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Machine Learning Applications to Maintain the NuMI Neutrino Beam Quality at Fermilab

Athula Wickremasinghe
Katsuya Yonehara
Pavel Snopok
Sudeshna Ganguly
Yiding Yu
Eduardo A. Ossorio Alfaro

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Outline

1. **Why Use AI?**
2. Introduction to the muon monitors
3. Responses of Muon Monitors to the beam parameters
4. Machine Learning Applications

Why Use AI?

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

AI helps to:

» **learn from reality**

» **untangle the correlations from the messy data**

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

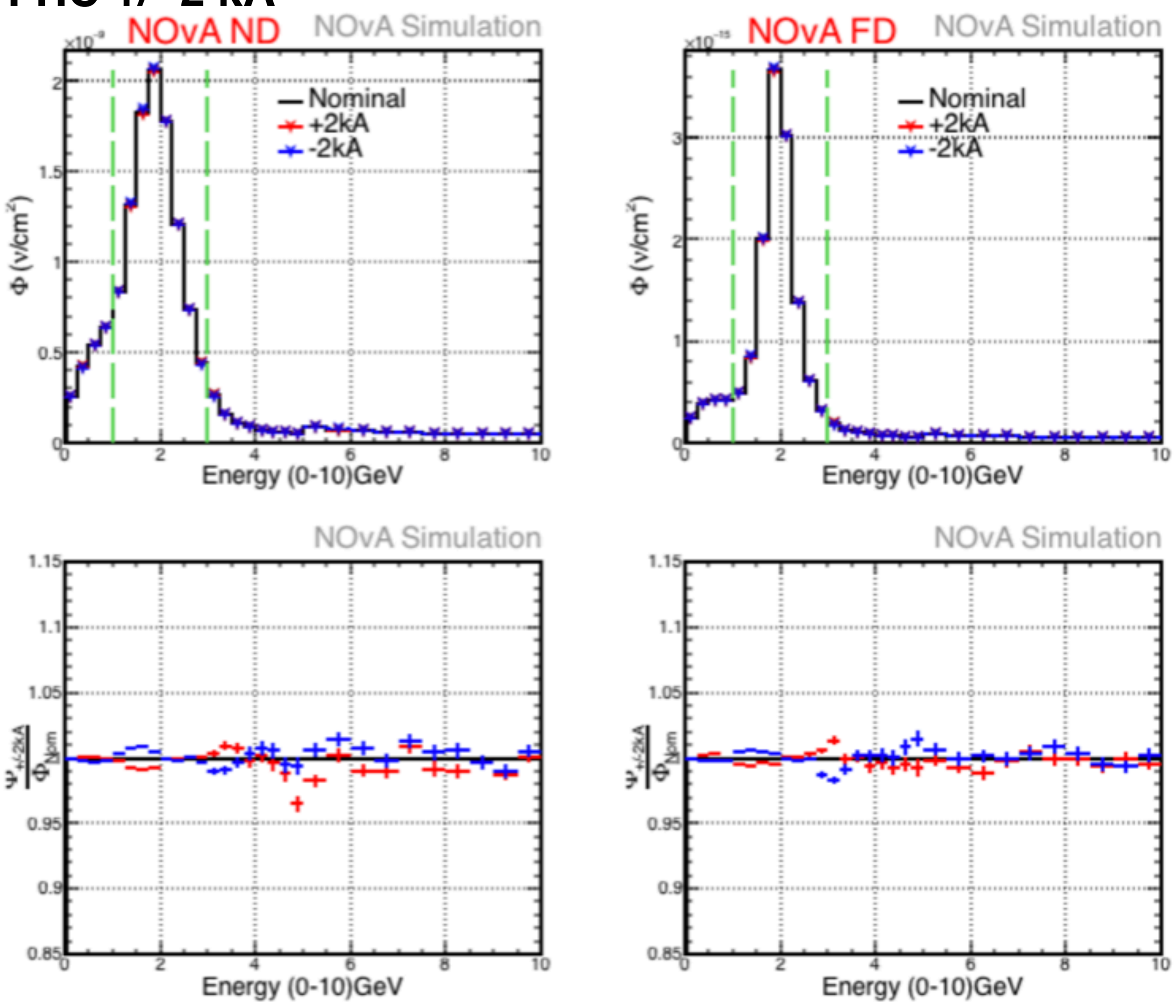
» **understand the physics tolerances in the real time operations**

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

Physics Tolerances for Neutrino Flux Predictions

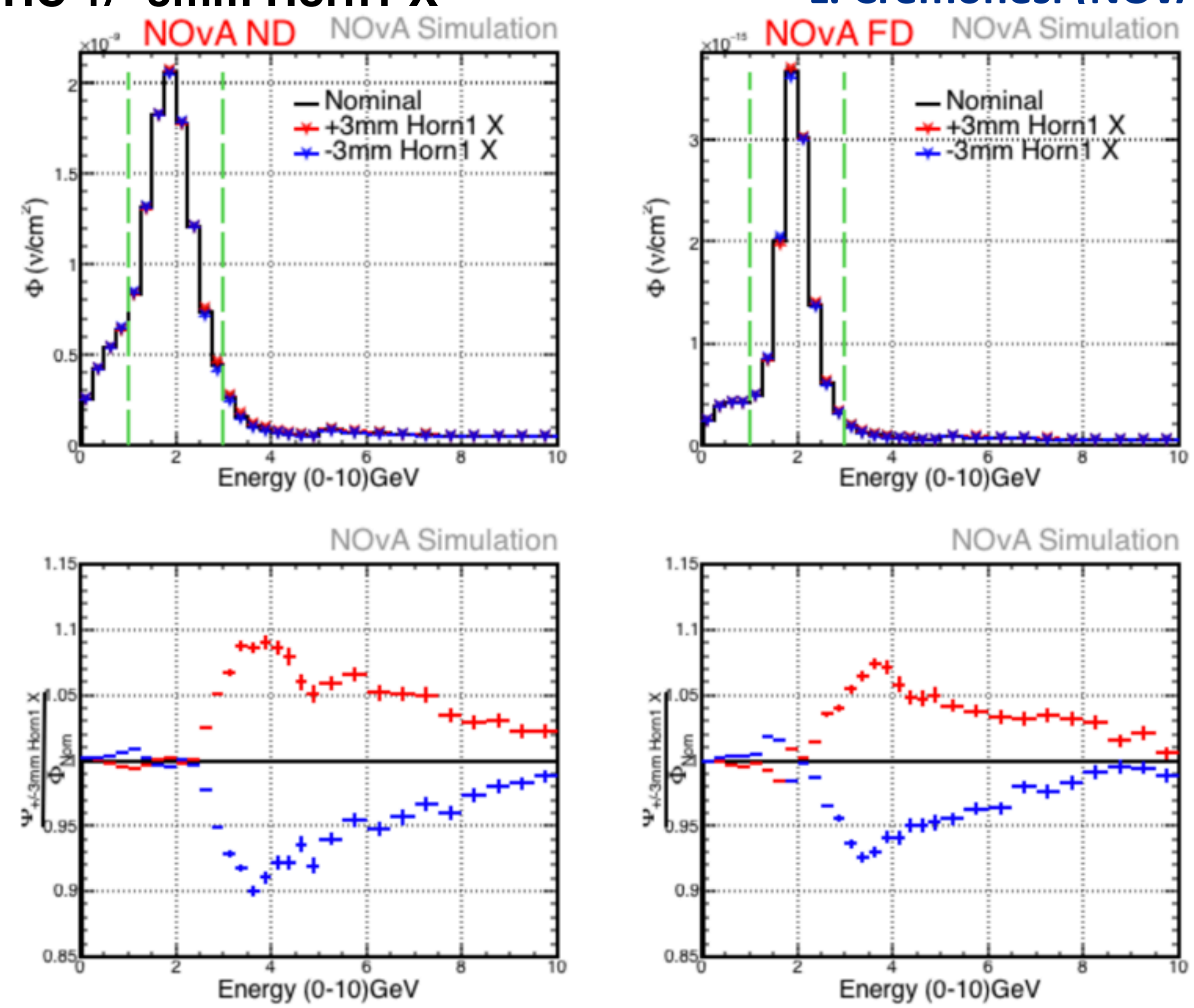
- **Physics tolerances: the acceptable limitations of possible upstream variables that have an effect on neutrino data quality**
- **Theses tolerances are set according to the simulation studies**
- **Flux systematic uncertainties are calculated according to the tolerances**
- **Any target change effects 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

DUNE preliminary

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

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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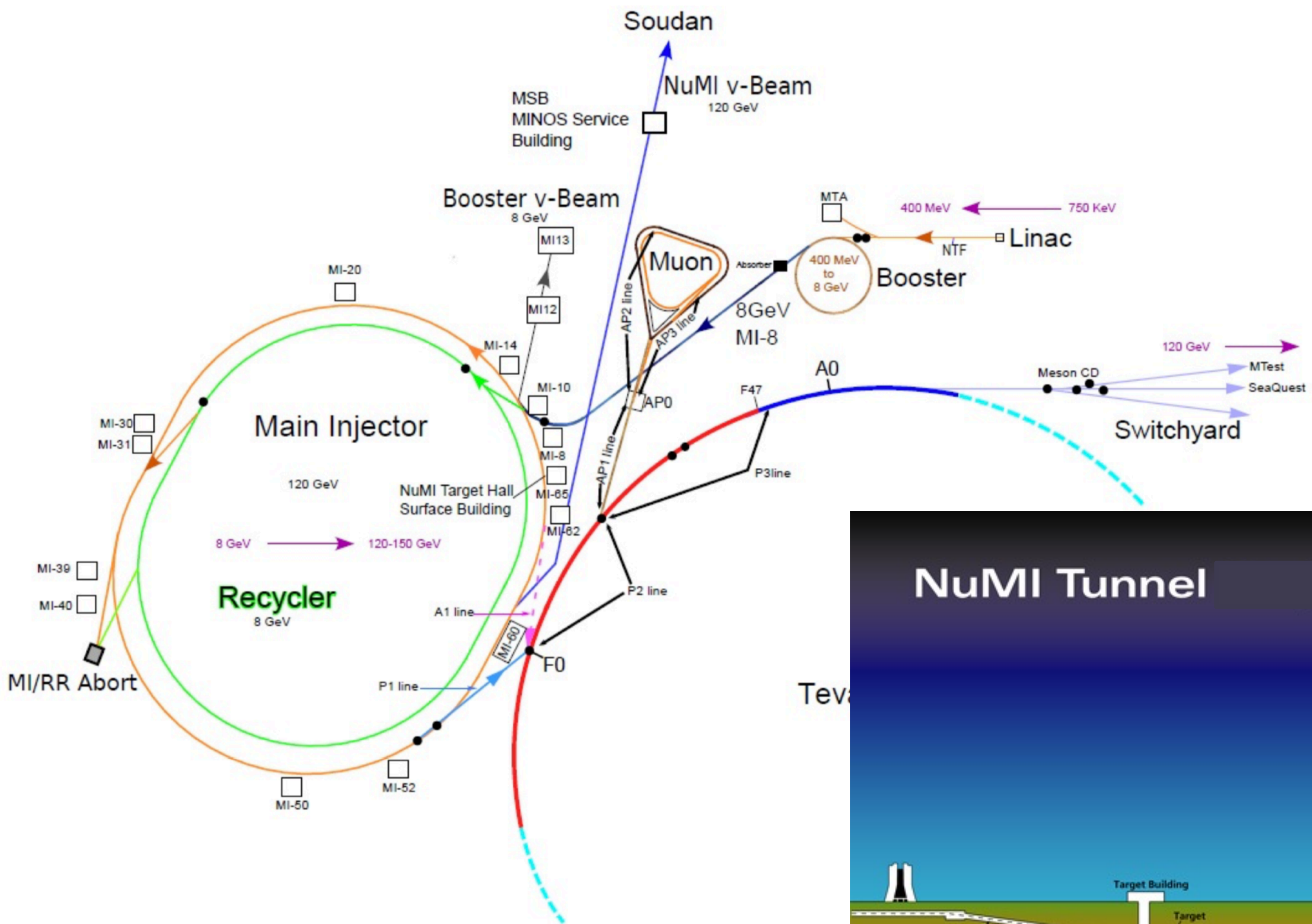
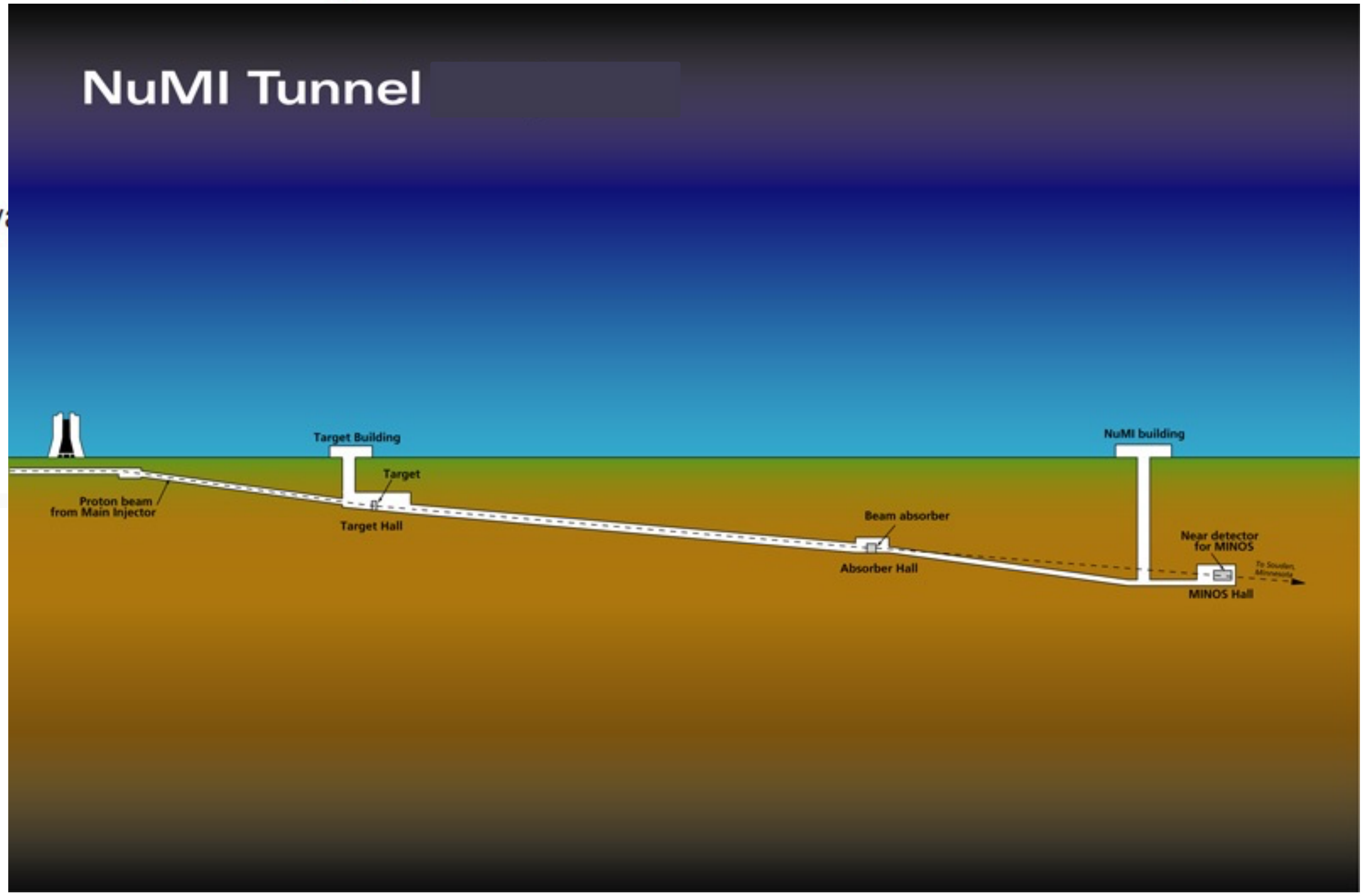
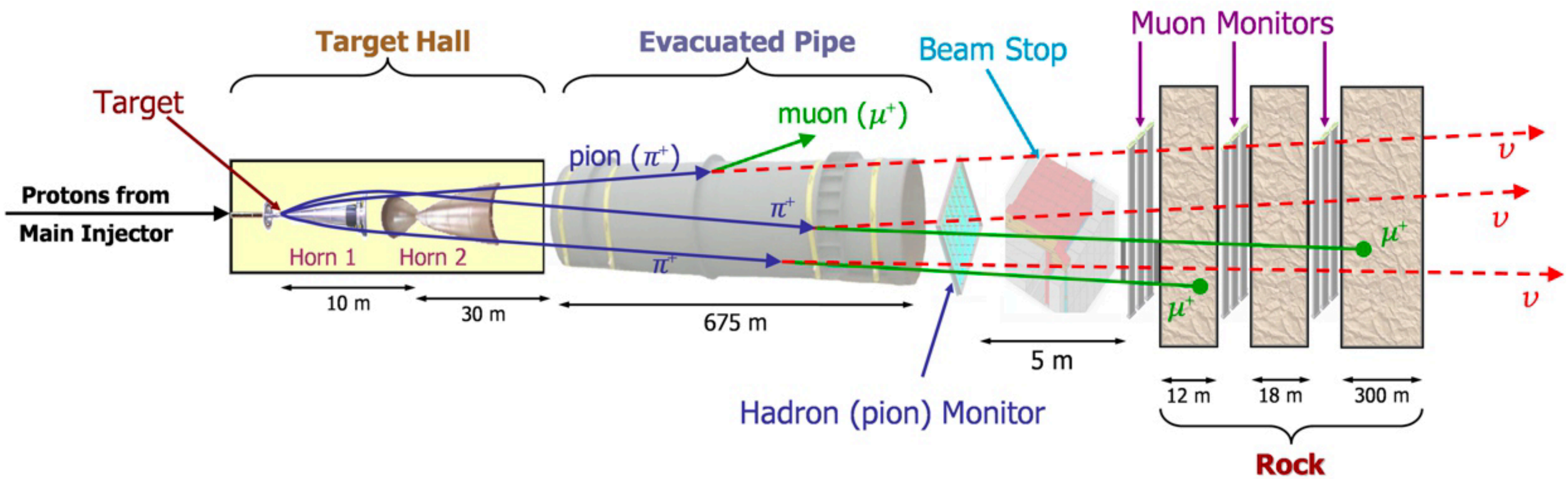
NuMI beamline

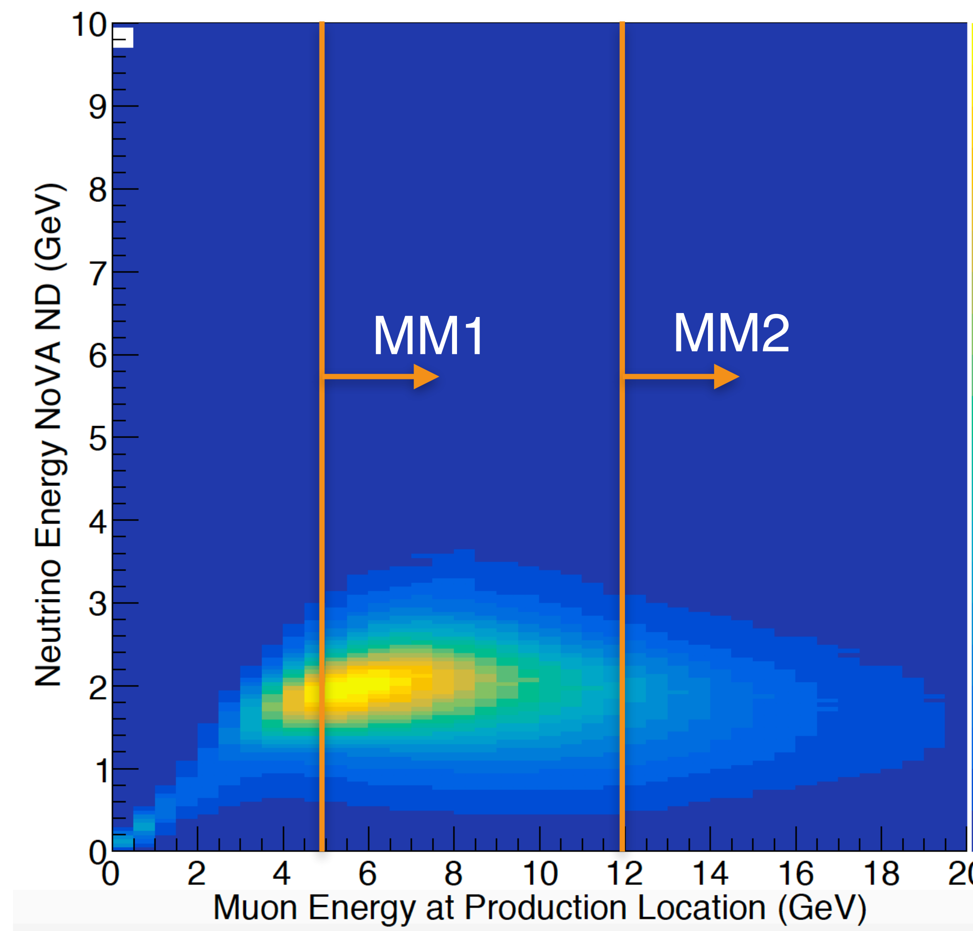




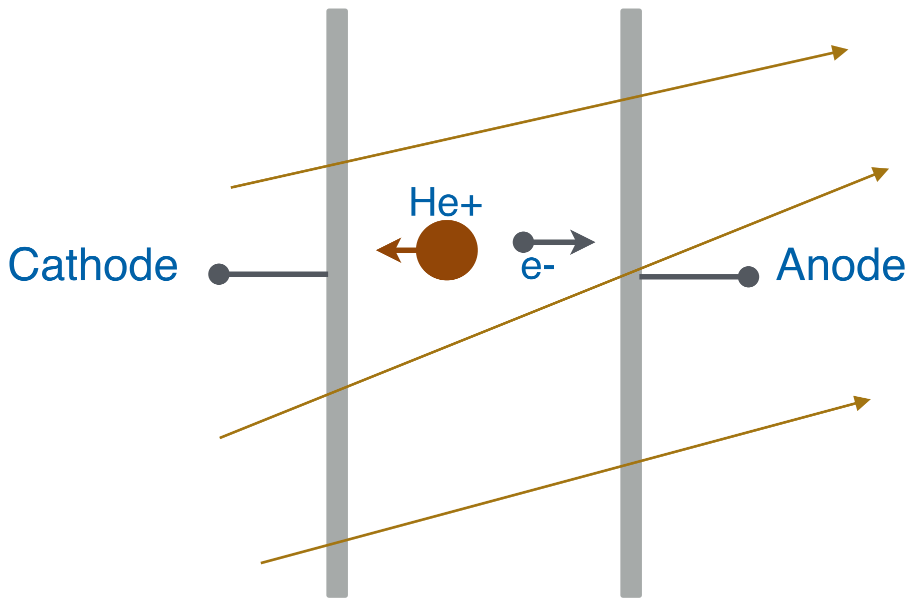
Introduction to Muon Monitors

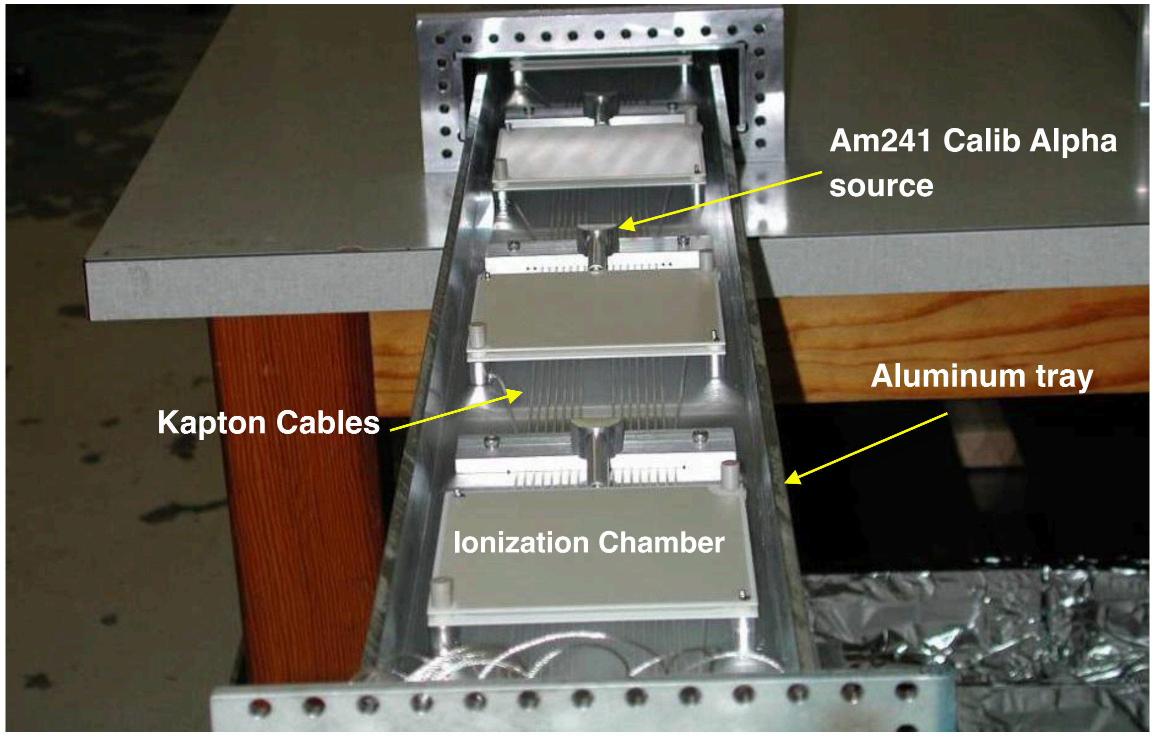


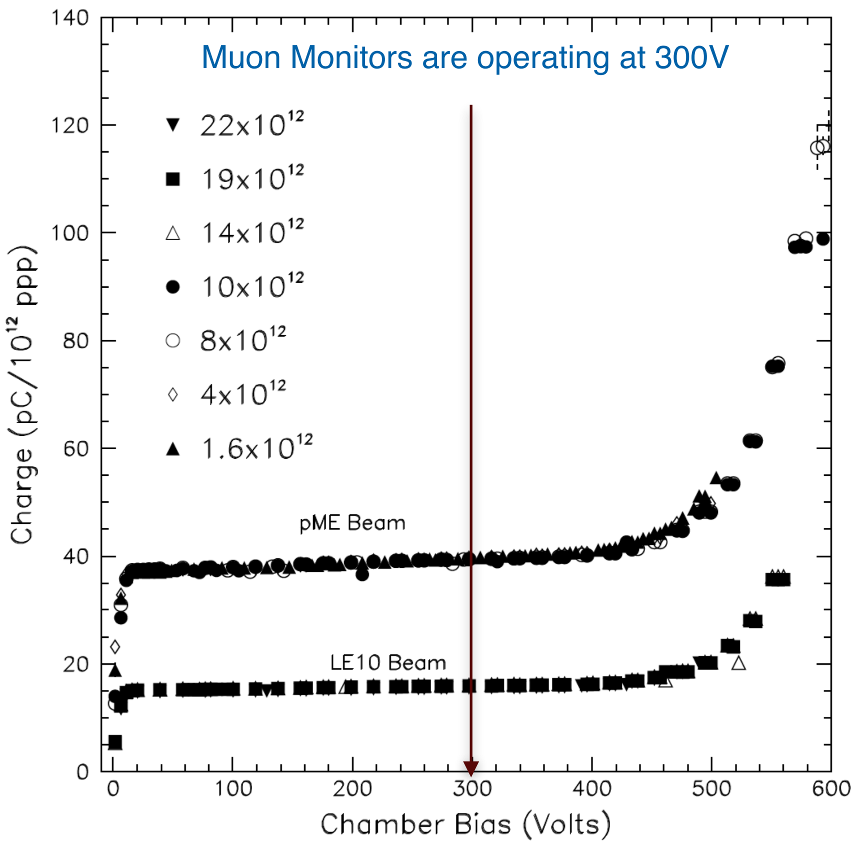
- Three muon monitors are located in the downstream of the hadron absorber
- Each muon monitor consist of 9x9 arrays of ionization chambers
- Each ionization chamber consists of two ceramic parallel plates with the separation of 3 mm gap
- The chambers are filled with He gas

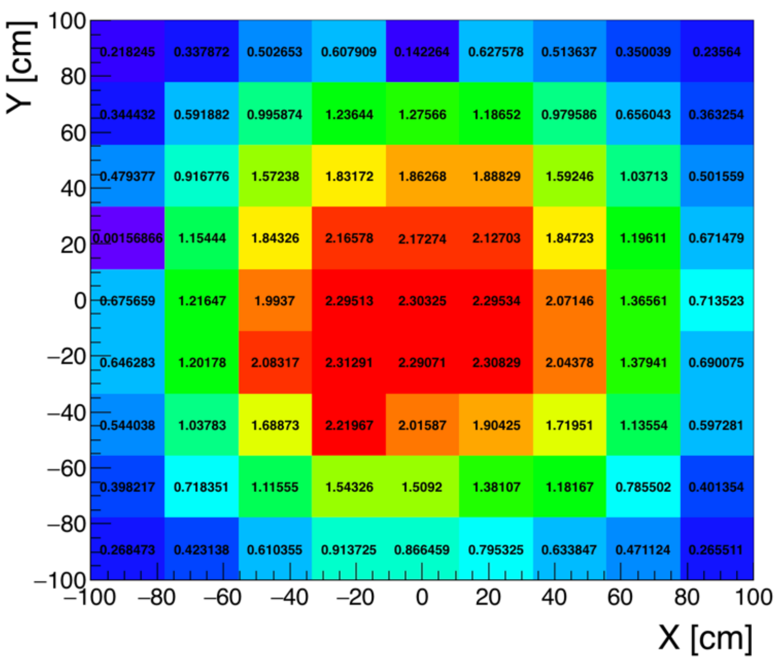


Introduction to Muon Monitors









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

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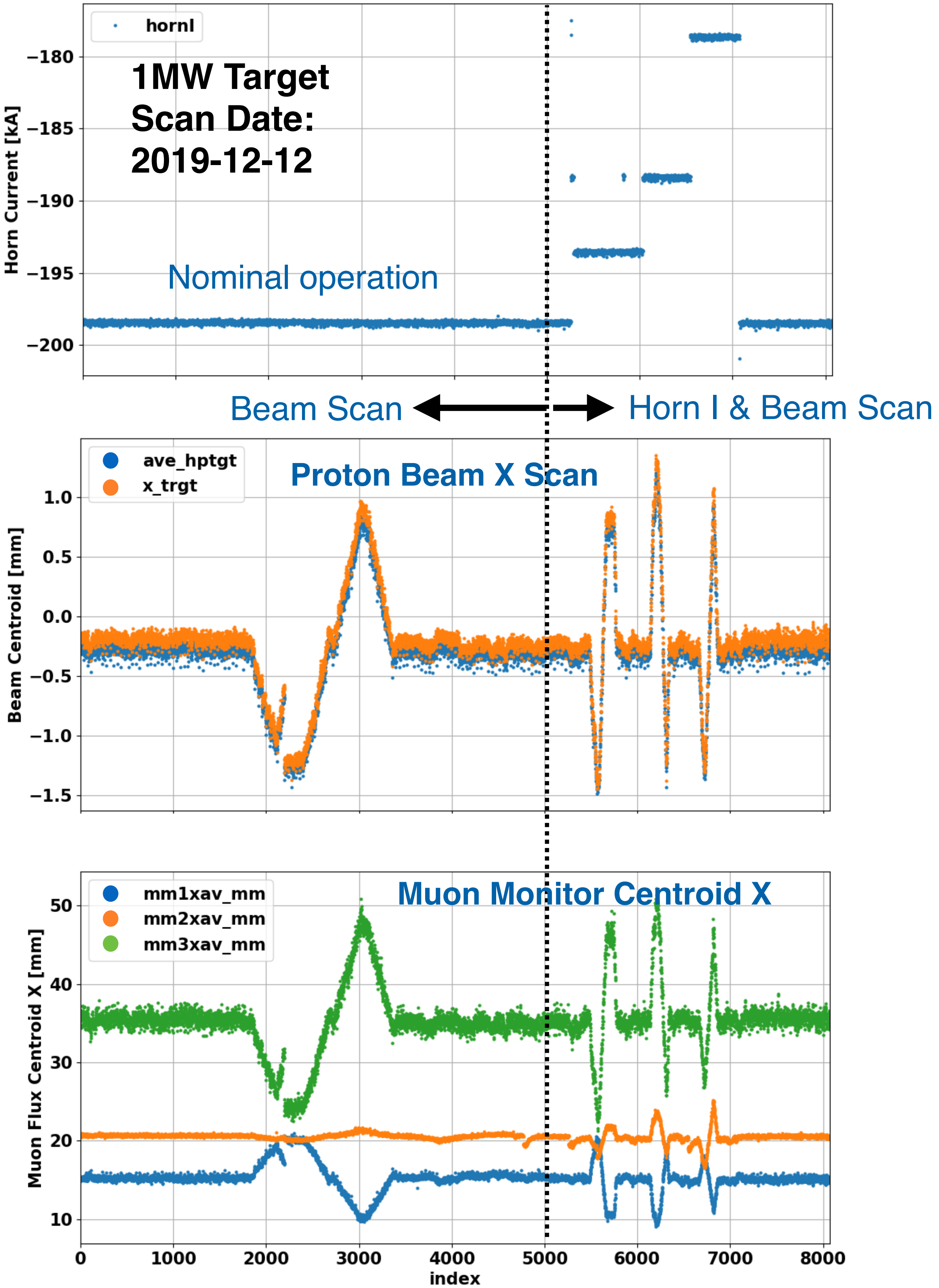
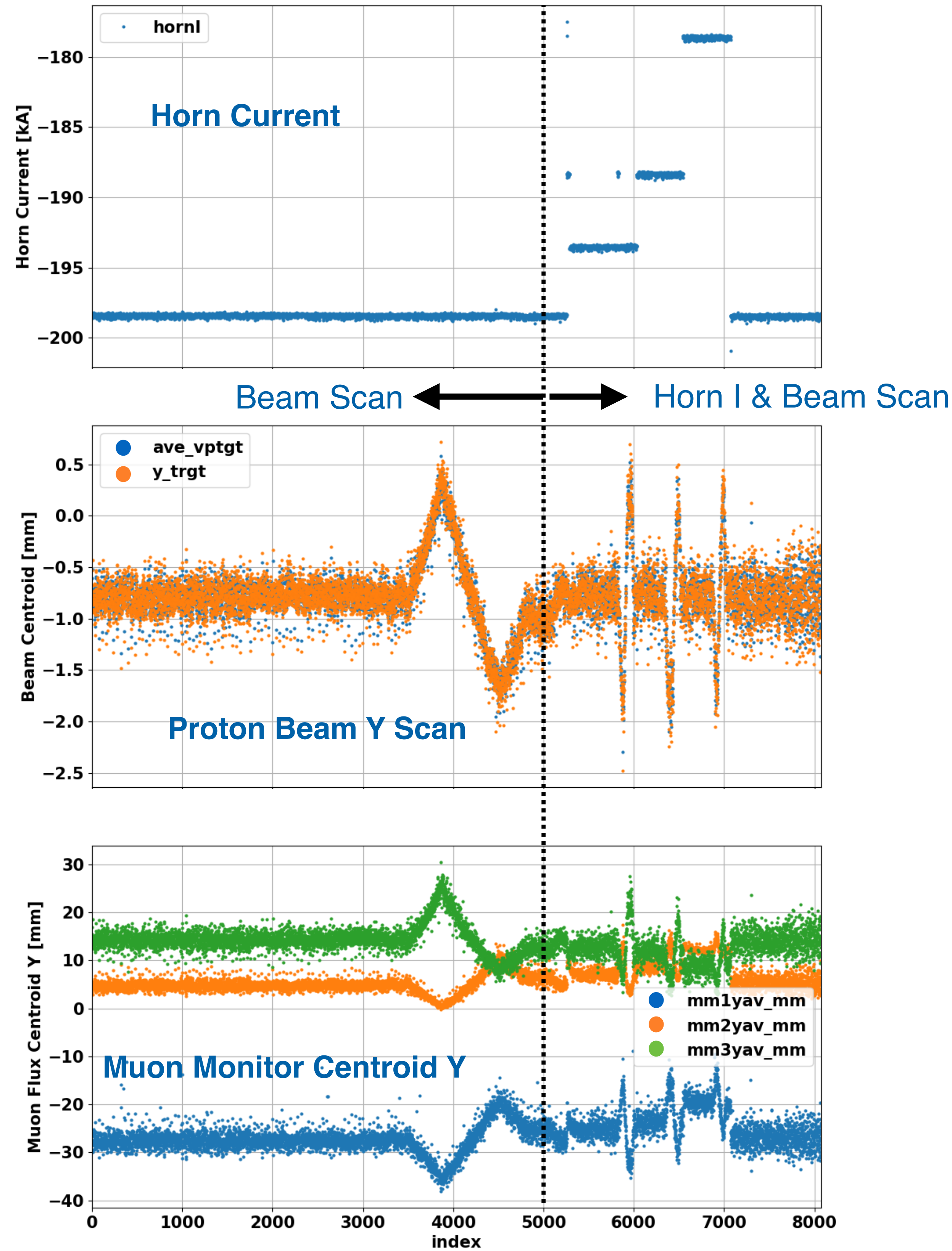
Horizontal and Vertical Scan

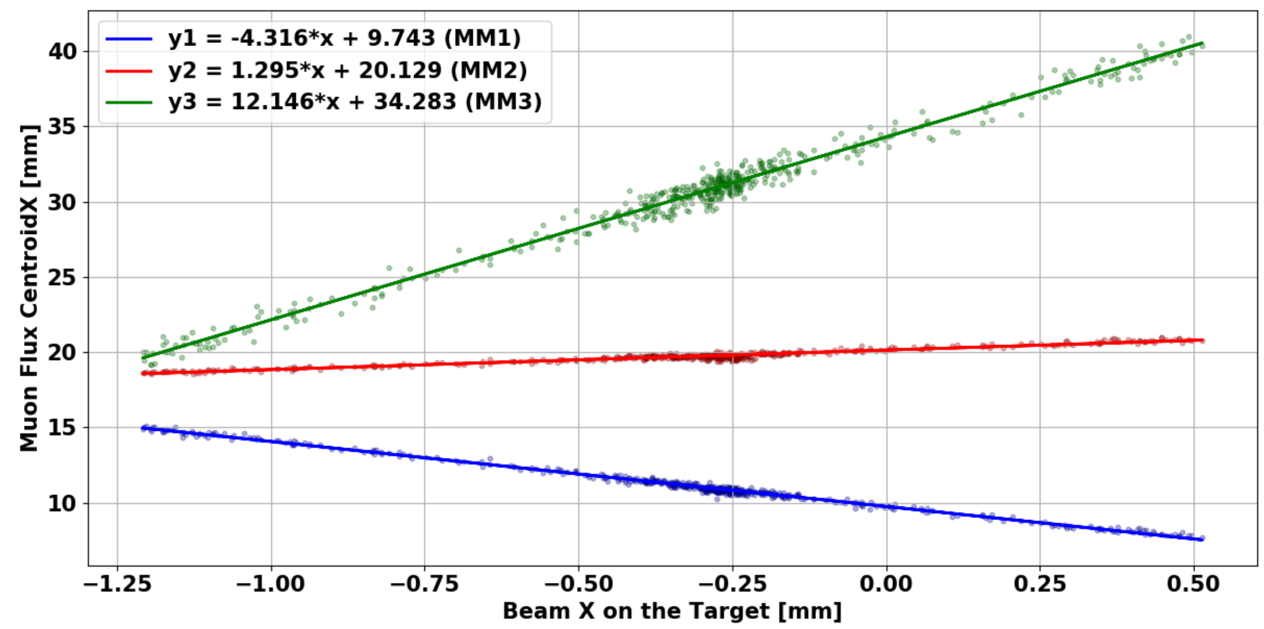


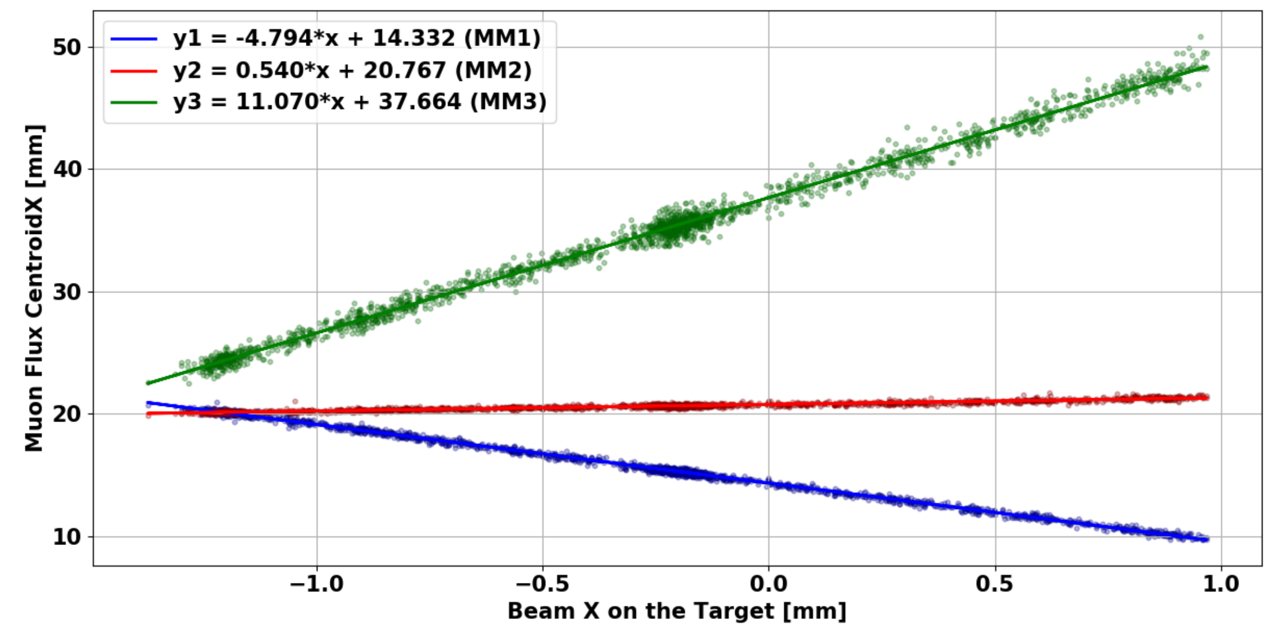


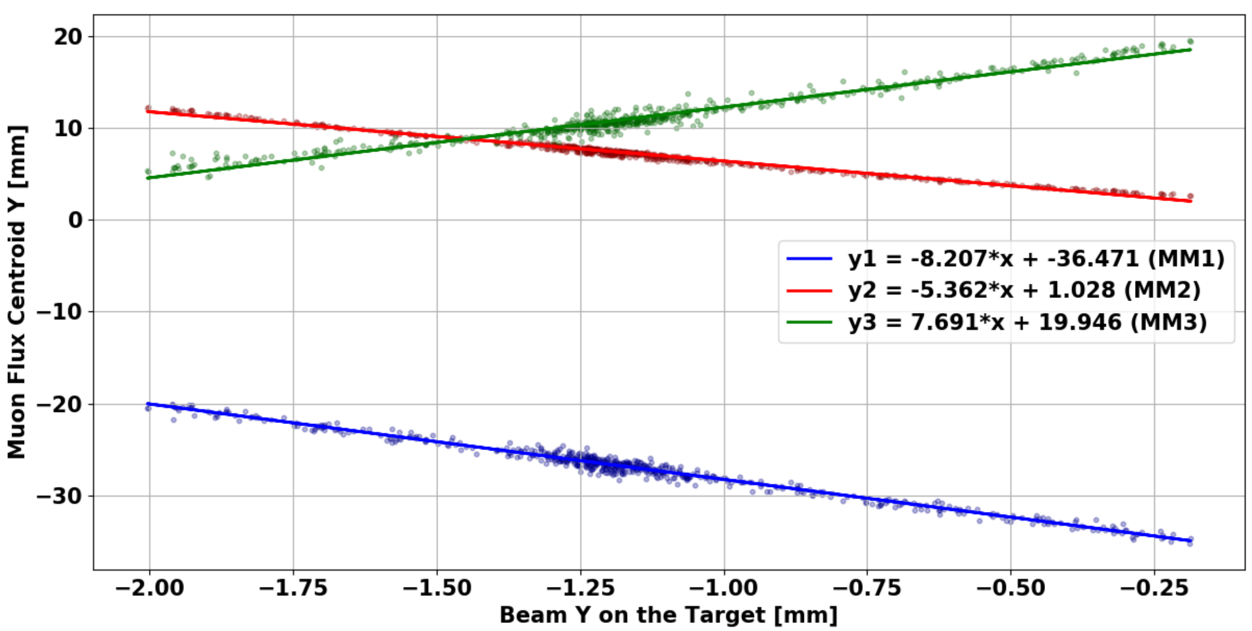
Correlations from beam scans

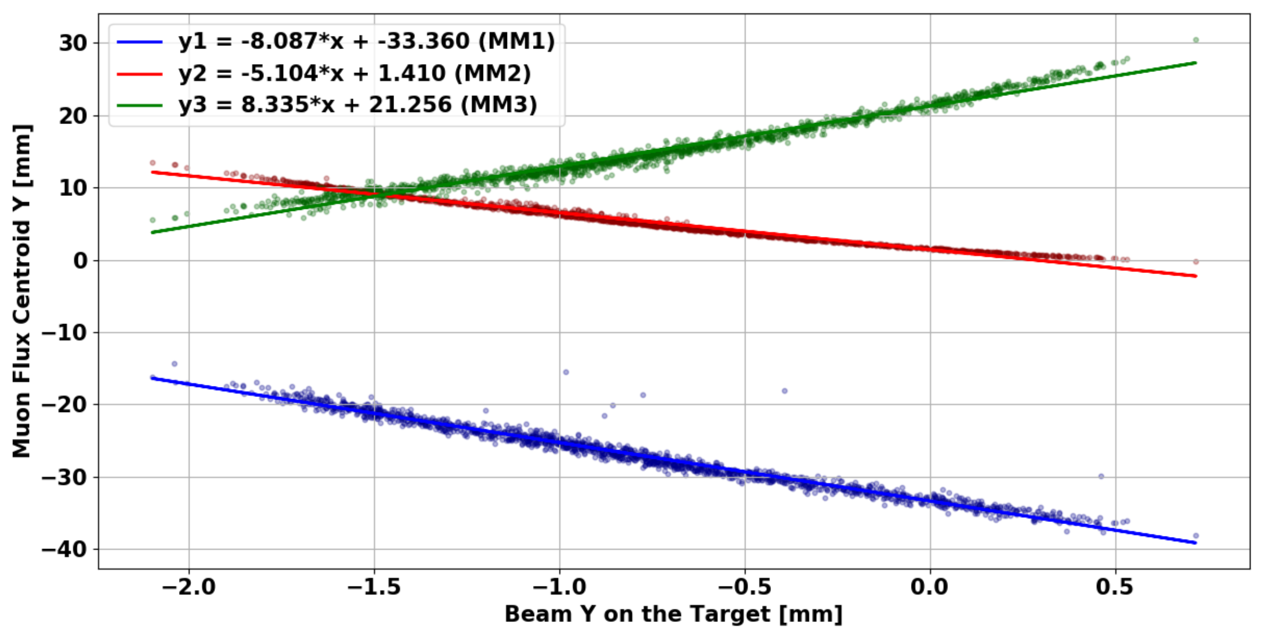
Scan data: 2019-07-03

Scan data: 2019-12-12









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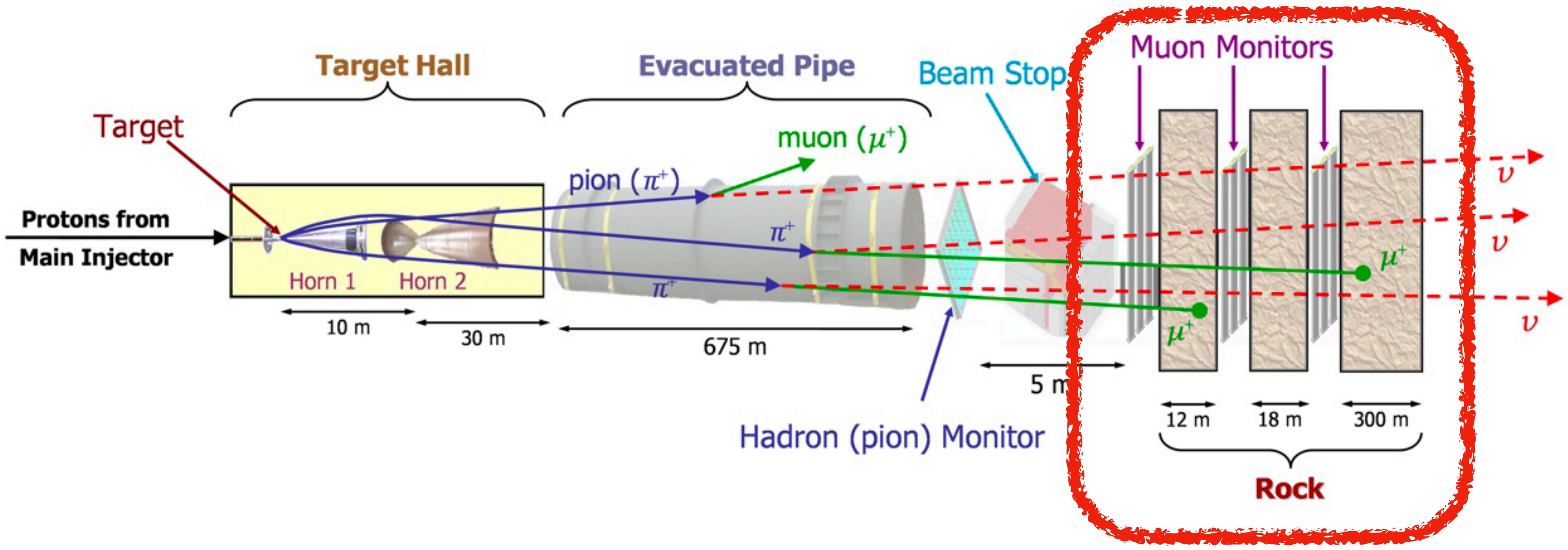
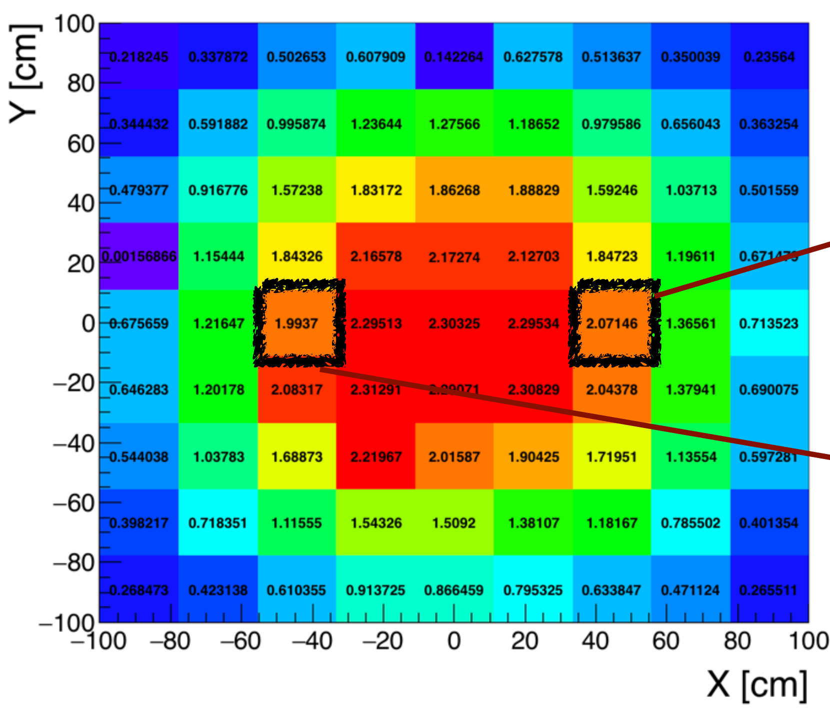
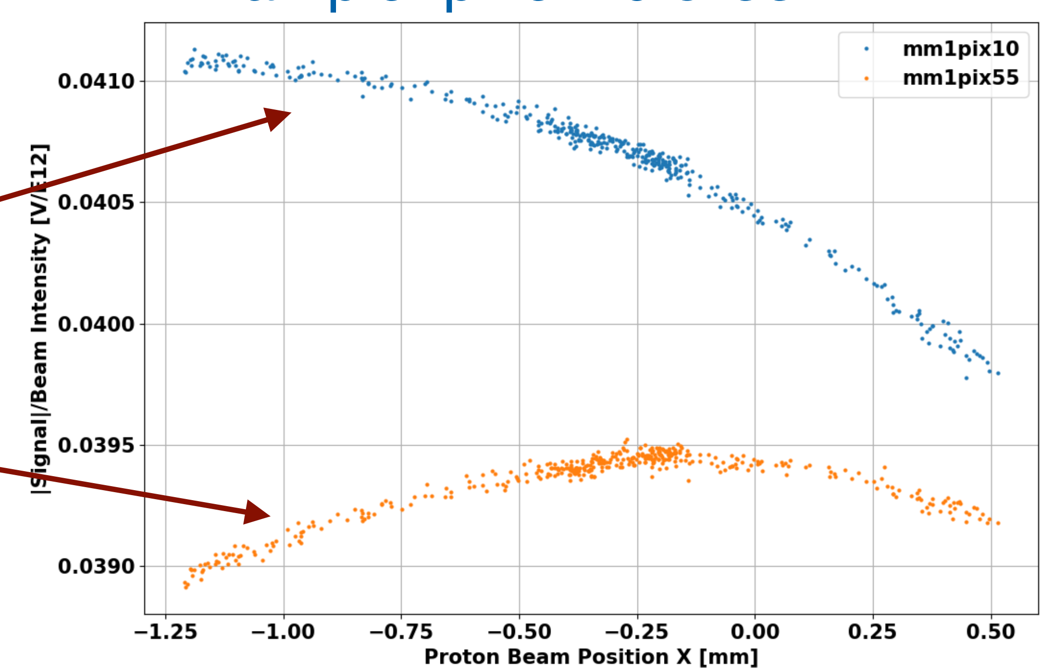
Pixel Response



- Each muon monitor sensitive to different hadron momentum threshold
- 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



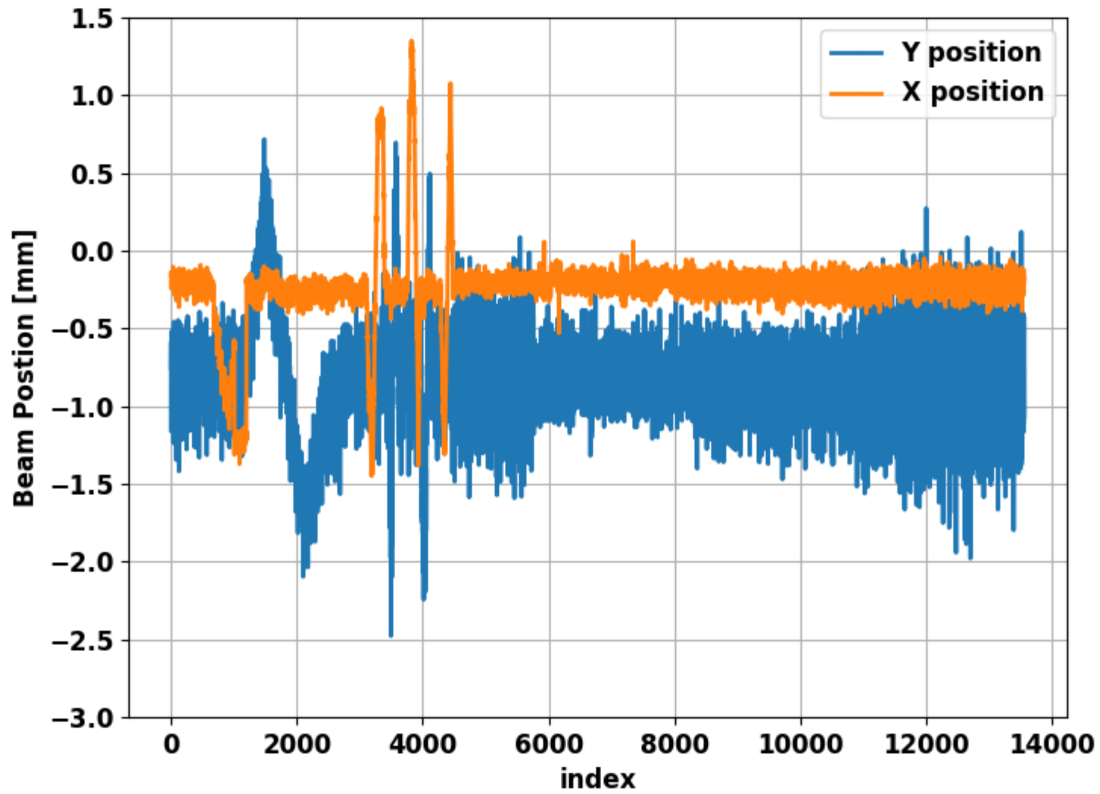
A Model to Predict Beam Variables and Horn Current

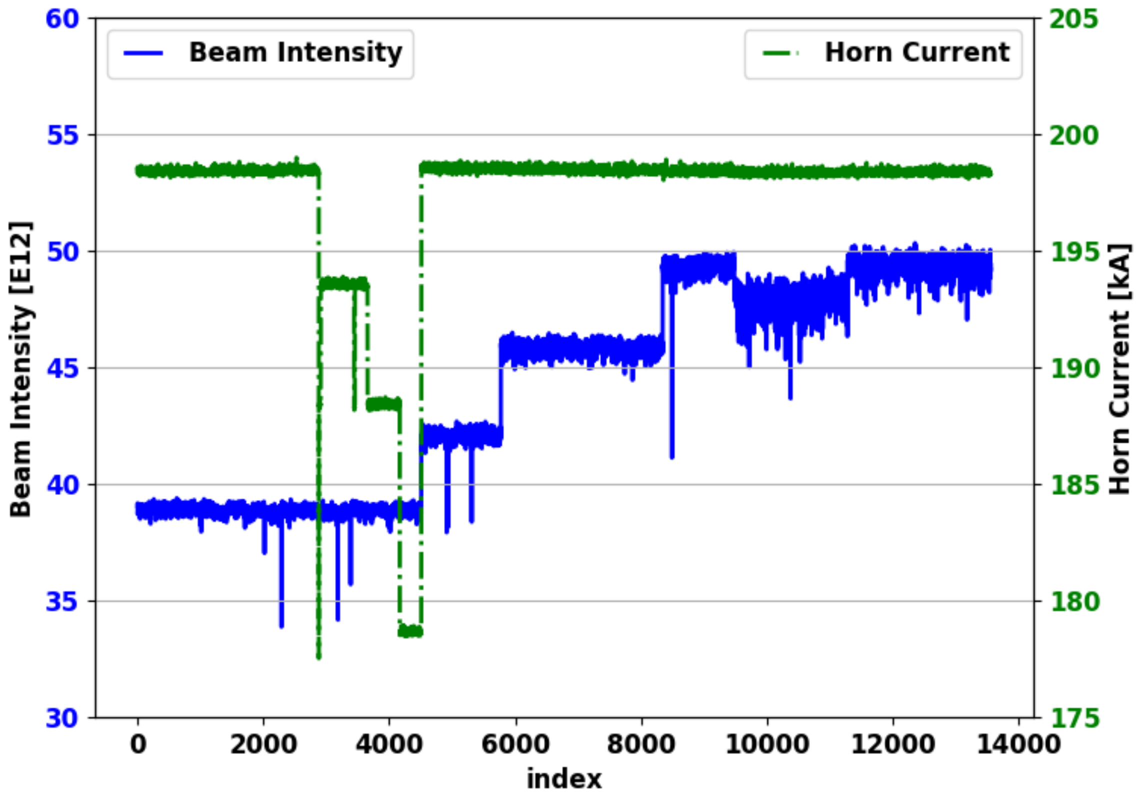
Data Preparation:

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

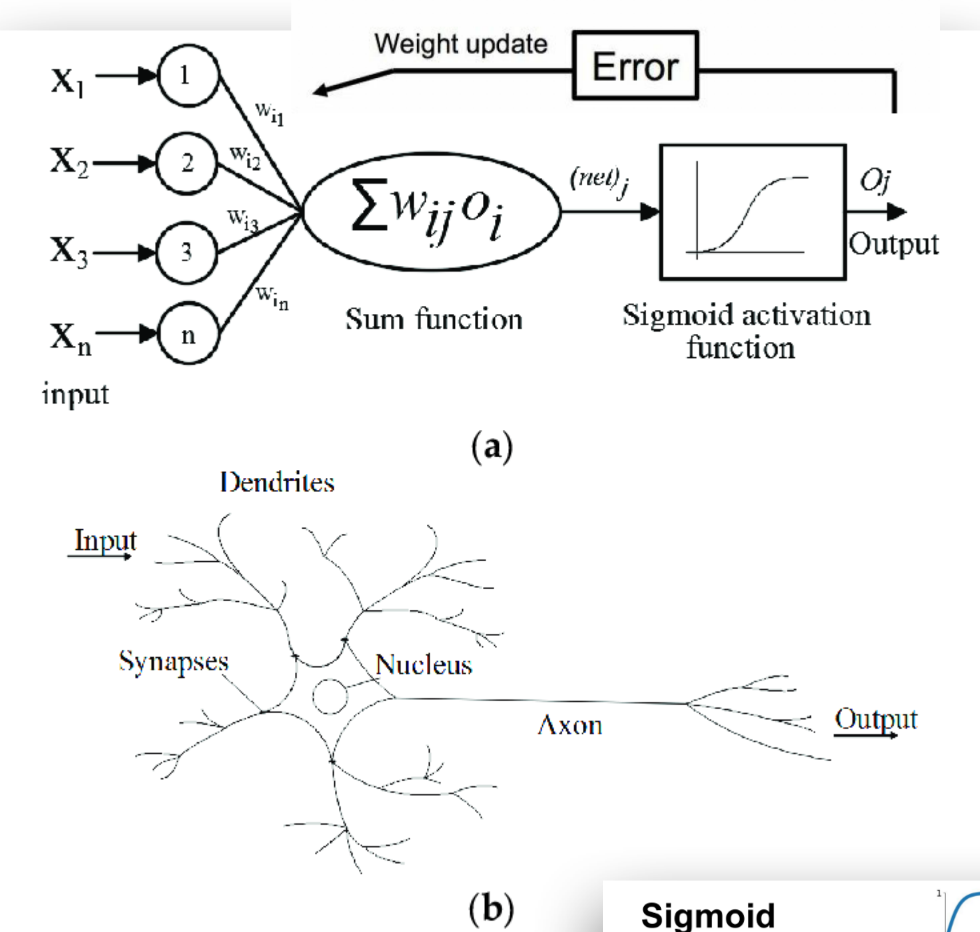
» The randomly sampled training (70%) and validation (30%) data samples were selected from the target scans and normal operations

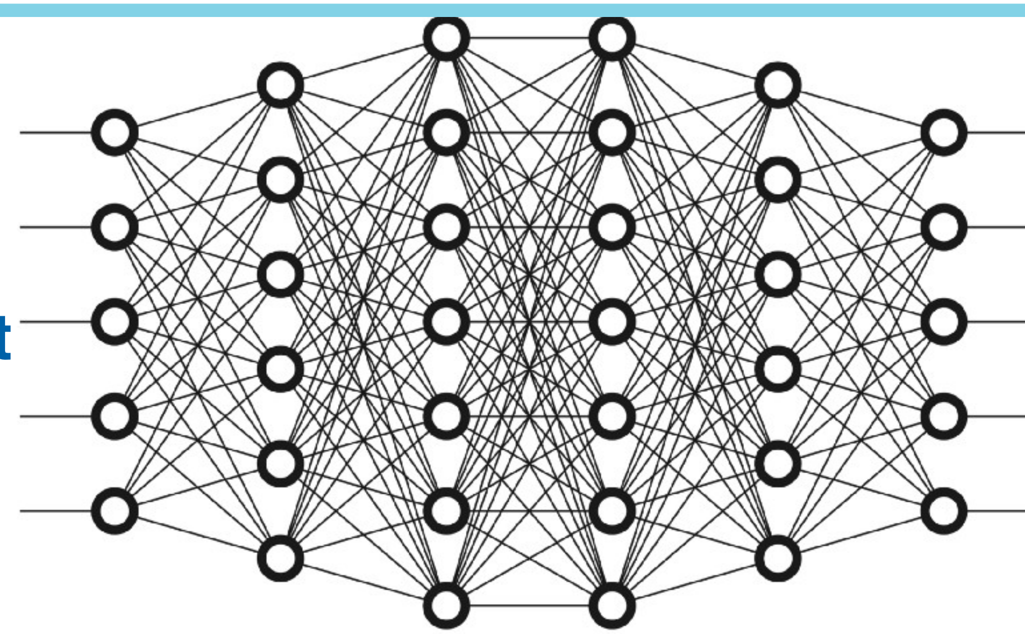
» A neural network has been trained by taking account 241 pixels as inputs





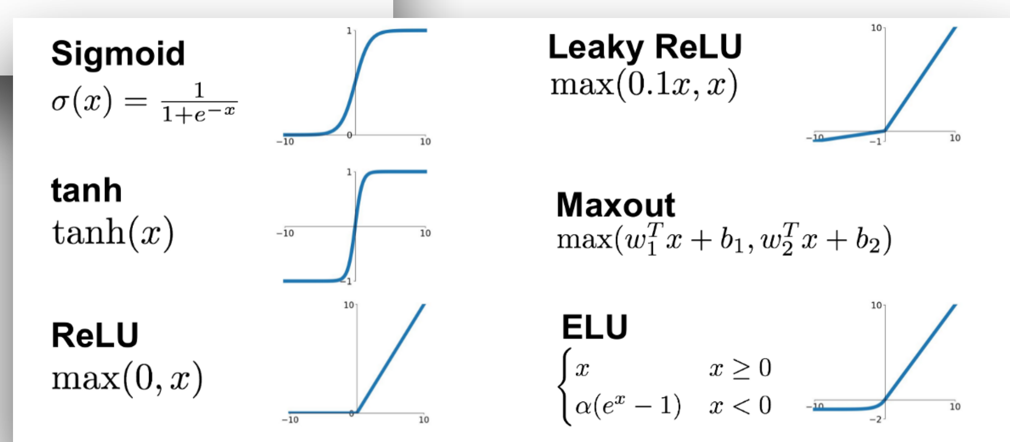
Neural Network Architecture





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

Activation function



Weights are updated according to the backpropagation 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
- » Number of hidden layers
- » Bias
- » Batch size

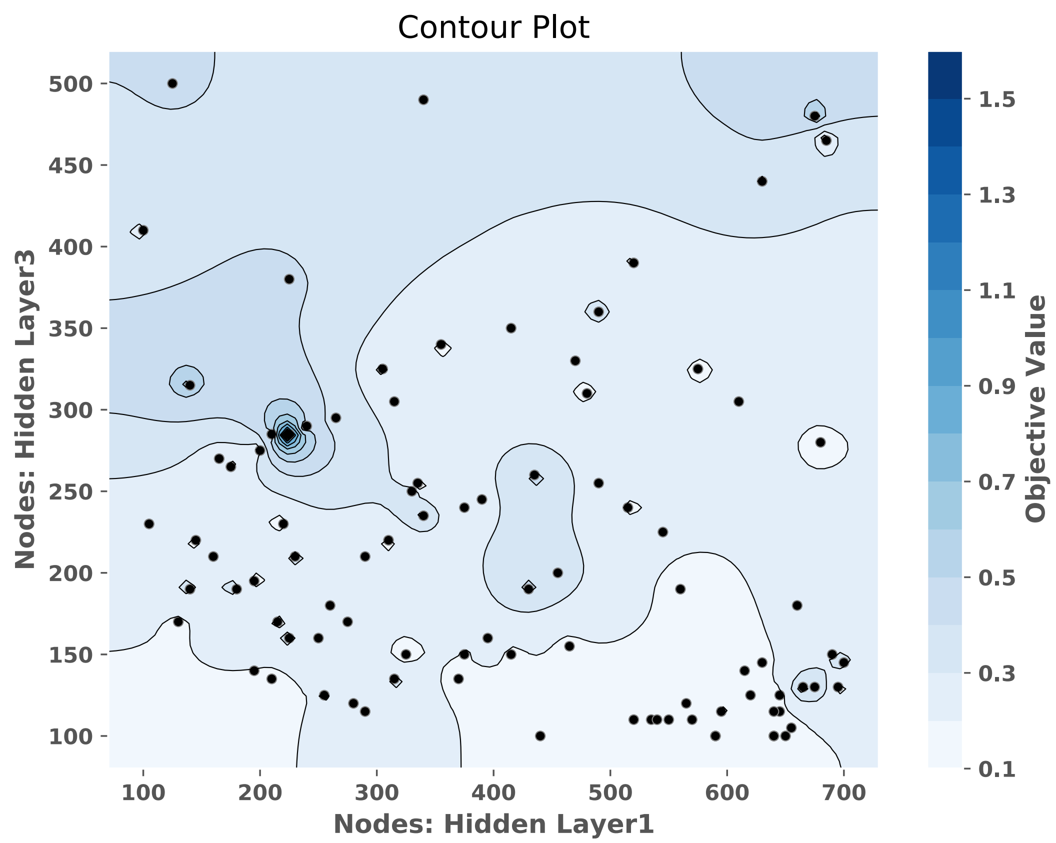
Hyperparameter Tuning

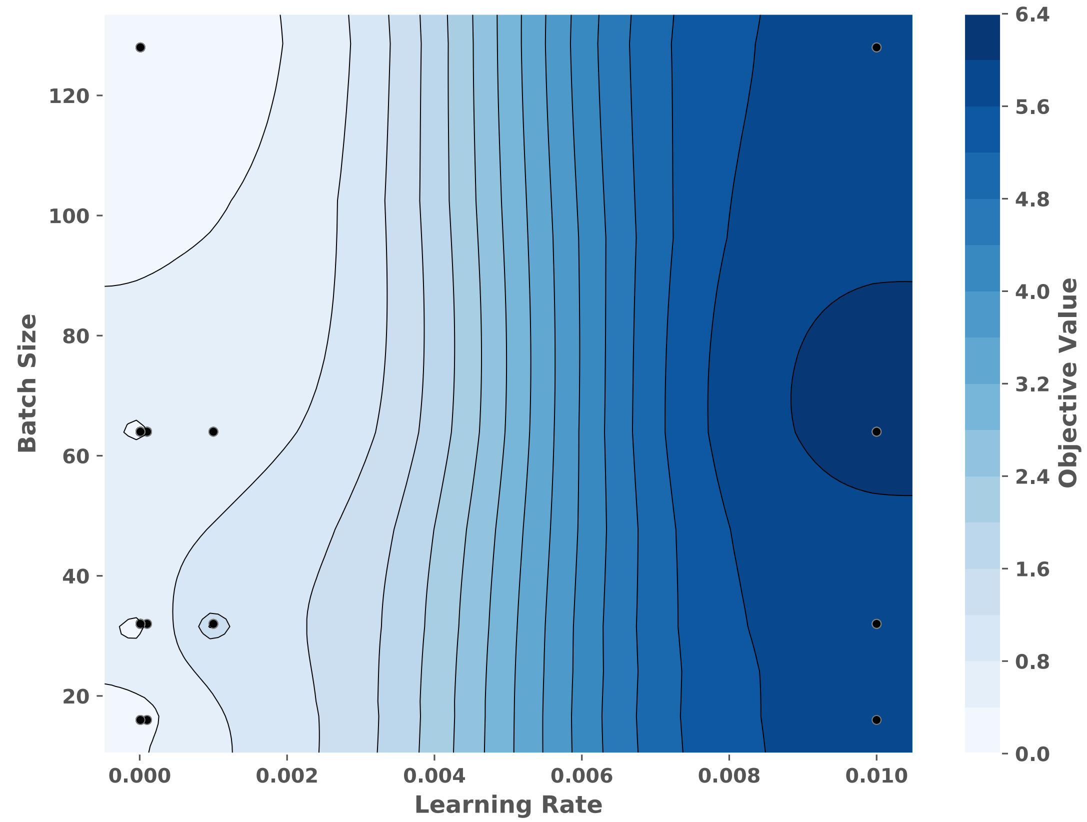
The process of searching for the best model architecture is referred to as hyperparameter tuning.

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

» **Searching parameter space with scans for selected parameter ranges**

Select the hyperparameter space for soft scan → **Select the suggested ranges from the soft scan for the next search** → **Repeat the procedure to achieve the optimal selection of parameters**





Optimized Model Architecture

An example of optimized NN architecture:

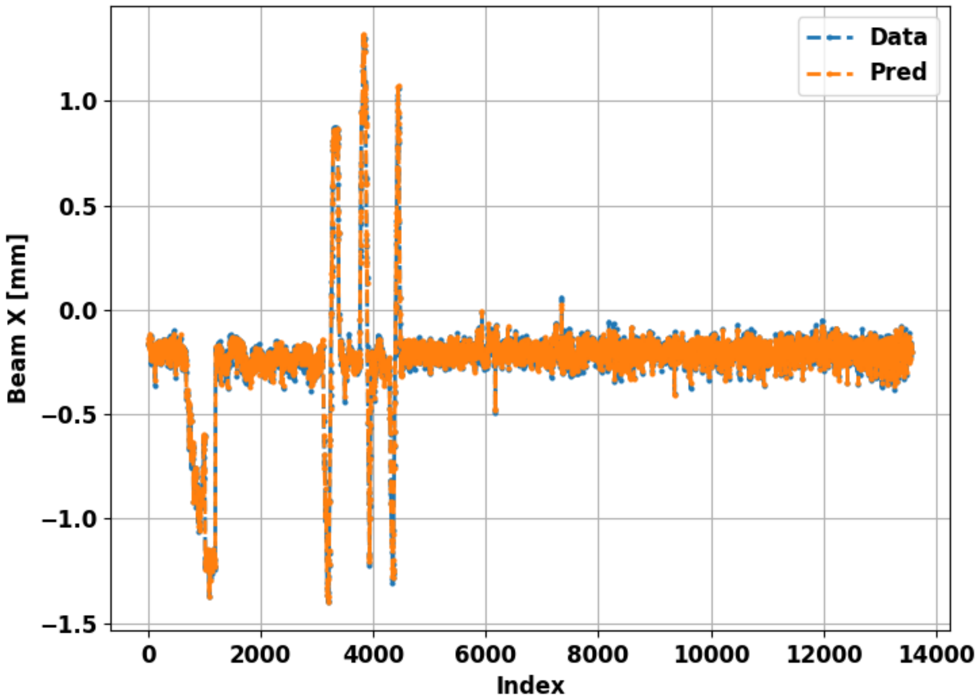
Input pixels = 241(removed 2 bad pixels)

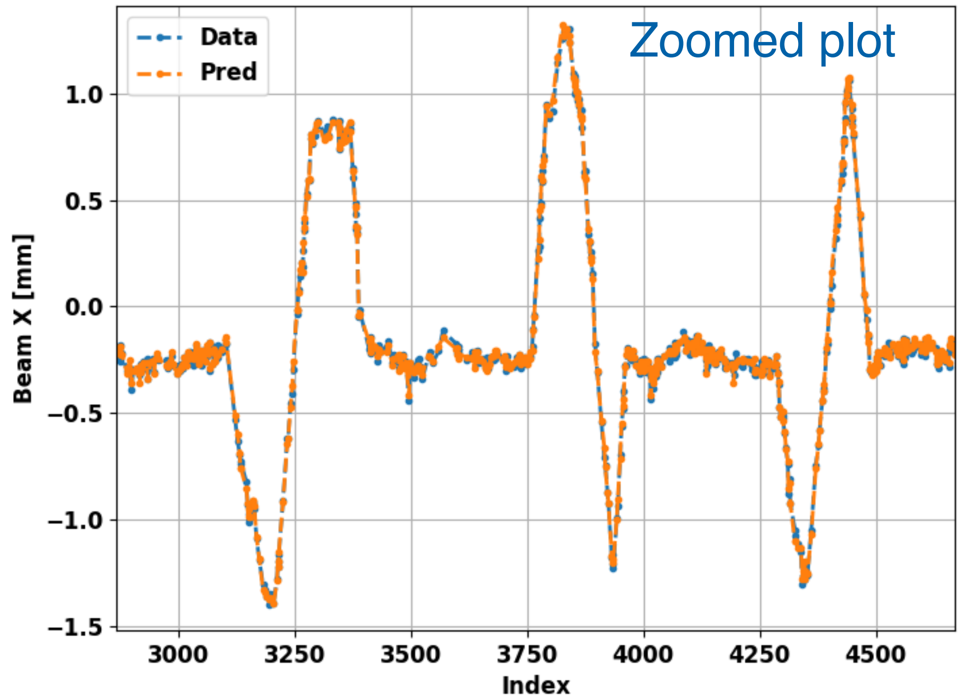
Batch size = 32

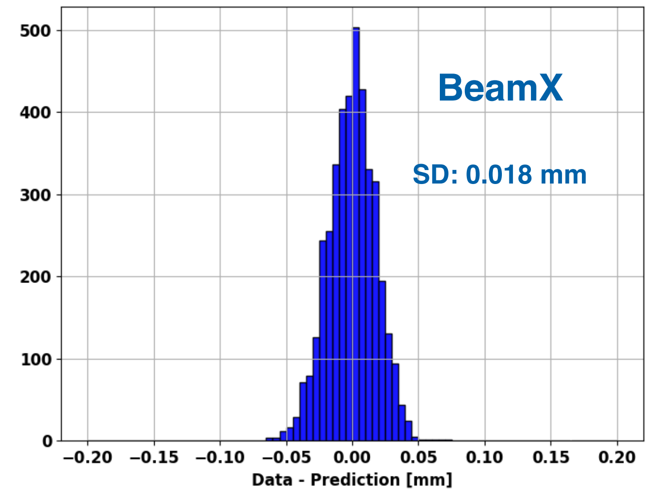
Learning rate = 1E-5

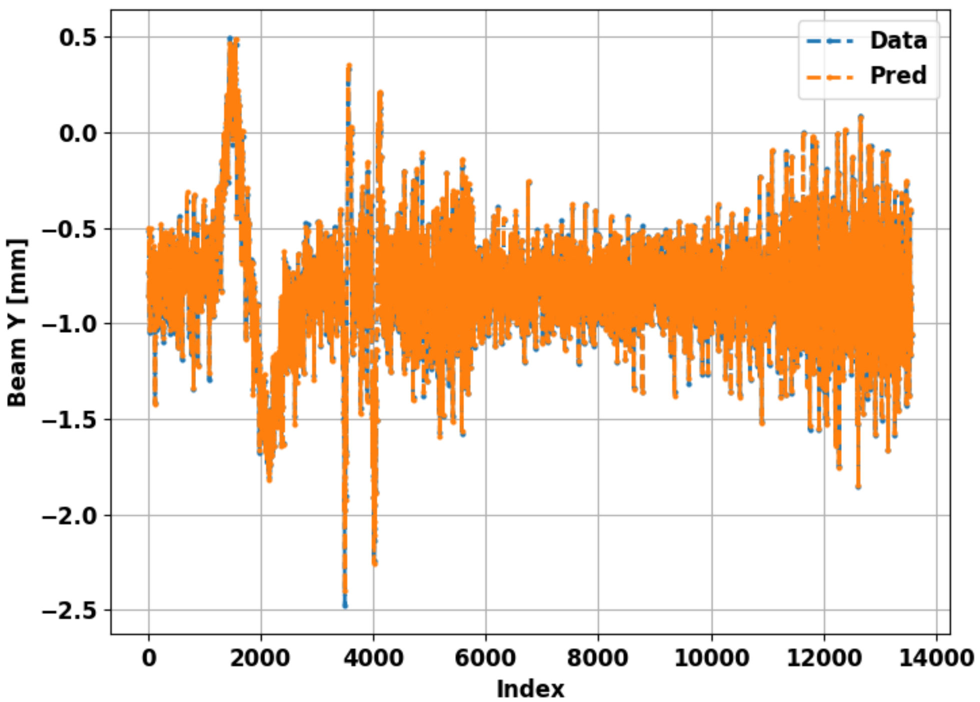
Layer (type)	Output Shape	Param #	Activation
dense (Dense)	(None, 480)	116160	Tanh
dense_1 (Dense)	(None, 130)	62530	Sigmoid
dense_2 (Dense)	(None, 135)	17685	Sigmoid
dense_3 (Dense)	(None, 11)	1496	Sigmoid
dense_4 (Dense)	(None, 4)	48	Linear

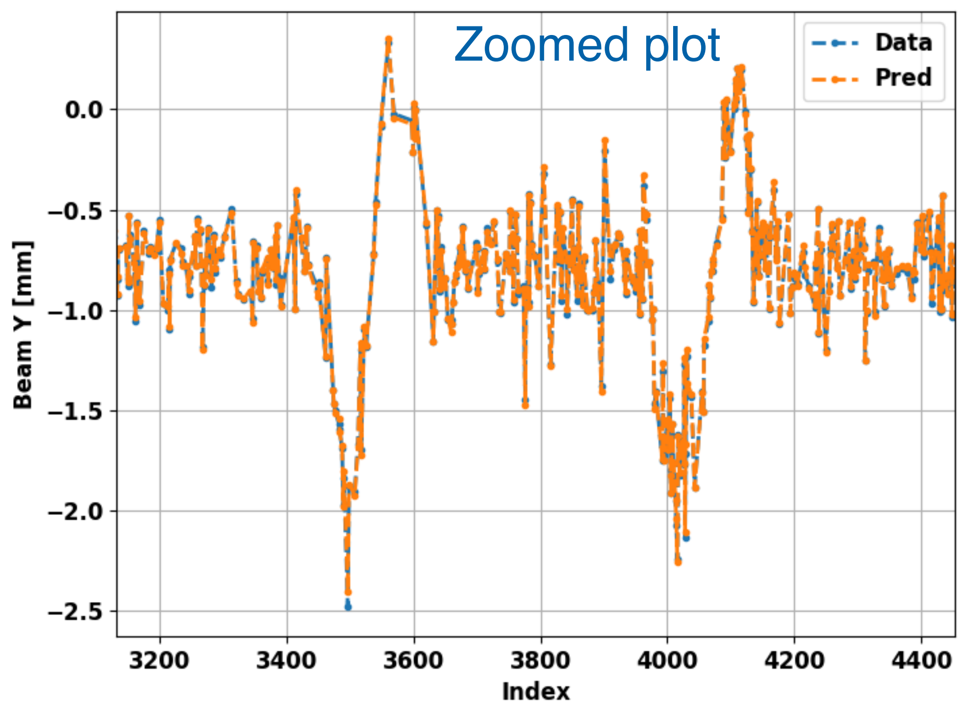
Summary of Predicting Beam Parameters and Horn Current

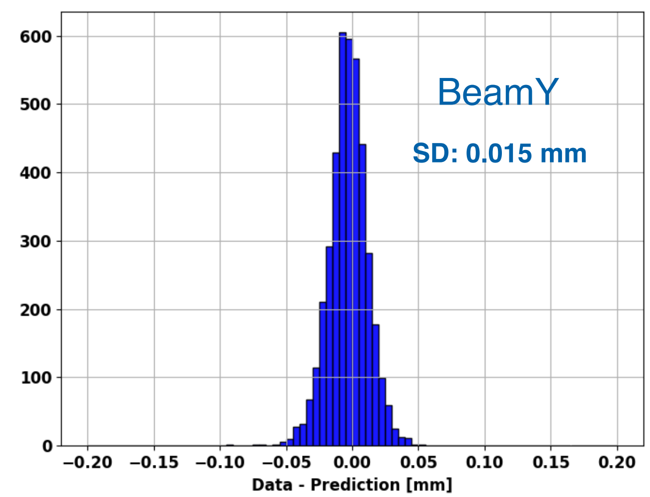




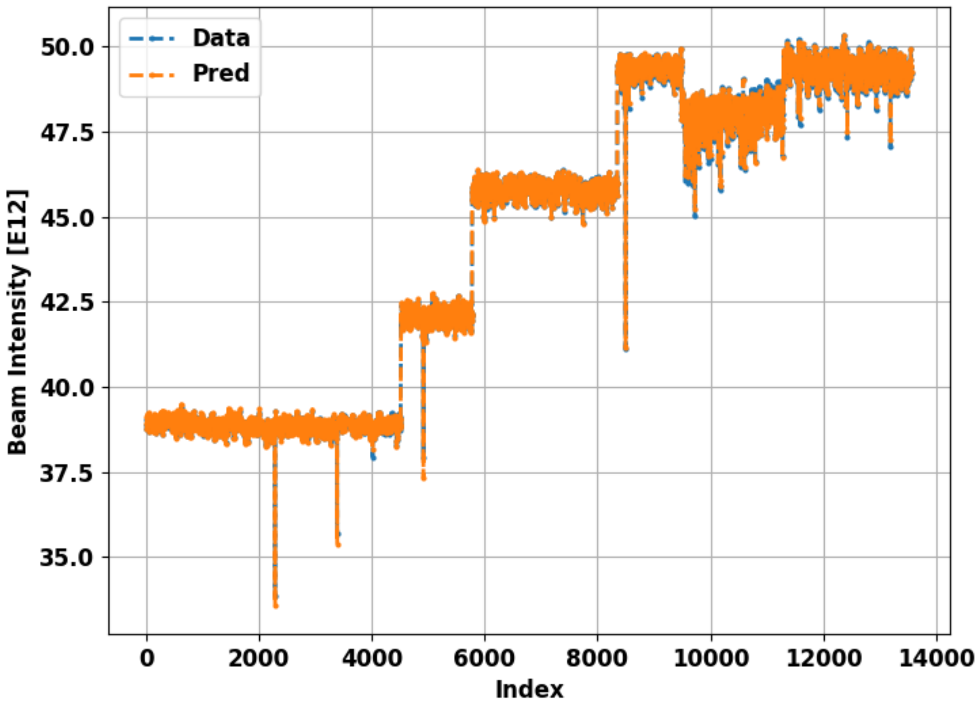


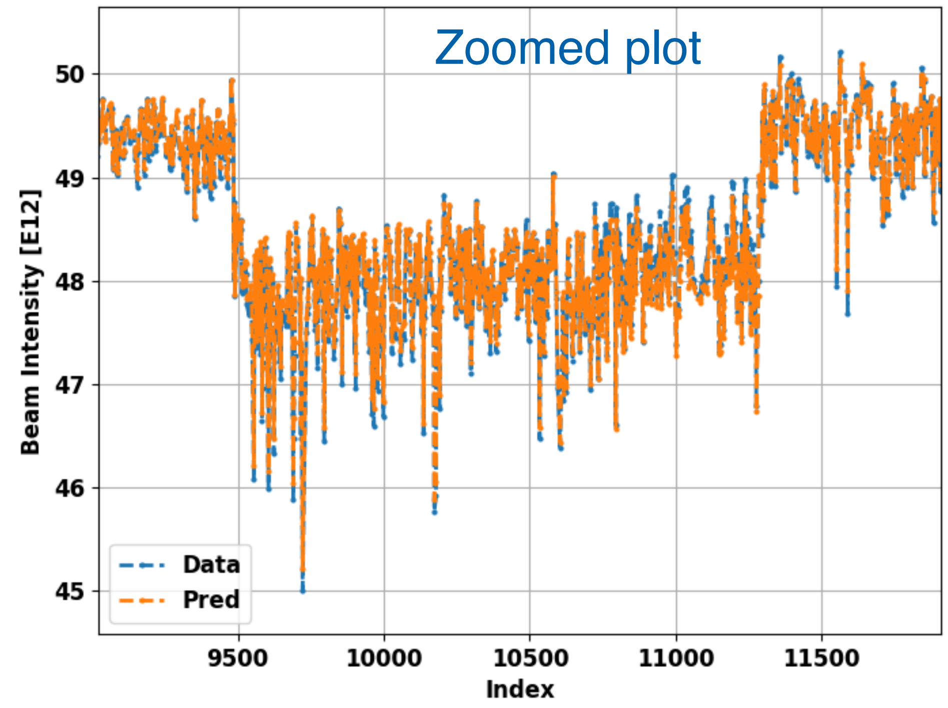


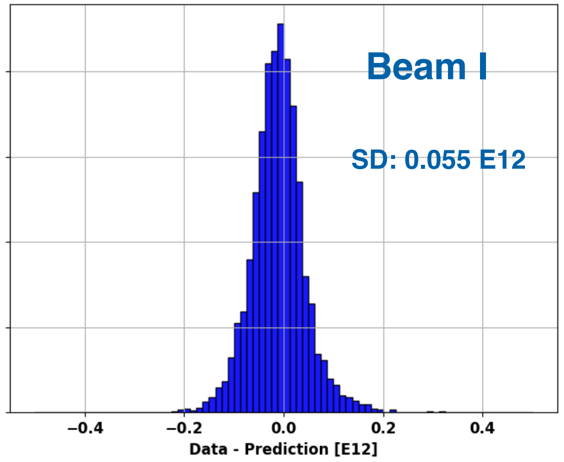


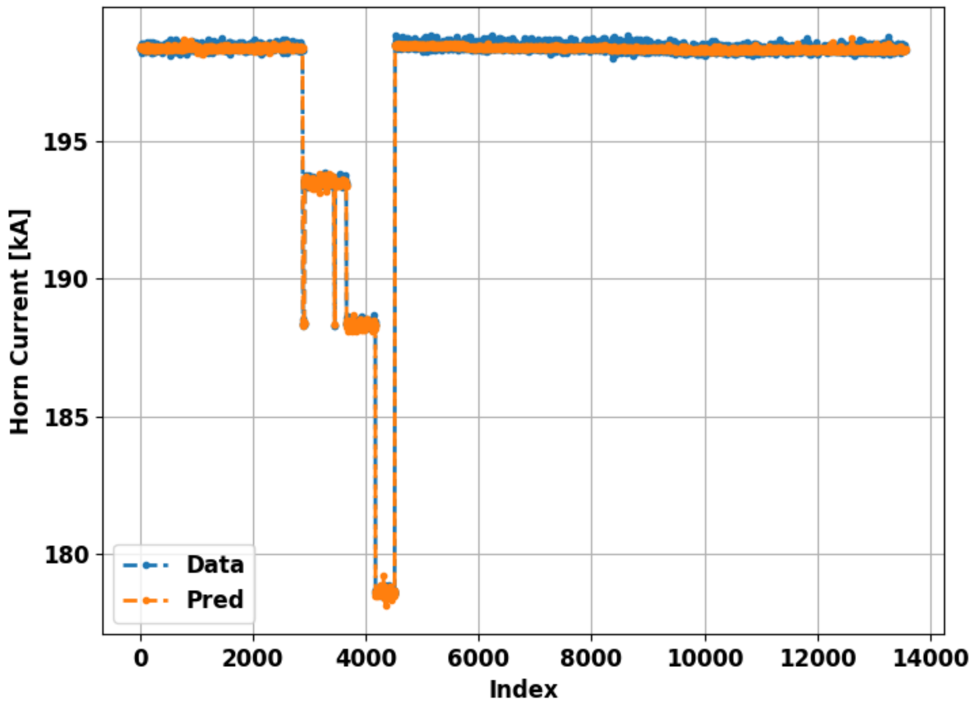


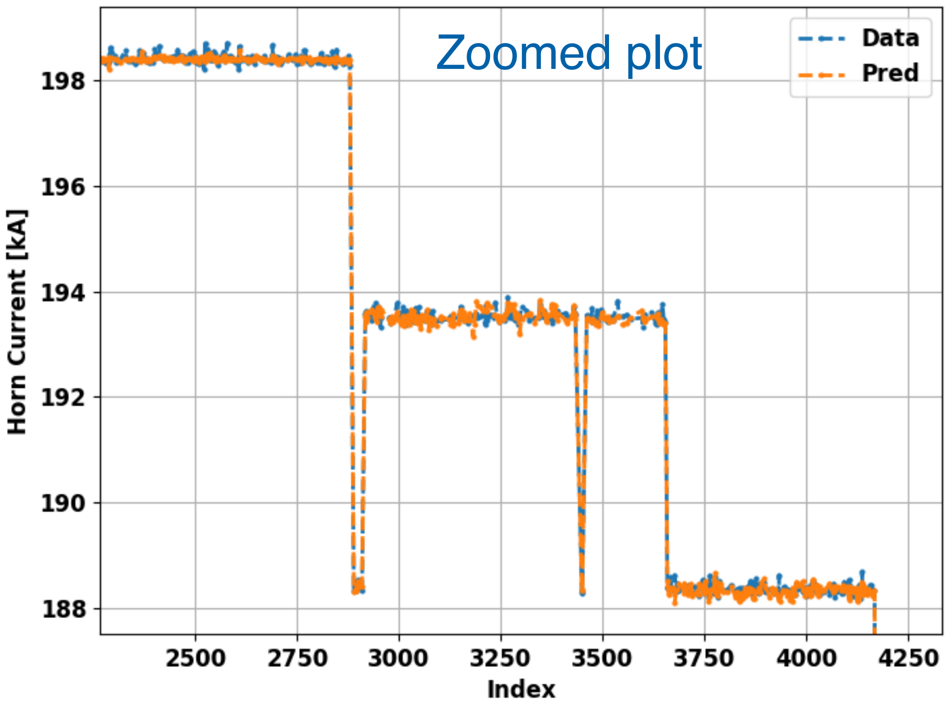
Summary of Predicting Beam Parameters and Horn Current

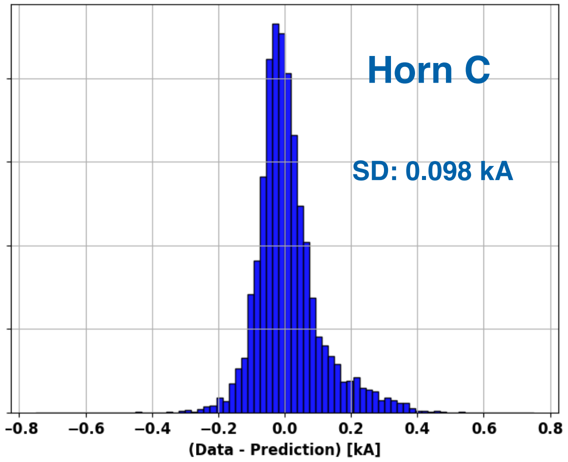












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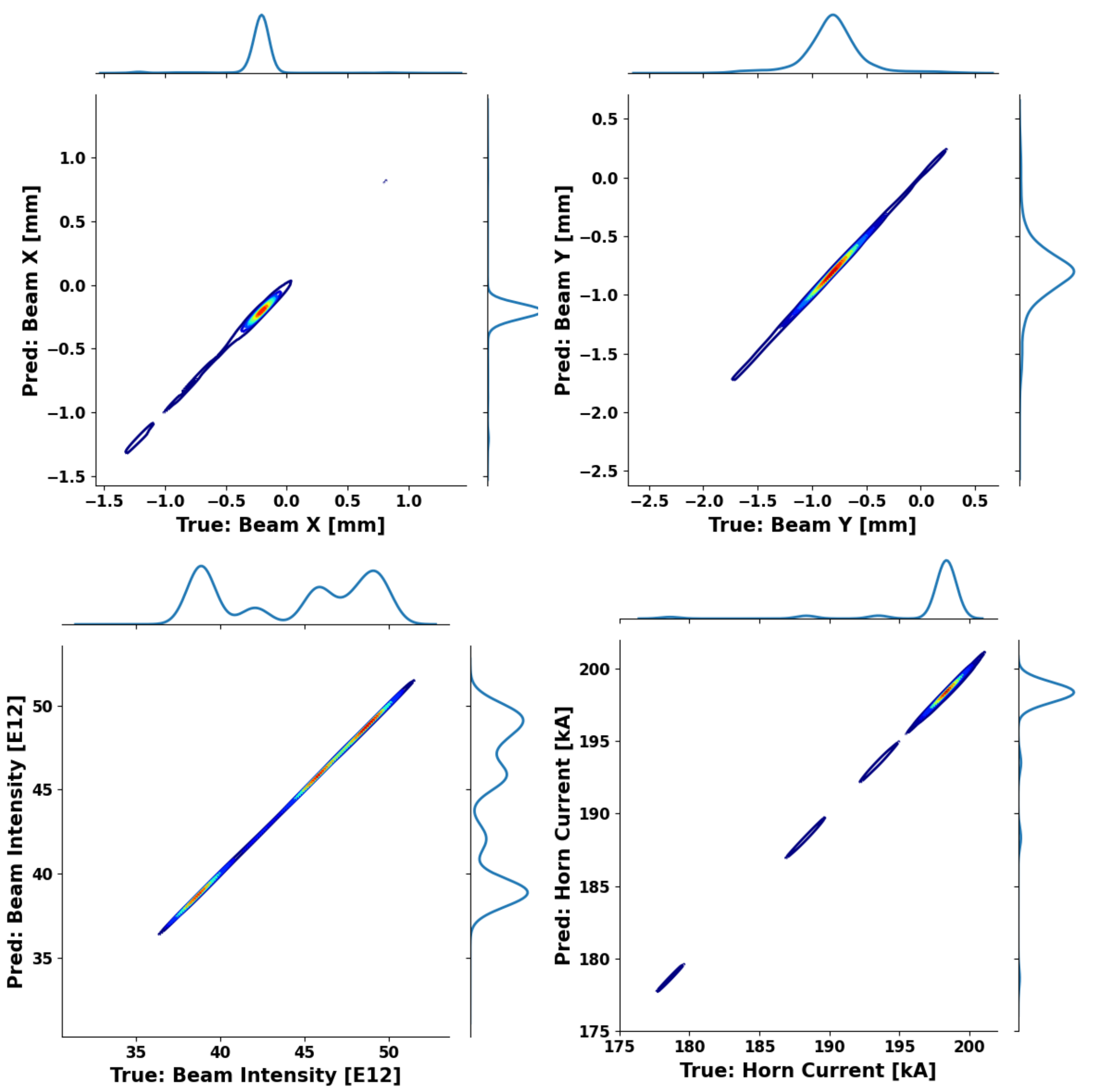
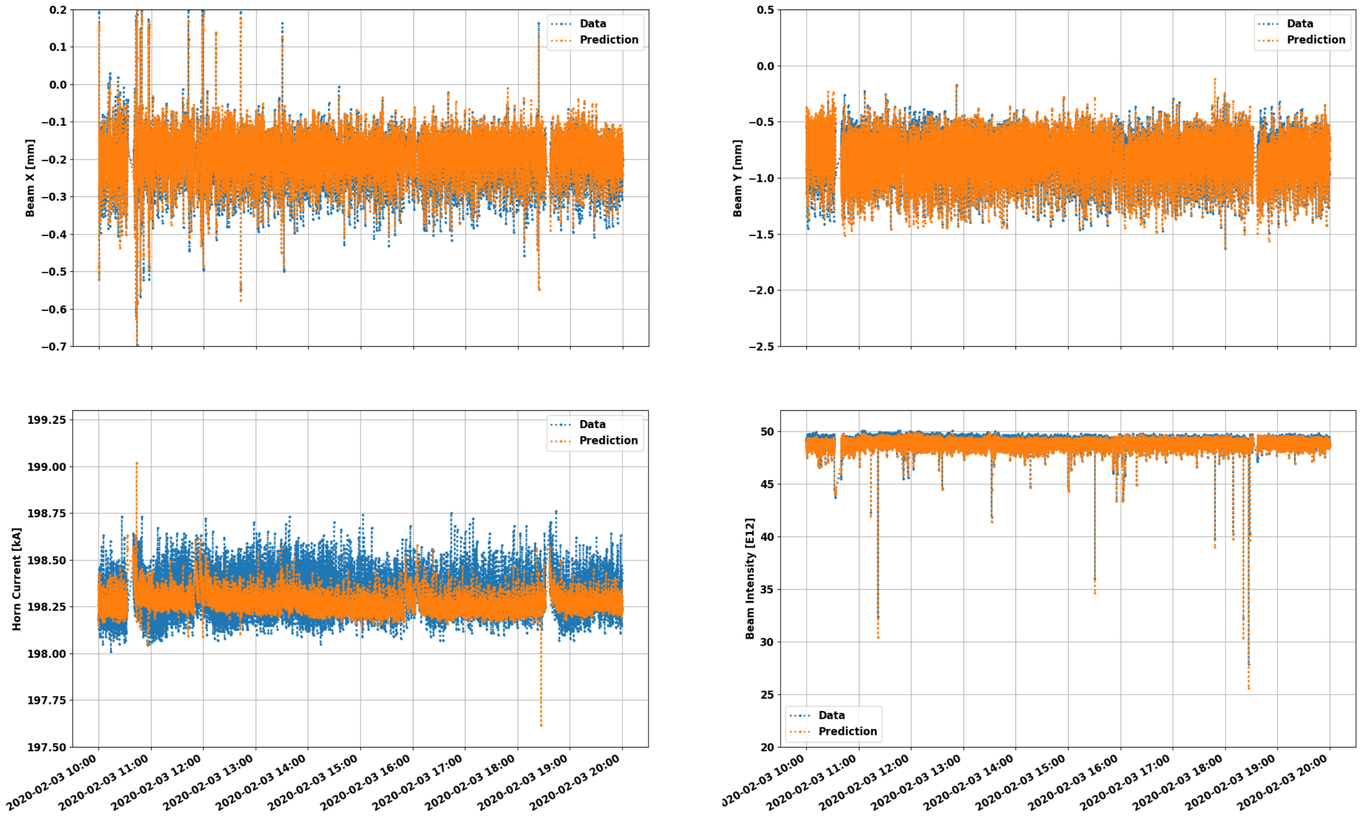
Summary of Predicting Beam Parameters and Horn Current

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**



Simulation Efforts

Goal:

- Perform NuMI simulation studies to understand correlation b/w muon monitor data & neutrino flux at ND
- Help catch "anomaly" scenarios; e.g. horn tilt or slip, target tilt, target deterioration, density effects, etc.

Steps:

Develop simulation technique to maximize statistics & minimize computation time → Validate new simulation technique → Generate large simulation sample for nominal case & each anomaly scenario → Use simulation sample for ML tools

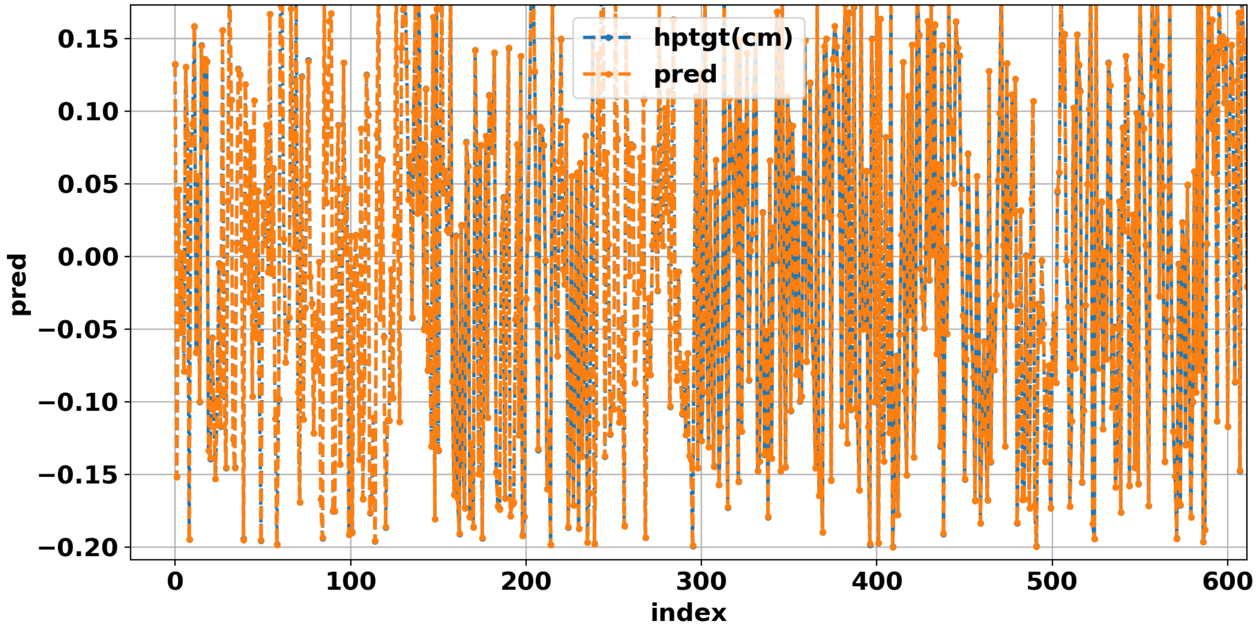
Please see Yiding Yu's talk (WG3 Today 2:50 PM) for more details

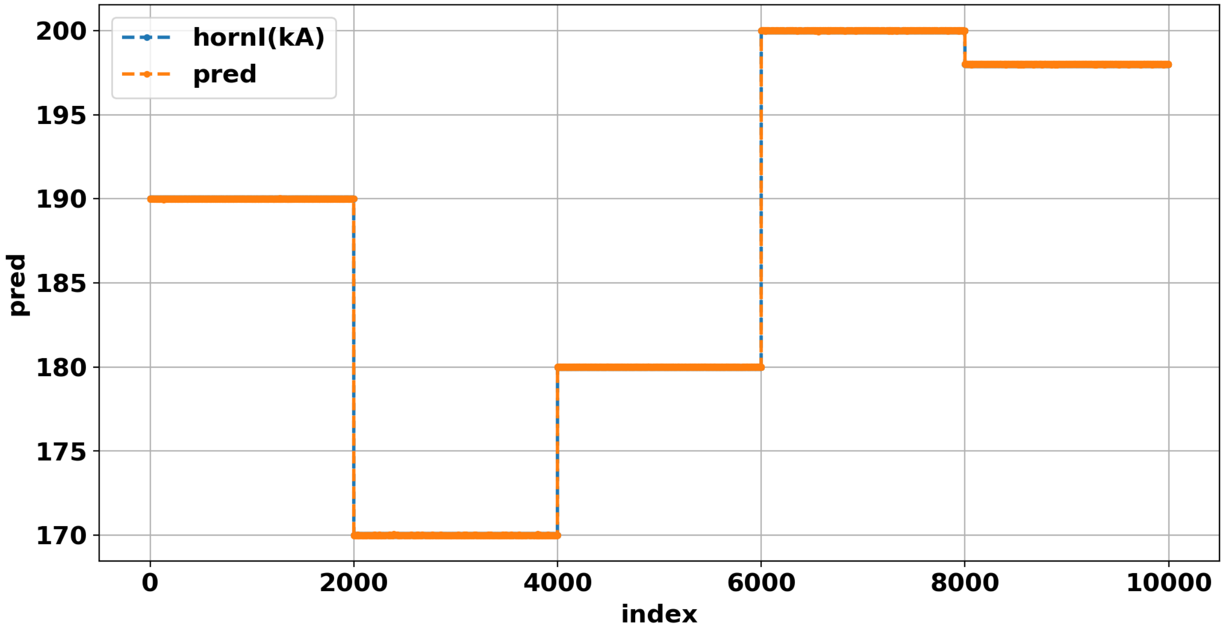
Linear Regression Model Approach

- Testing a linear model by taking account 243 pixels as inputs
- Predicting beam variables independently
- This is helping to understand the linear correlations and also non-linear effects on predictions

$$prediction = \sum_{i=0}^{N} \alpha_i \cdot X_i + \beta_i$$

Yiding Yu





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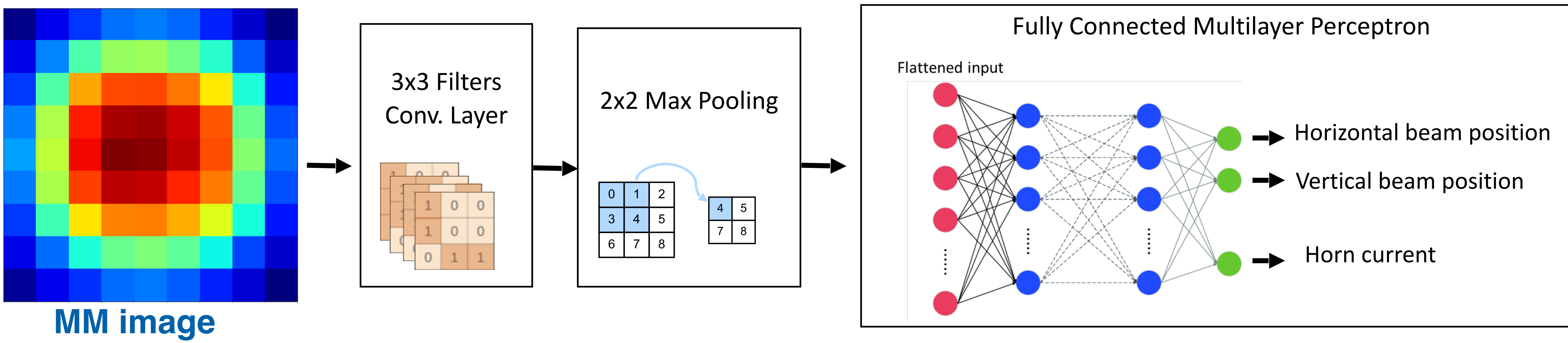
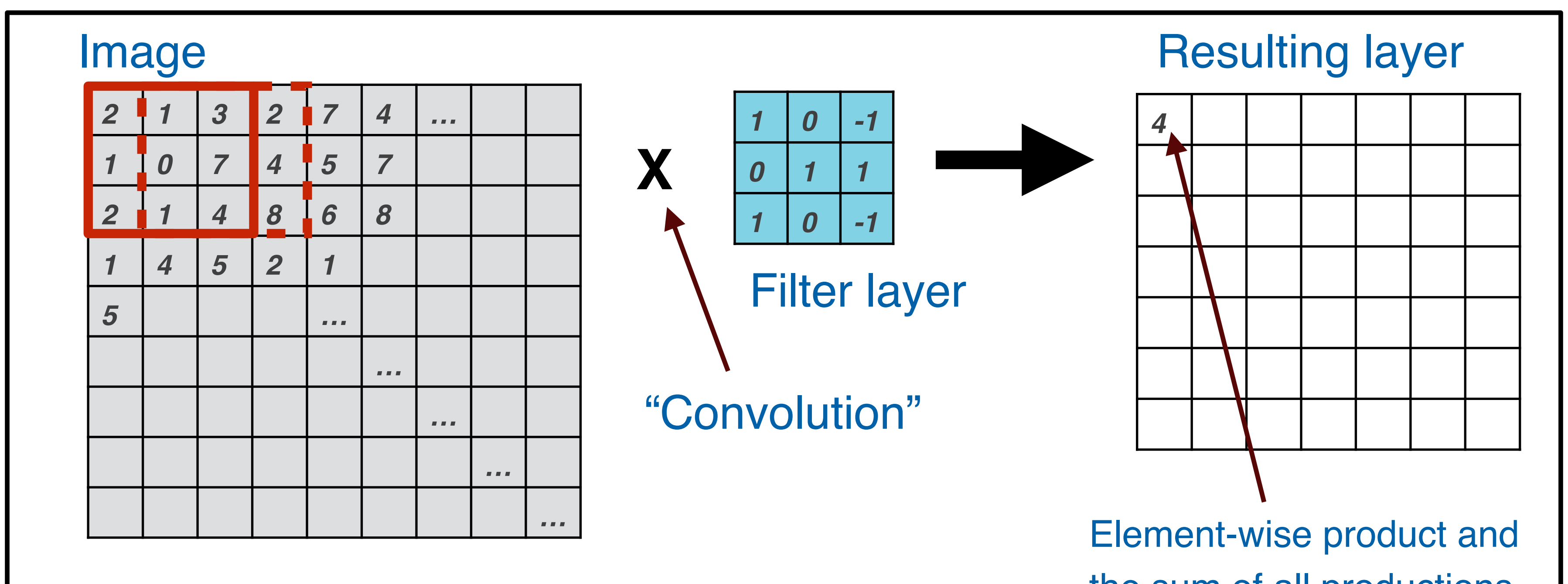
CNN Model Approach

- **Muon monitor pixel data is taken account as an image analysis**
- **CNN has the capability to handle with important features**

Eduardo Ossorio Alfaro





Simple example of the CONV layer

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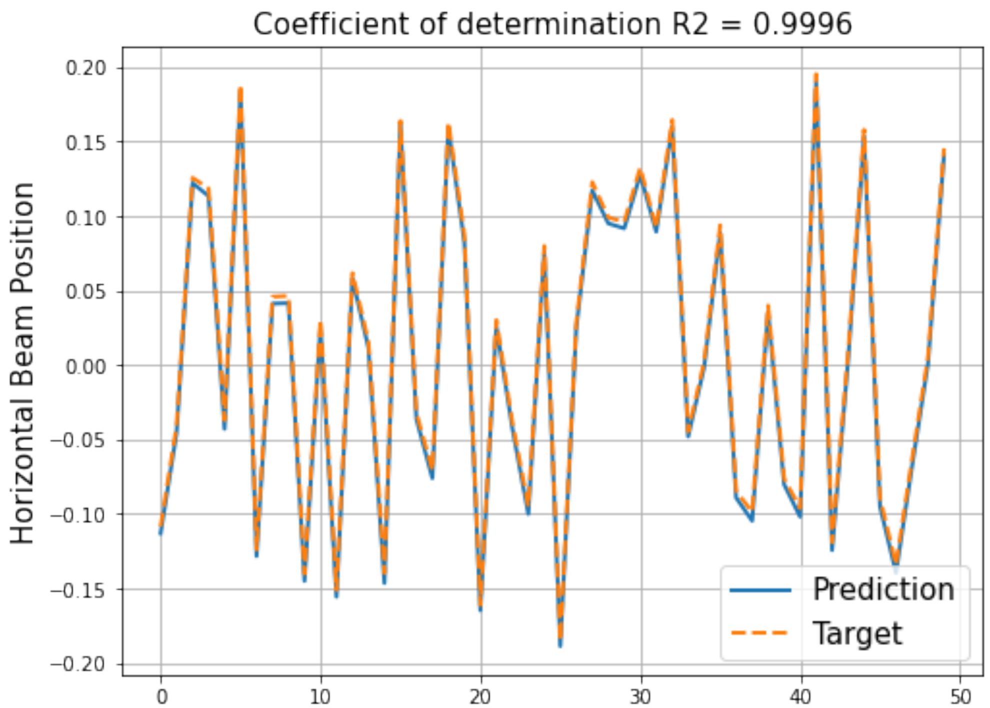
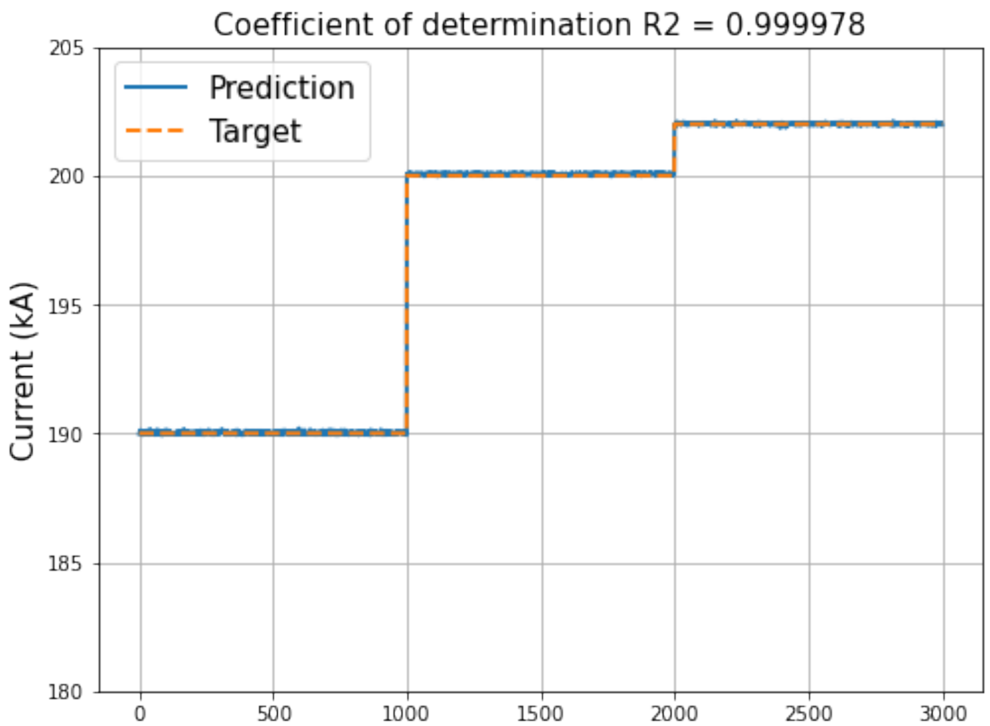
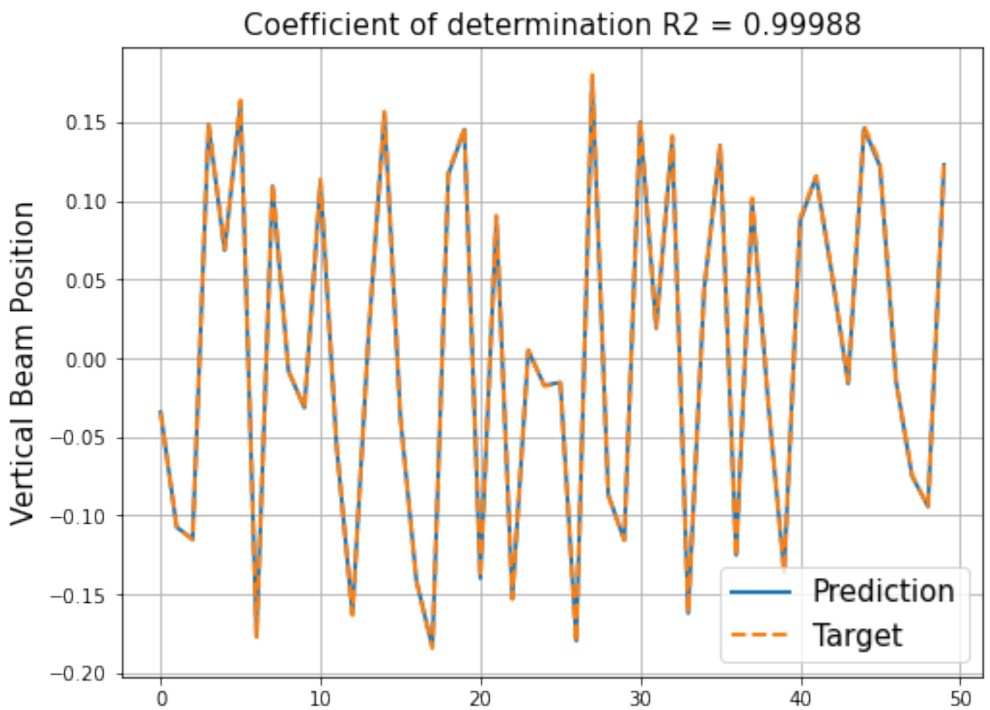
CNN model building progress

Example of testing / validating a CNN model

Eduardo Ossorio Alfaro







Status:

- **Planing to add neutrino flux information**
- **Searching for the optimal model architecture**
- **Tuning the parameters based on the performance**
- **Testing the model with simulation data**

A summary of ongoing simulation projects

- Testing and validating the use of simulation data to build ML applications
- Building models to predict neutrino information at the NOvA near detector for different beam, horn and target conditions
- Preparing simulation data with rare incidents such as:
  - » target tilt or slip, target density effects, horn tilt or slip, etc
- Planing to build ML applications to detect rare incidents and anomalies

Please see Yiding Yu's talk (WG3 Today 2:50 PM) for more details

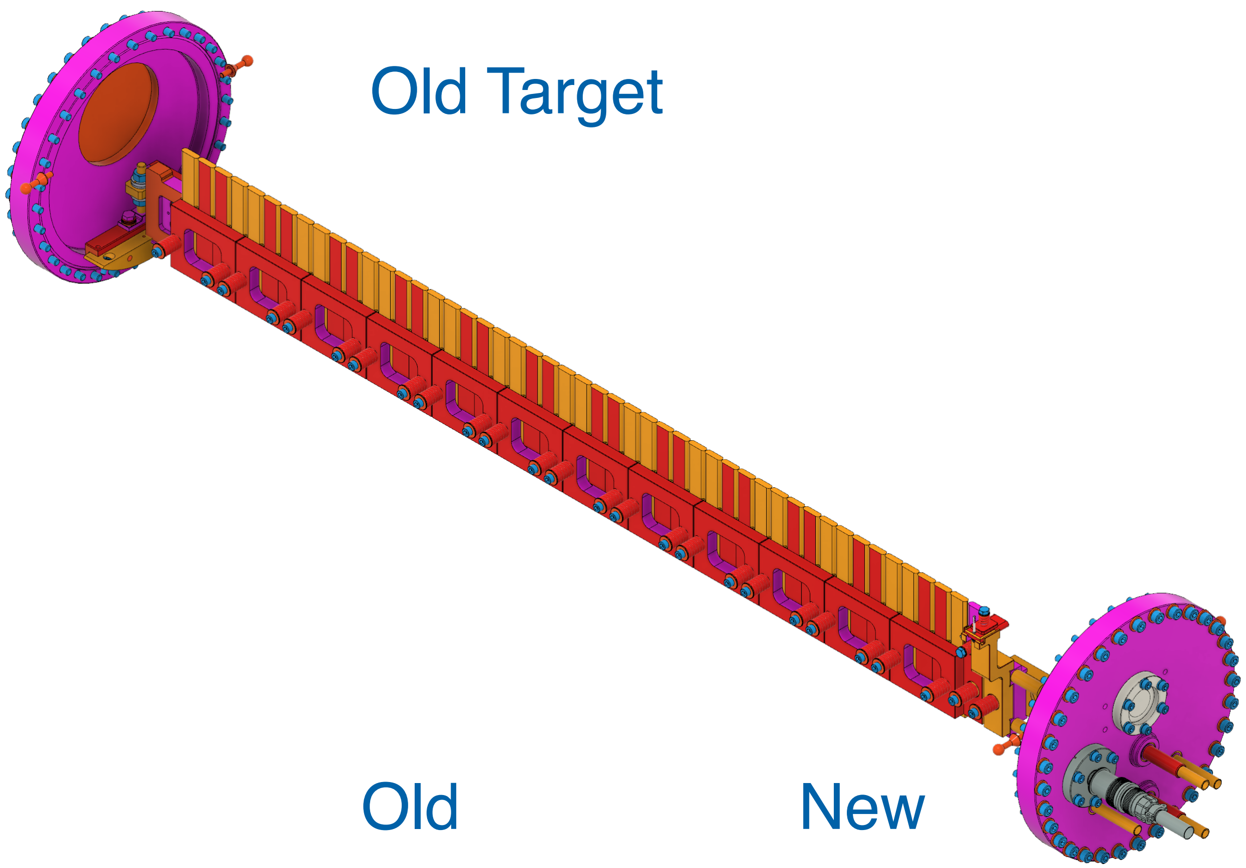
Remarks

- Muon monitor signals can be used as an independent monitoring system to understand the beam performance
- We demonstrate a machine learning approach to predict the beam parameters by using muon monitor signals
- ML predictions give an extra measurement of the beam parameters and horn current for neutrino experiment
- ML applications are helpful to monitor the beam quality, issues and anomalies
- ML applications will be useful to reduce the neutrino flux systematics with the help of simulation studies
- Development of simulation techniques is promising to build useful ML models to predict the neutrino information
- This simulation efforts are opening to build ML tools to understand and identify rare events such as target deterioration, horn tilt/slip, etc.

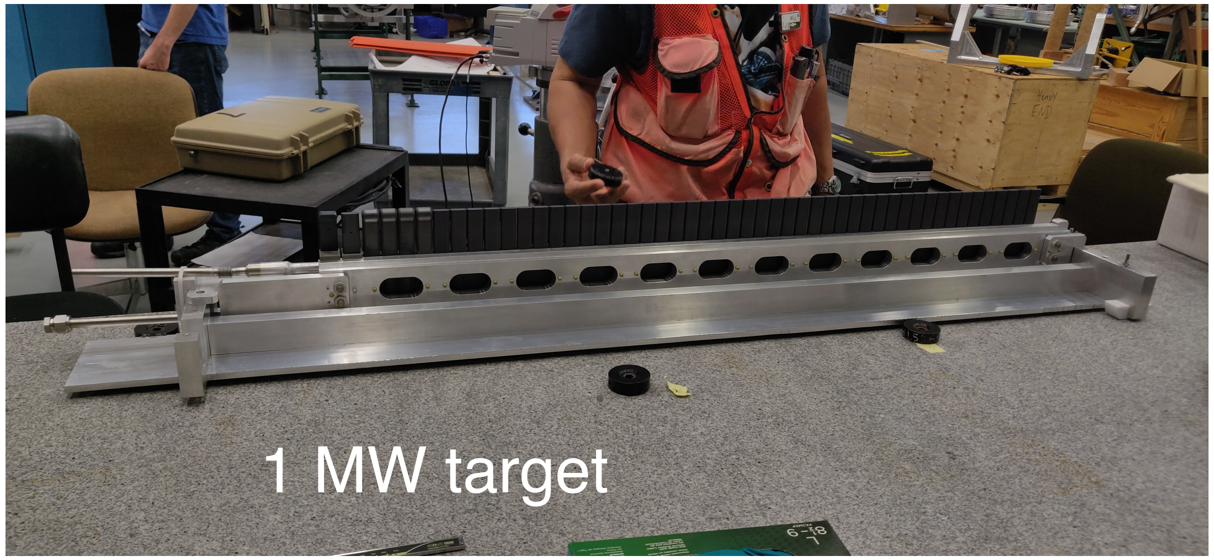
Thank you

Time to introduce New vs Old Targets

1-MW NuMI target has been installed during the summer shutdown in 2019



Old Target



	Old	New
Width :	7.4 mm	9.0 mm
Height:	14.30 cm	15.53 cm
Segment length:	2.5 cm	2.5 cm

- Four target segments have cylindrical shapes tops in the new target system
- Densities are same

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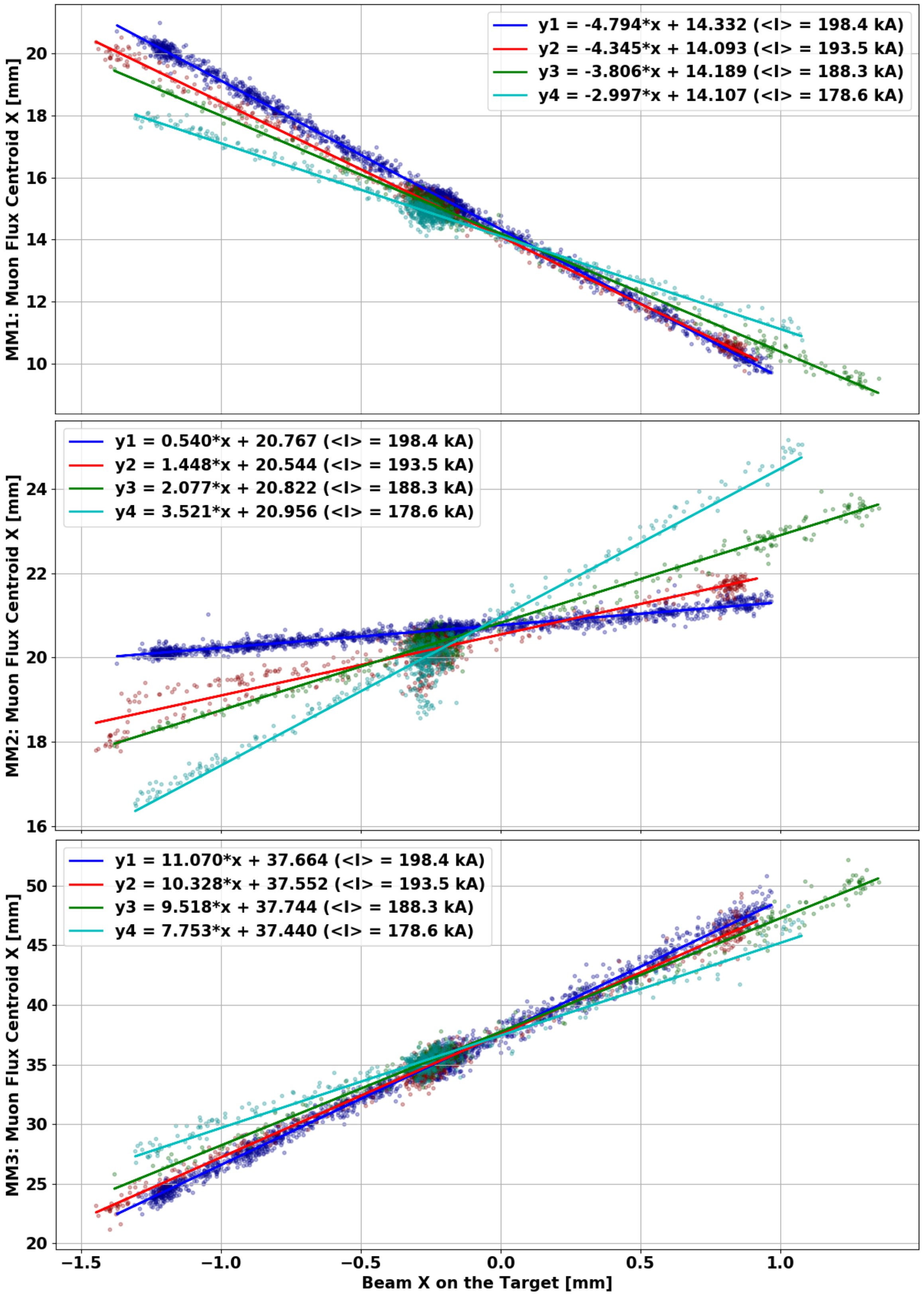
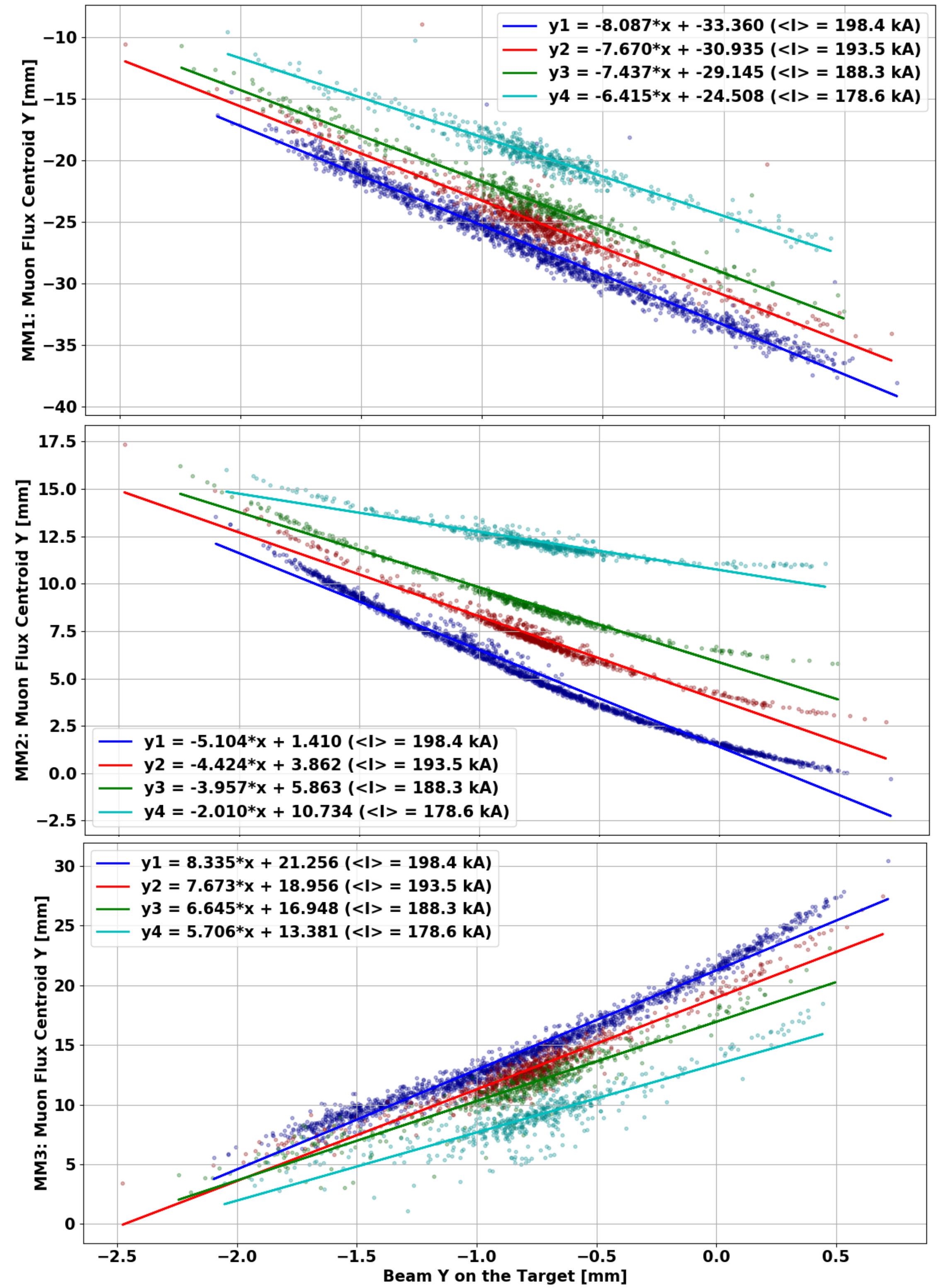
Beam scans with horn current settings

Horizontal Scan



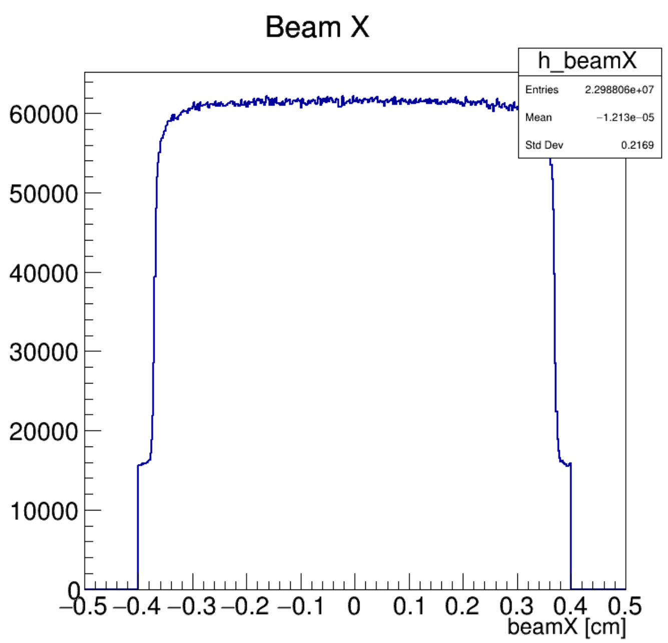
Vertical Scan

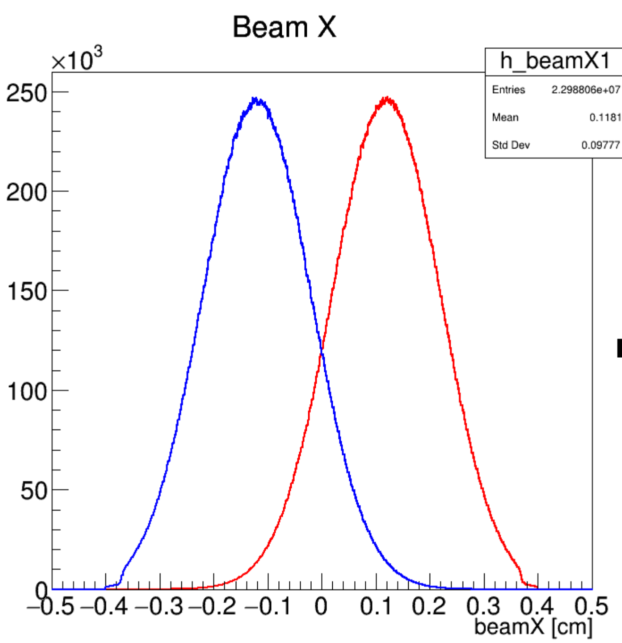


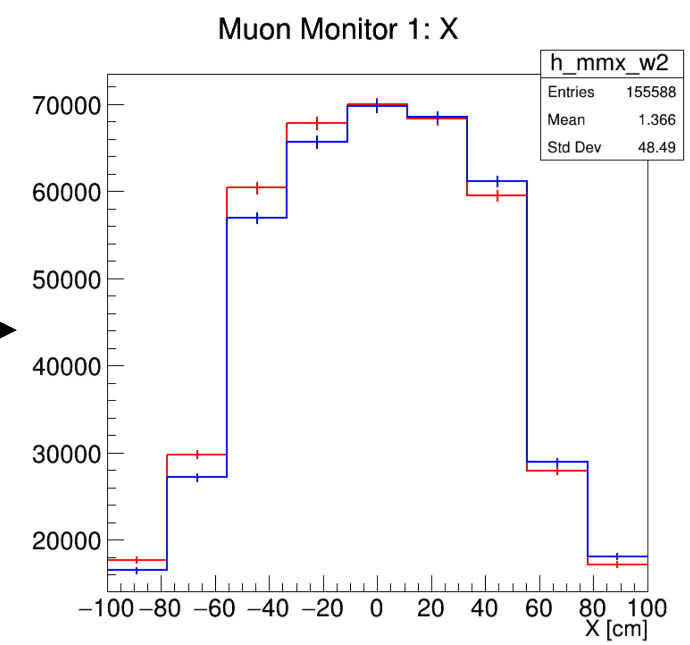
Simulation Data Preparation

Preparing a single high-statistics simulation sample for variables by simulating a uniform distribution, then use post-processing with calculating gaussian weights to generate the data points.

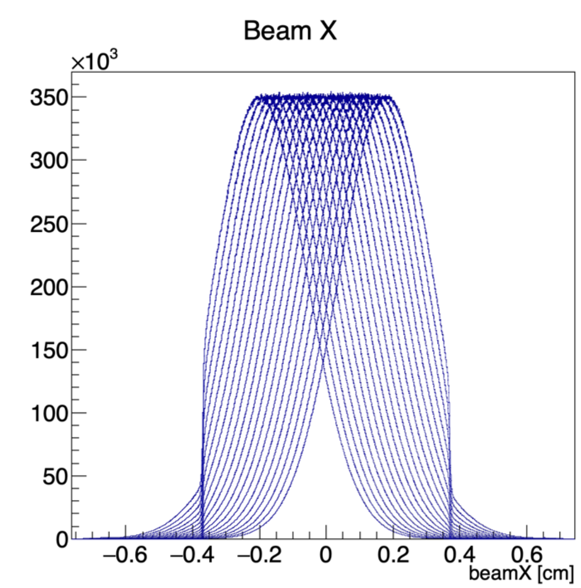
$$GW_i = \frac{1}{2\pi\sigma_x\sigma_y} \cdot exp\left\{ -\frac{(x_i-\mu_x)^2}{2\sigma_x^2} - \frac{(y_i-\mu_y)^2}{2\sigma_y^2} \right\}$$







- **This technique is useful to generate large set of data samples for ML applications**
- **We have combined this technique with pions multiple decay technique to generate large statistical samples**



Please see Yiding Yu's talk for more details