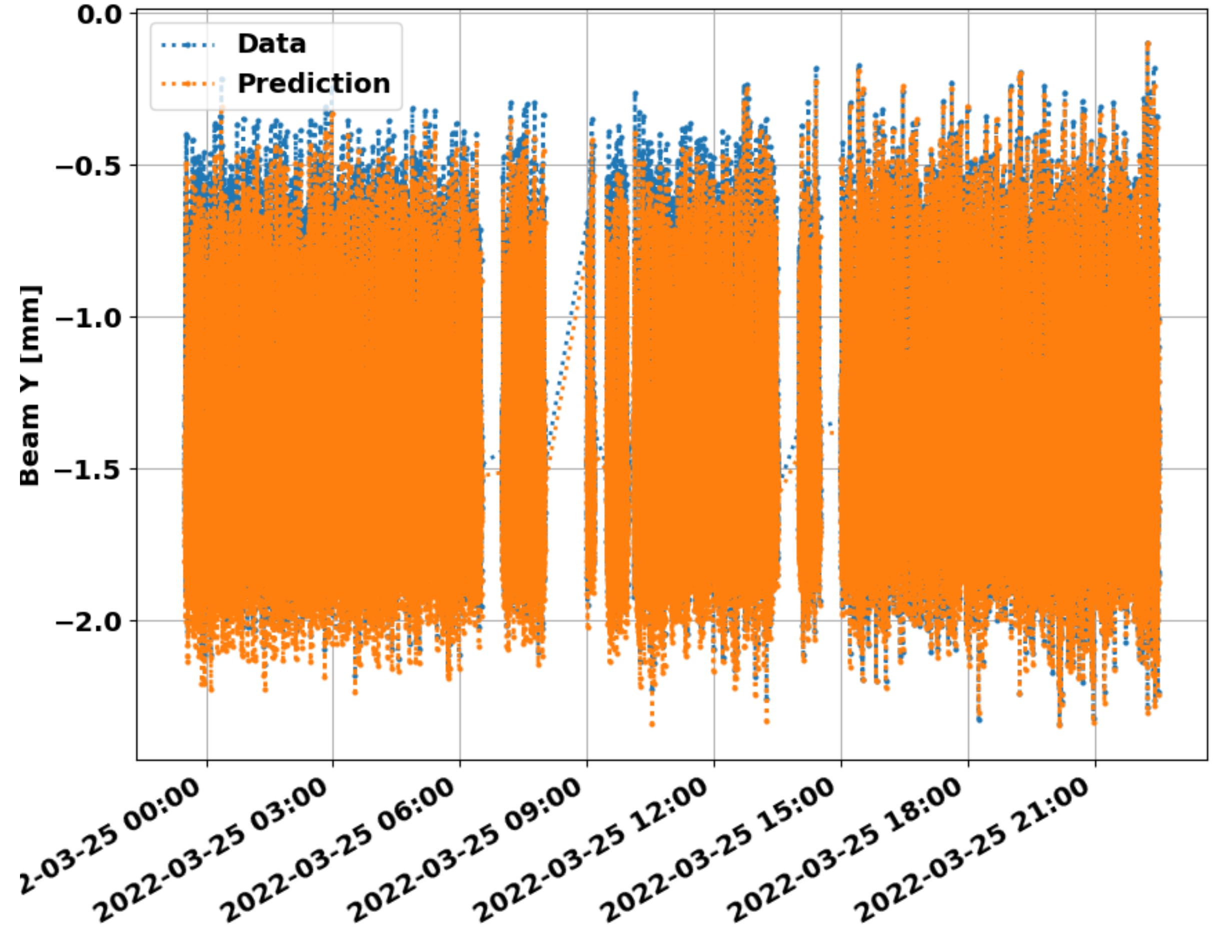
Testing with normal operation data :

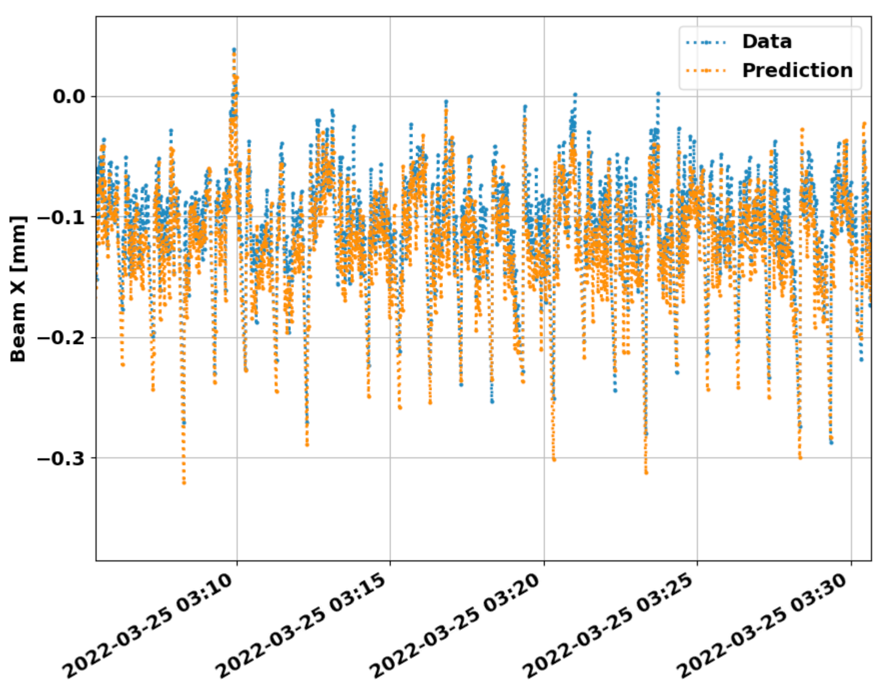
- **The model has been tested with randomly selected data sets for the normal beam operations**
- **The predictions are promising to use the model as a monitoring tool for the normal operations in the future**

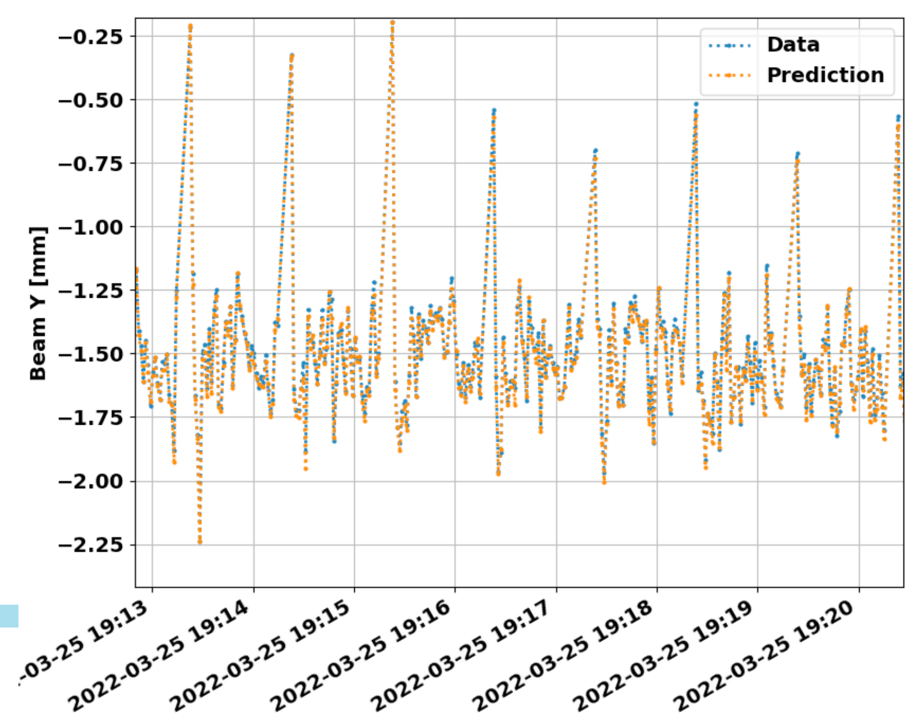


Testing 2022 data with a new model









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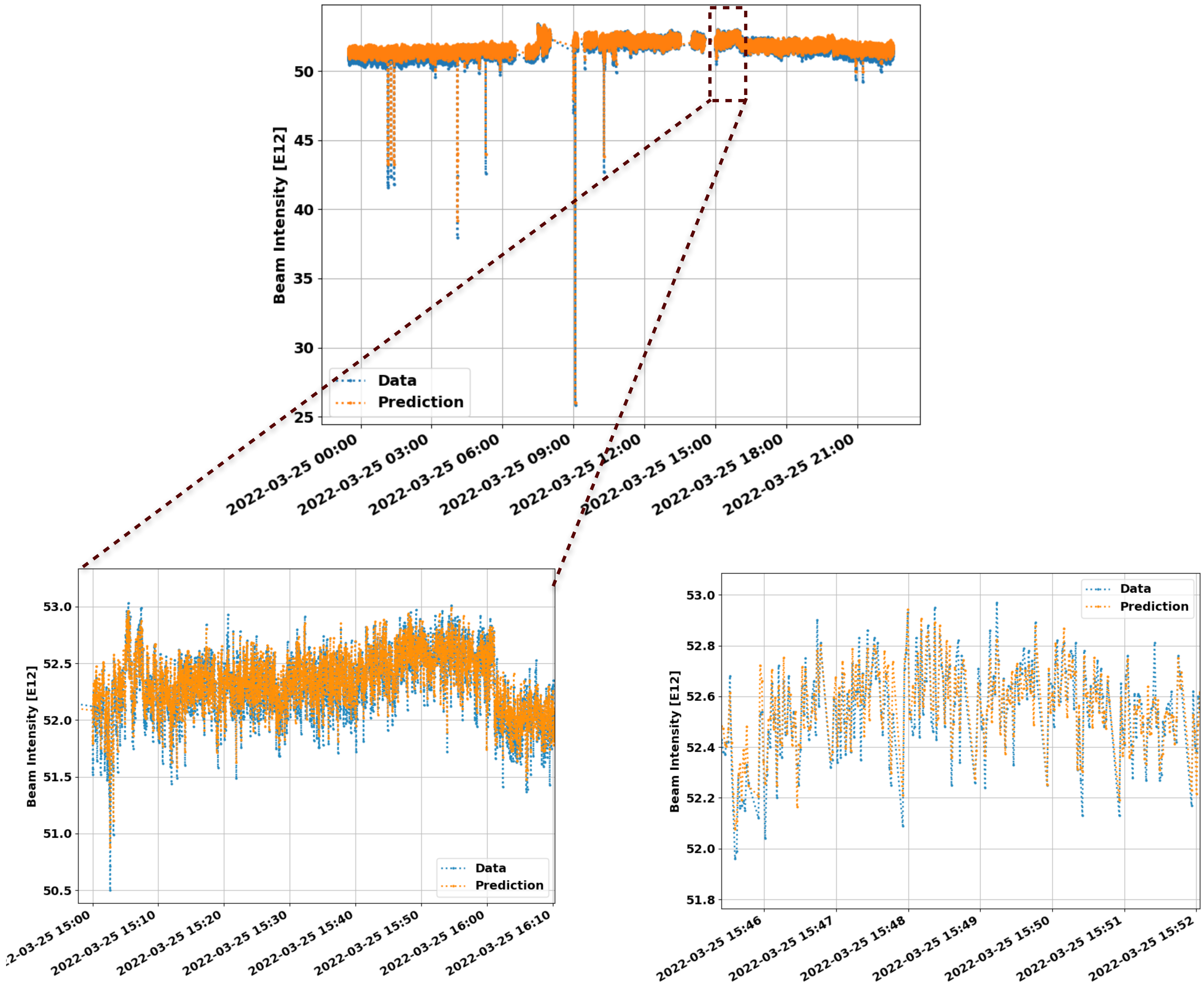

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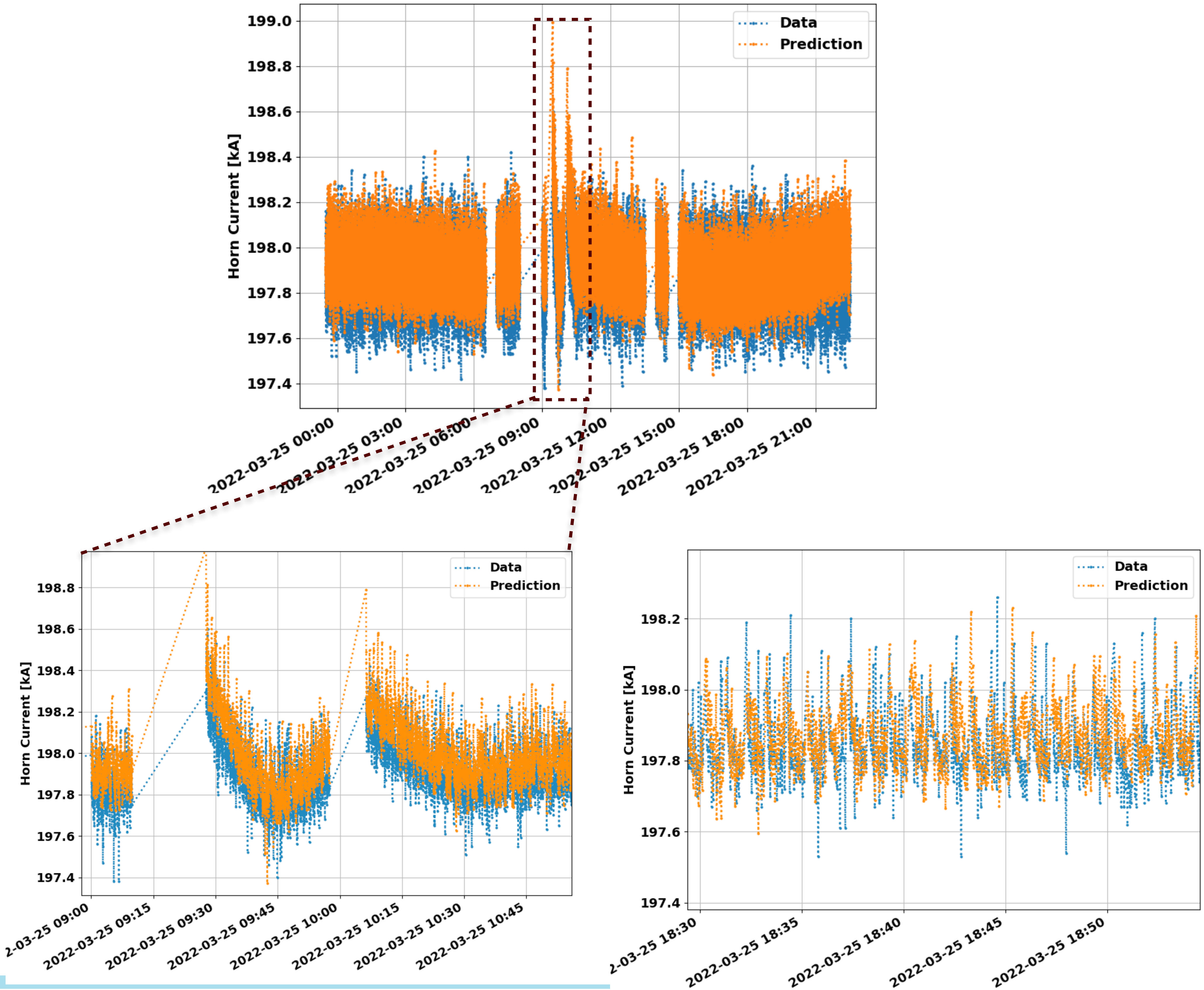
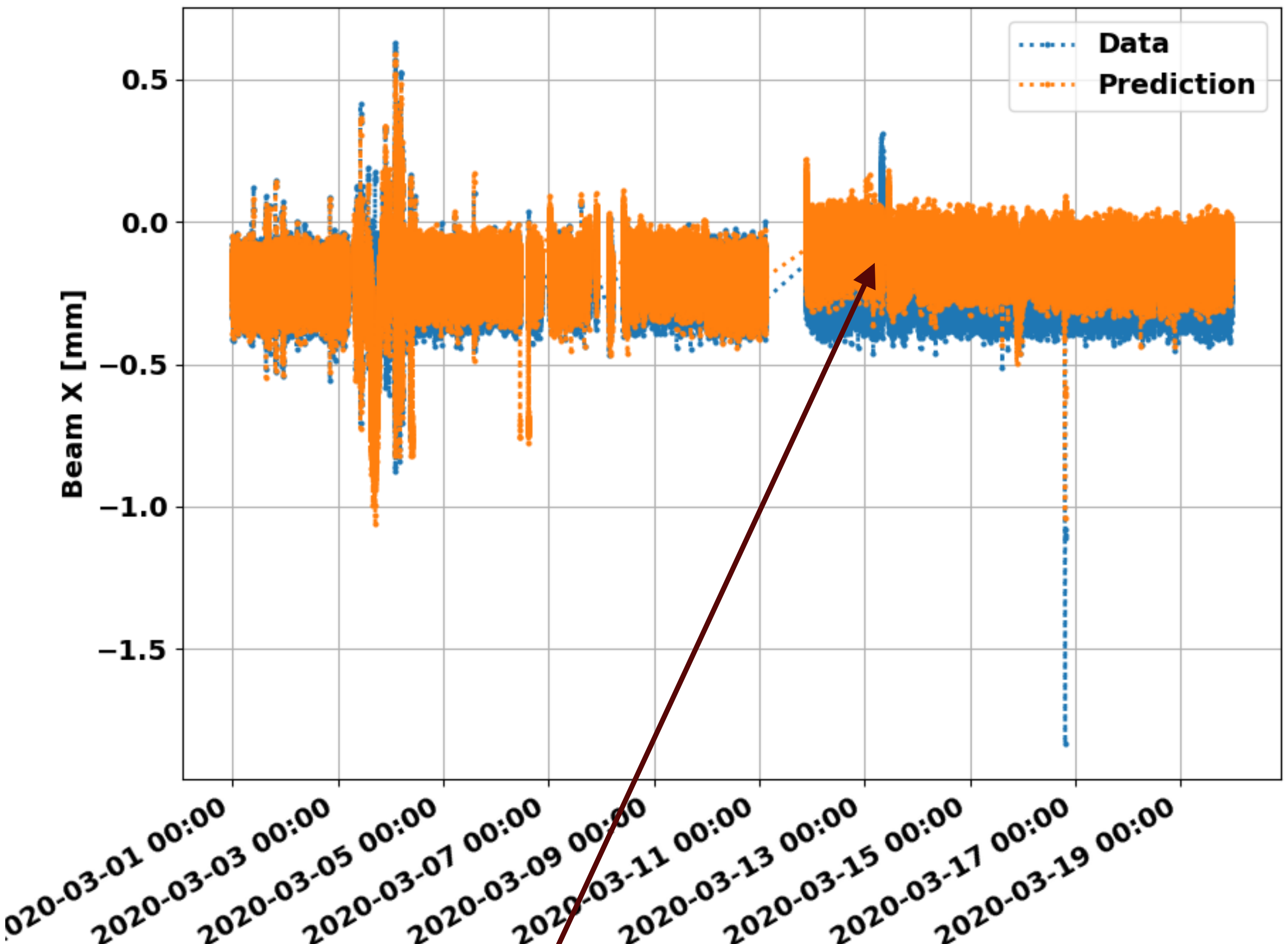
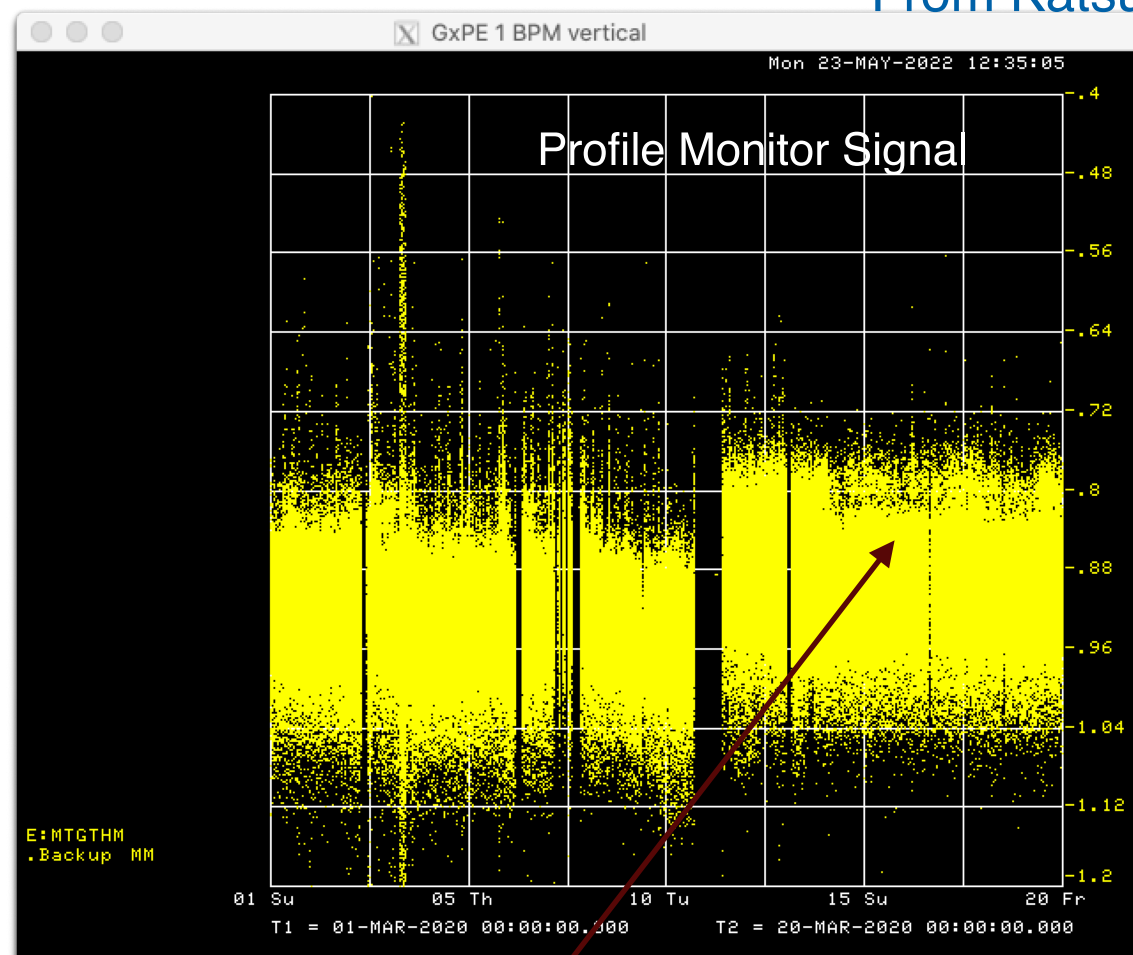


ML Predictions to Find Upstream Data Quality

Example of finding a BPM signal issue with ML predictions

From Katsuya





Predictions show a shift from the BPM signal

Same shift is visible on the PM signal

Concerns

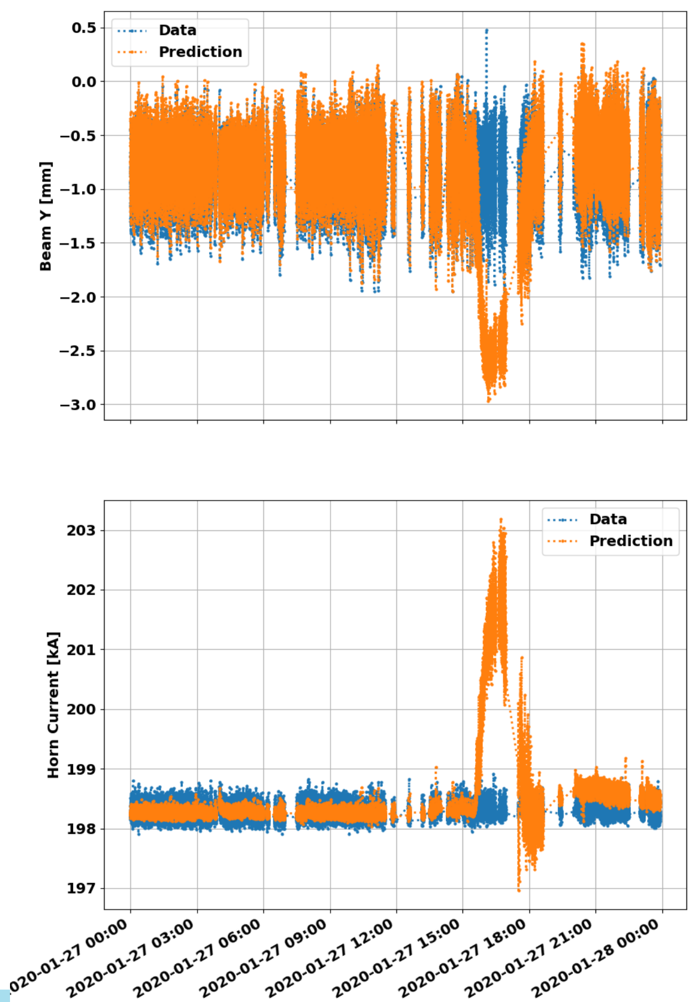
ML models depend on:

* the data quality of the training samples,
* the special data samples like beam scan data.

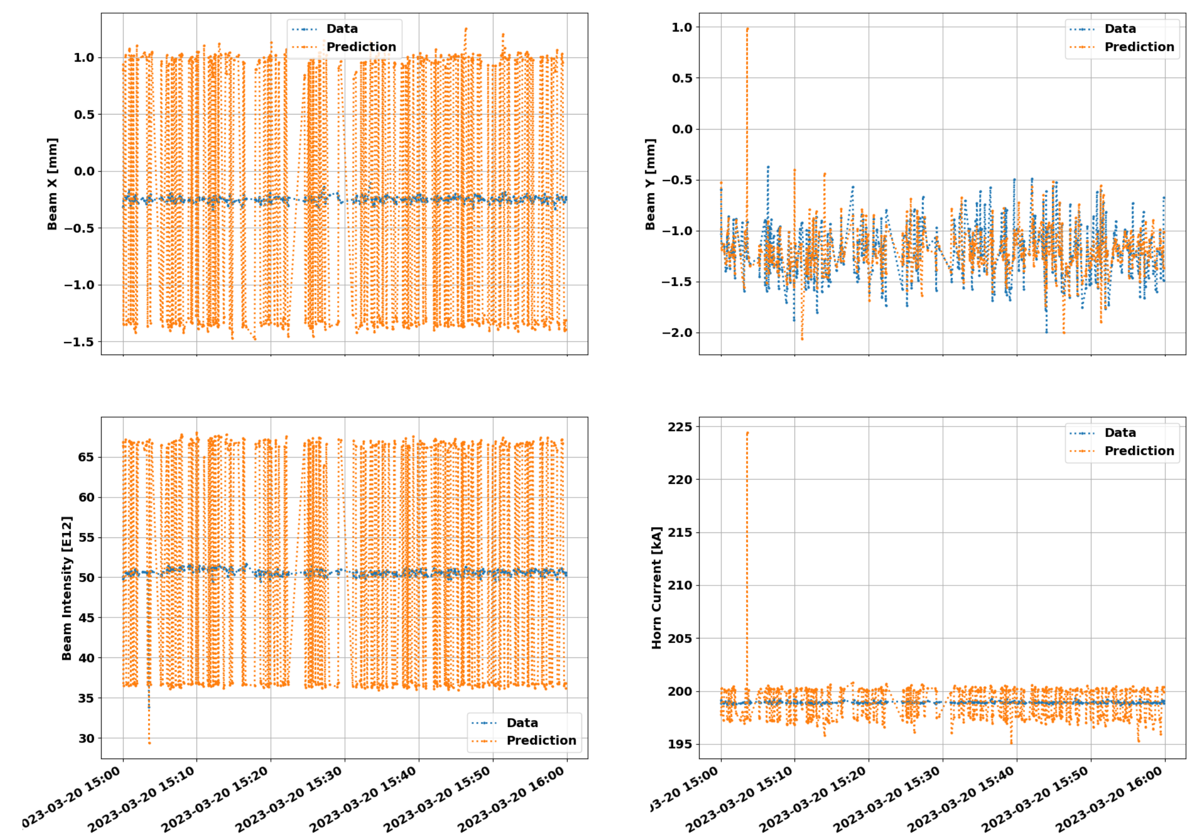
ML predictions with normal operations depends on:

* muon monitor signal quality,
* beamline changes such as the target, horn focusing, etc.

Example of He gas quality effecting on predictions



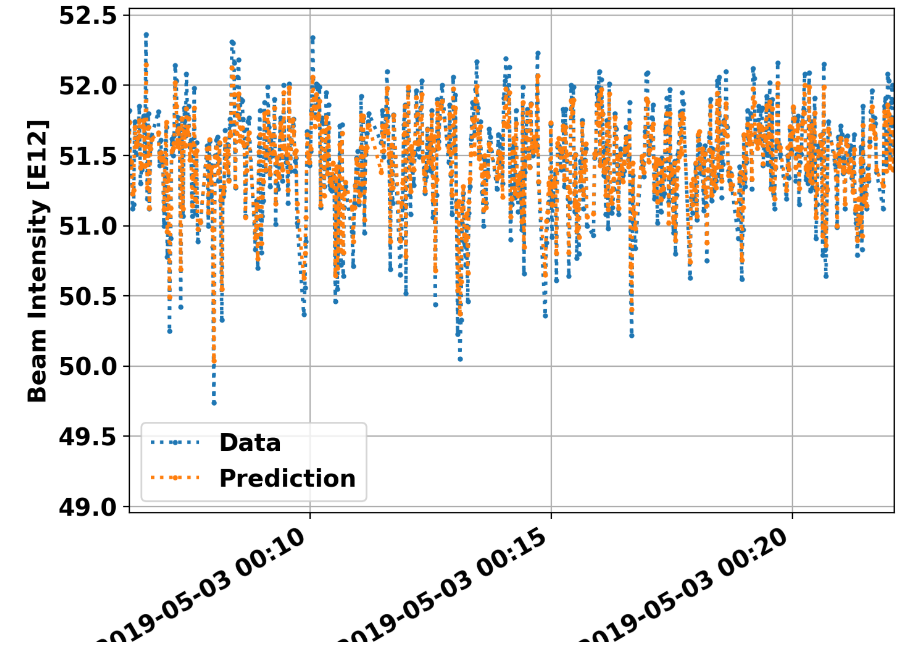
Predictions on 2023 data from 2022 ML model

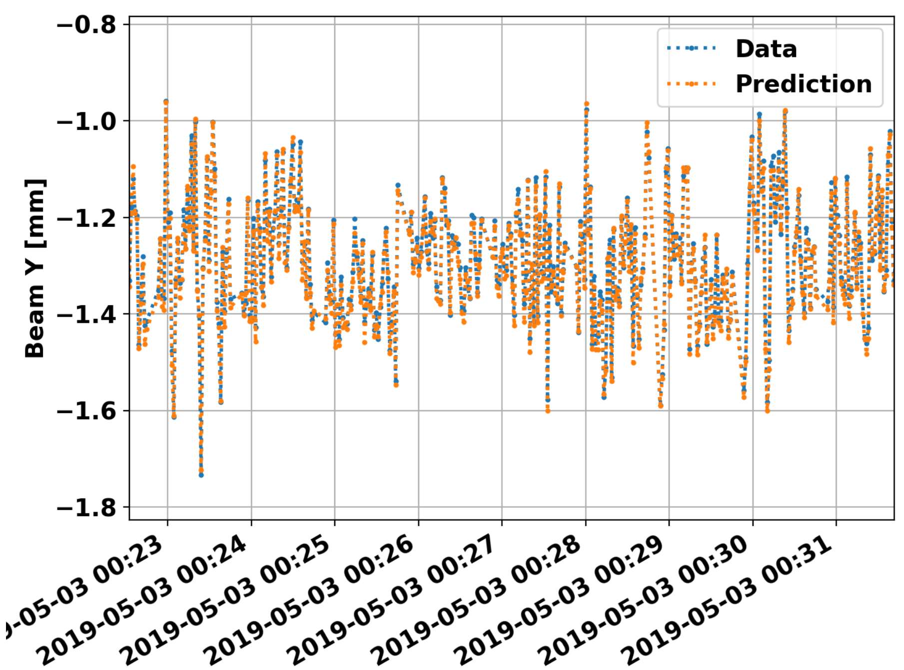


Can't use the same model after doing any beam line changes

Remarks

- **Every single changes on the beam parameters are sensitive to the muon monitor signal**
- **Demonstrated the capability of separating the correlations of beam variable changes to the muon flux.**
- **Muon monitor signals can be used as an independent monitoring system to understand the beam performance.**
- **ML applications can be helpful to monitor the beam quality, issues and anomalies.**





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