Machine Learning Based Tuning and Diagnostics for the ATR line at BNL

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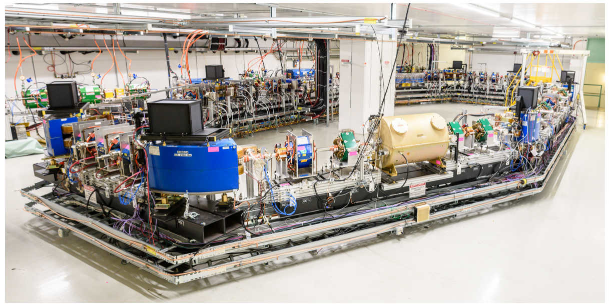
Overview of Accelerator Operations

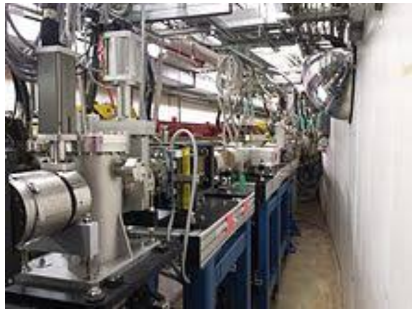
Accelerator R+D

Machine Development Time

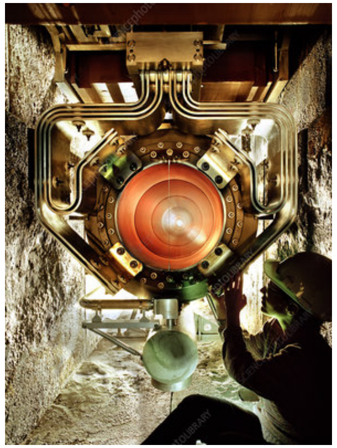
Specialized R+D Facilities



Beam for Experimentalists



Small single user end stations

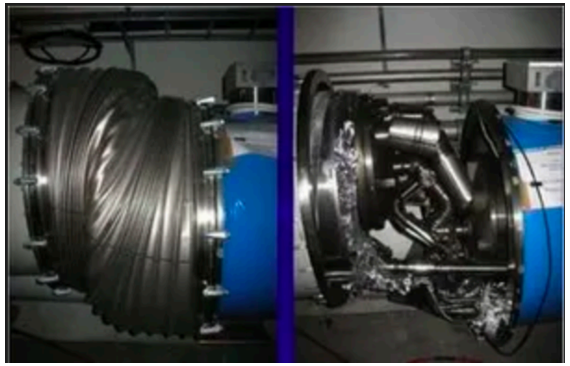


Large experimental collaborations

Down Time

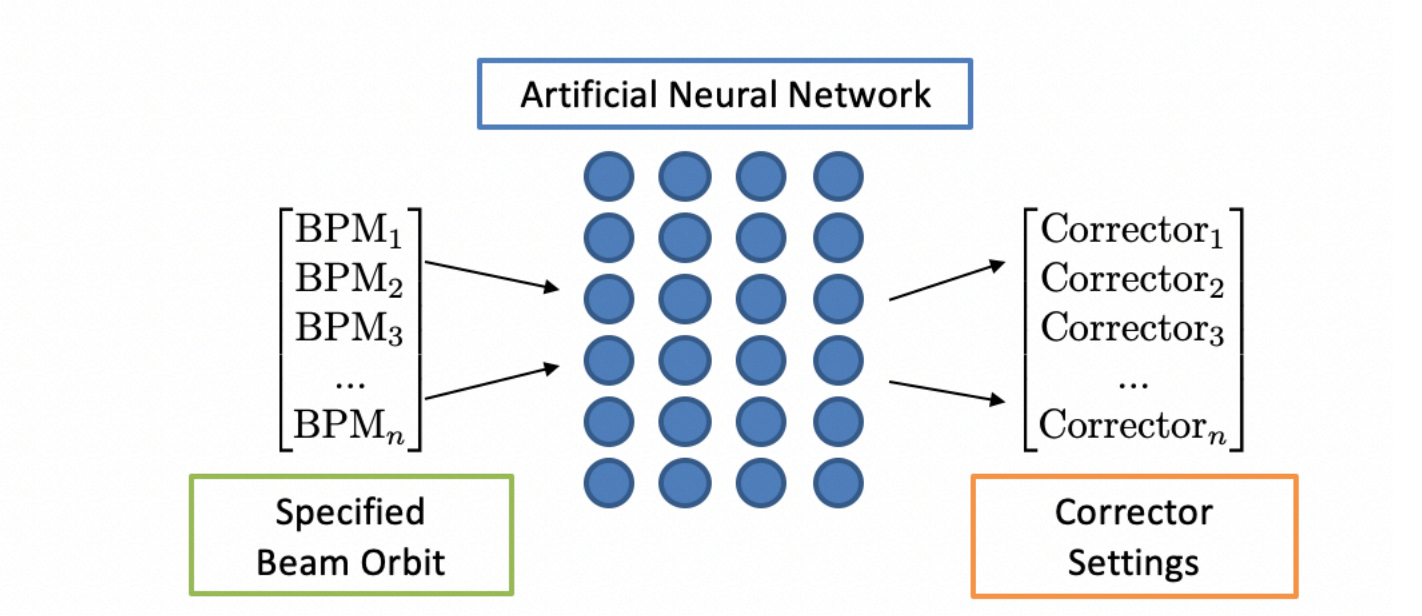
Scheduled Maintenance

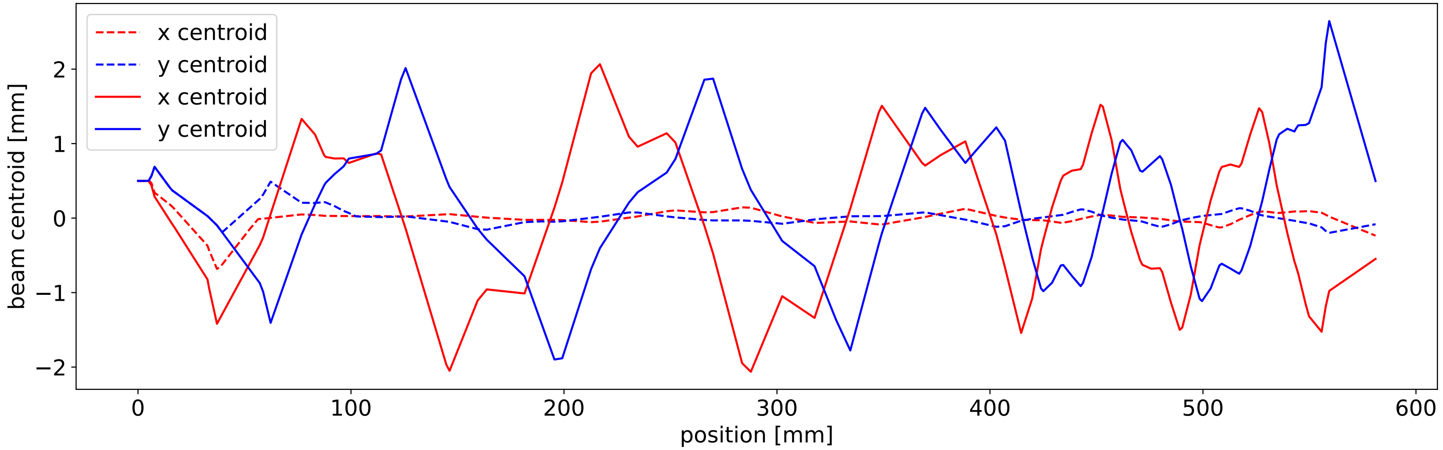
Unscheduled Maintenance



Inverse Models for Diagnostics and Tuning

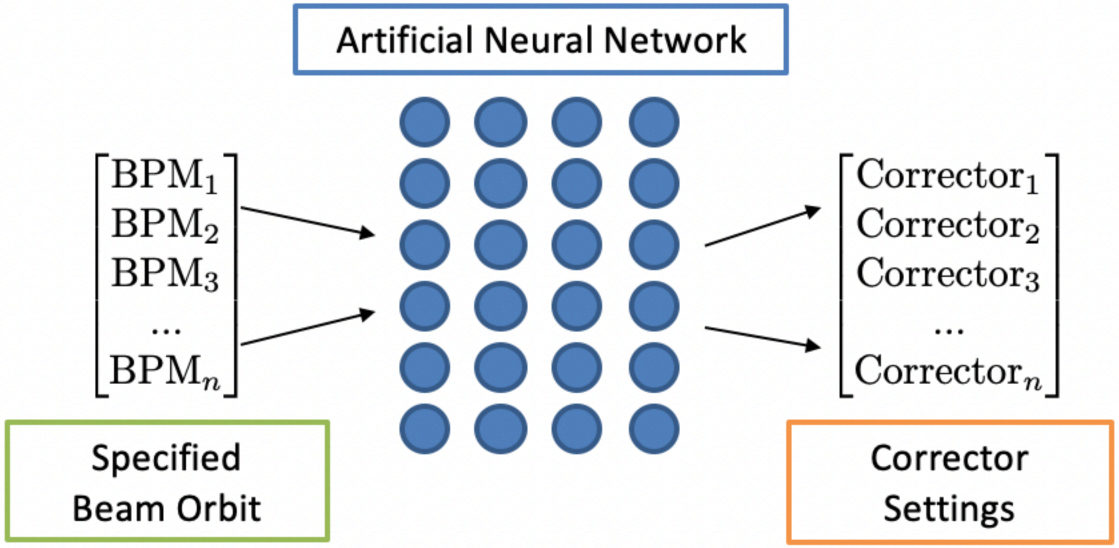
- Direct use of inverse models for tuning
  - Train a model to predict settings from desired diagnostic output
  - A common application is beam steering
    - Inputs are the requested BPM readings
    - Outputs: Suggested corrector settings

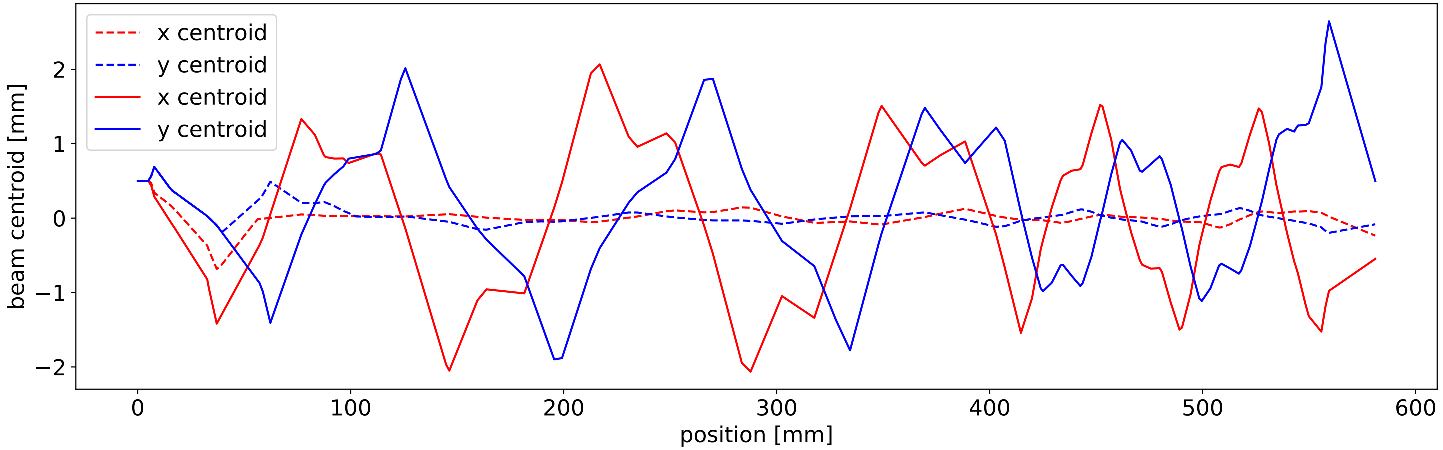




Inverse Models for Diagnostics and Tuning

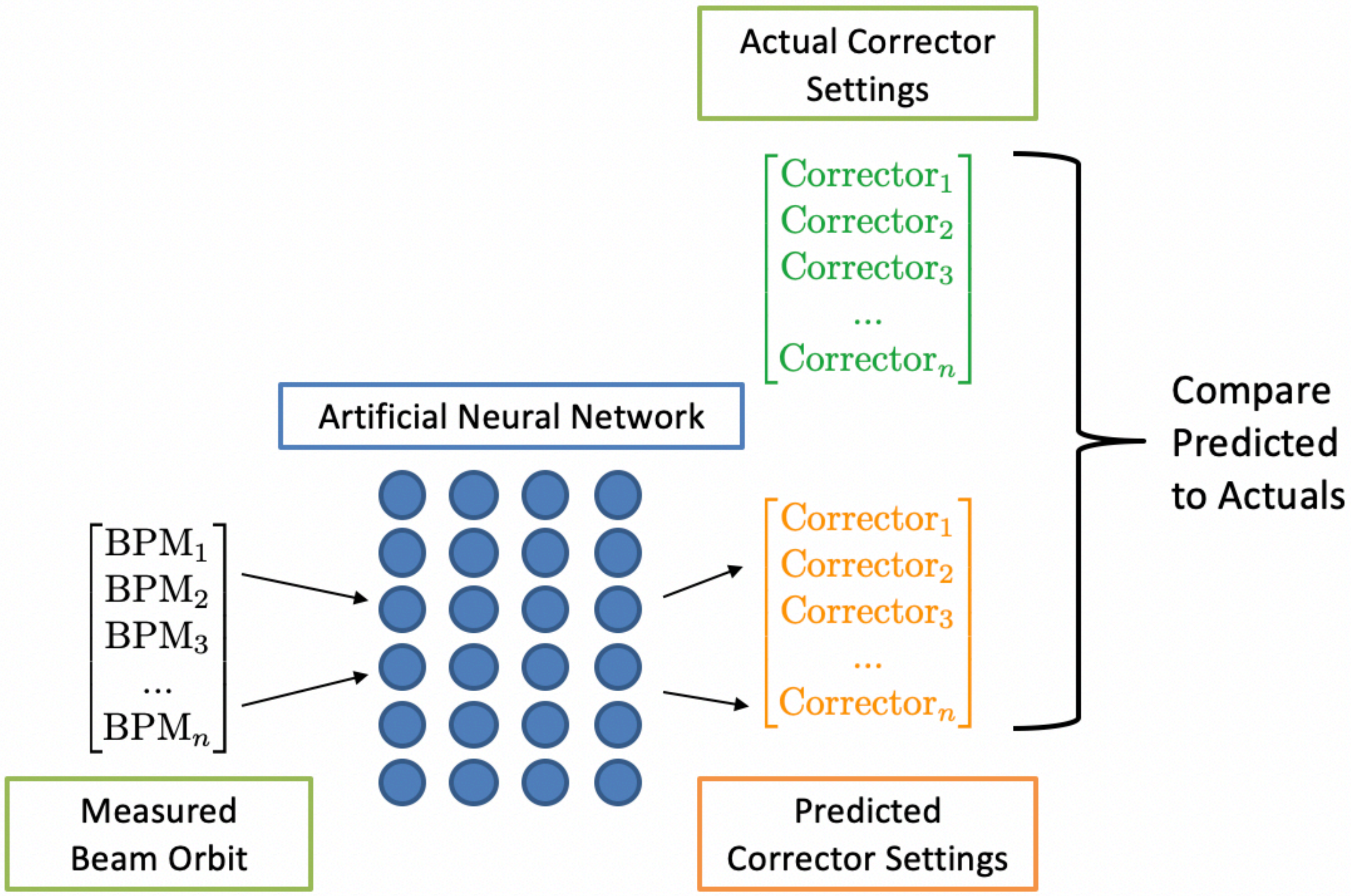
- Direct use of inverse models for tuning
  - Train a model to predict settings from desired diagnostic output
  - A common application is beam steering
    - Inputs are the requested BPM readings
    - Outputs: Suggested corrector settings
- Use inverse model as a starting point for optimization
  - Speeds up switching between beamline configurations
- Both use supervised learning





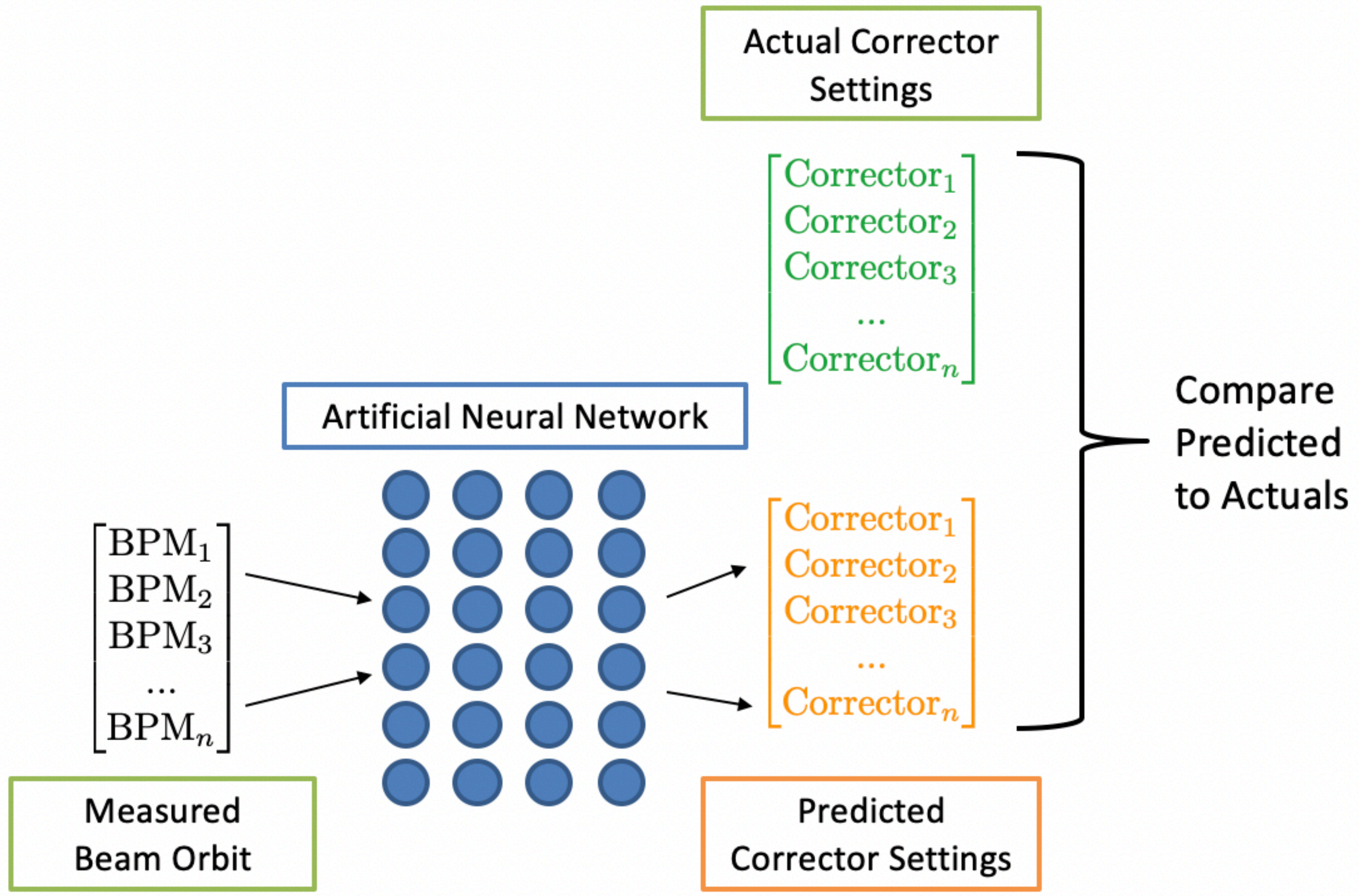
Inverse Models for Diagnostics and Tuning

- Inverse models as a diagnostic in a supervised fashion
  - Direct comparison between predicted settings and actual settings informs operations of a potential anomaly with that magnet

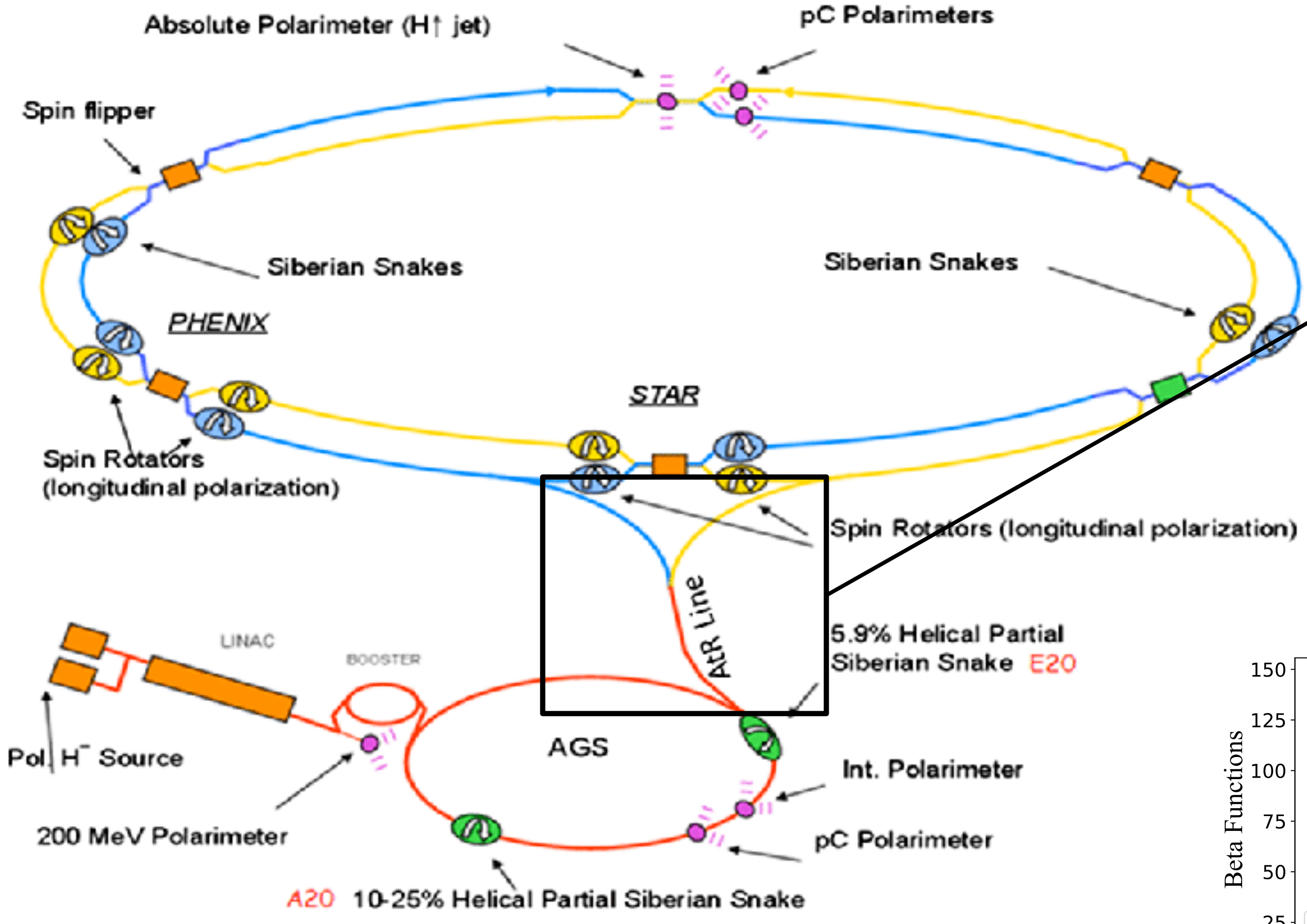


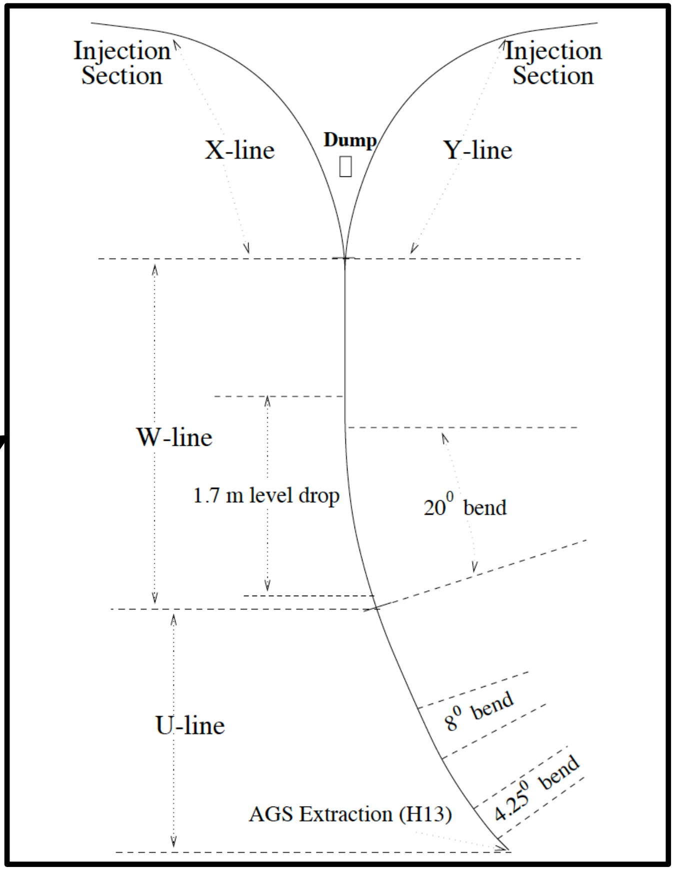
Inverse Models for Diagnostics and Tuning

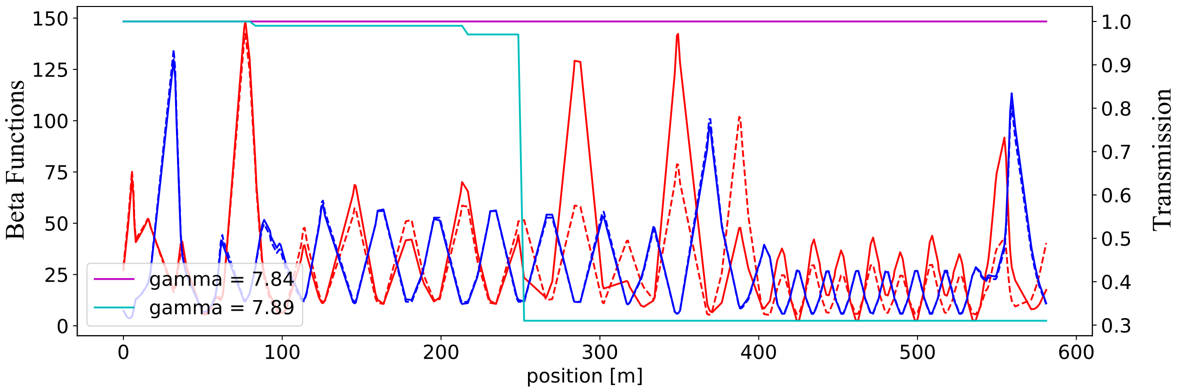
- Inverse models as a diagnostic in a supervised fashion
  - Direct comparison between predicted settings and actual settings informs operations of a potential anomaly with that magnet
- Inverse models as a diagnostic in an unsupervised fashion
  - Assumptions
    - model errors are caused by other beamline elements
    - each beam-line element will have a unique error signature
  - Use this for tuning



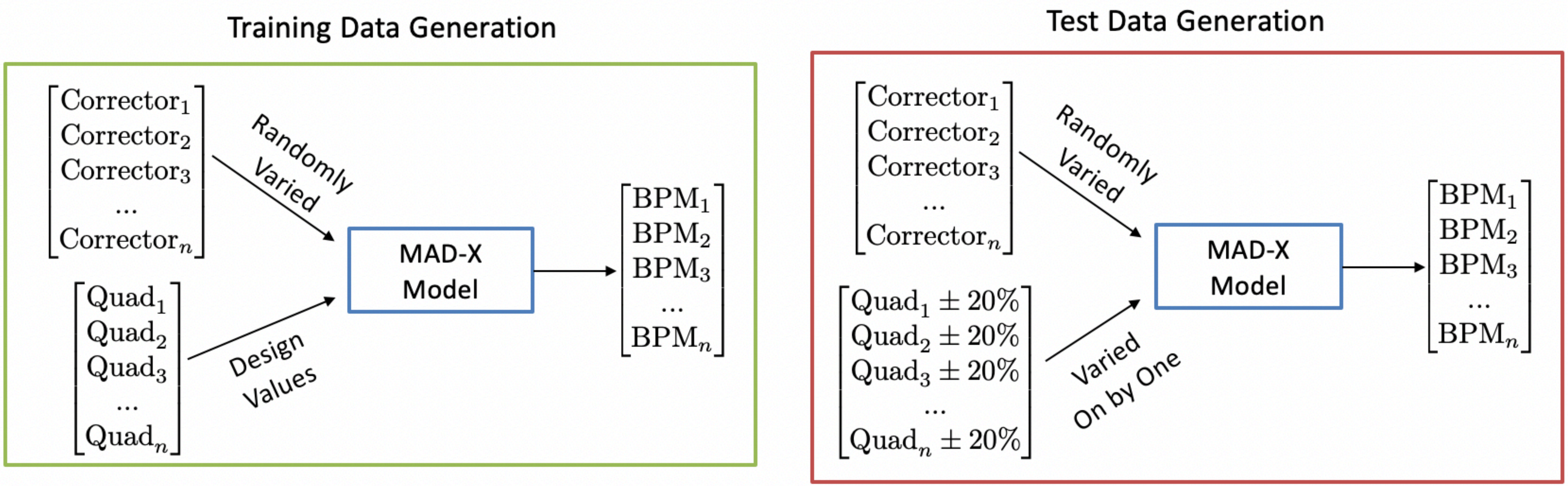
The AGS to RHIC Transfer Line





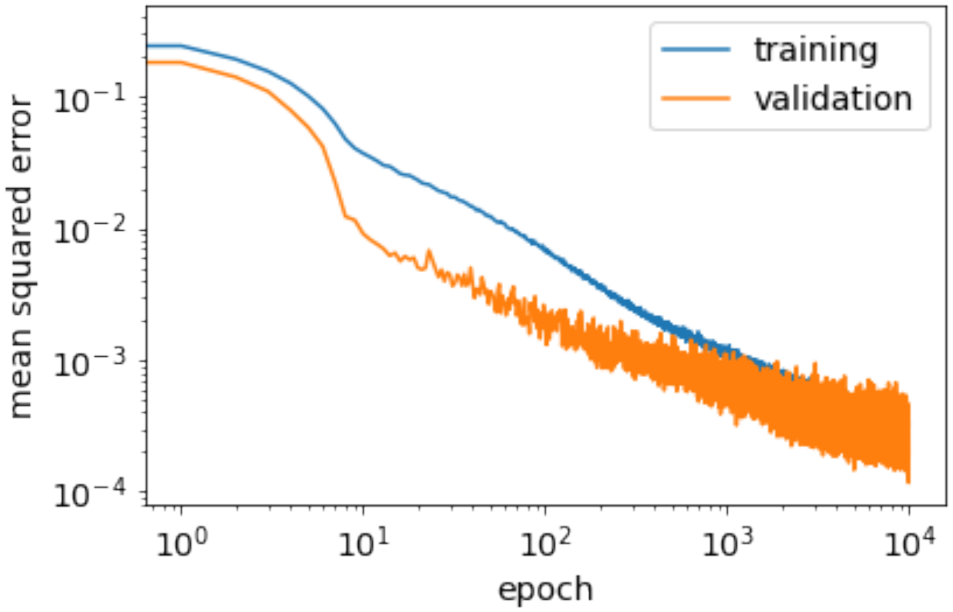


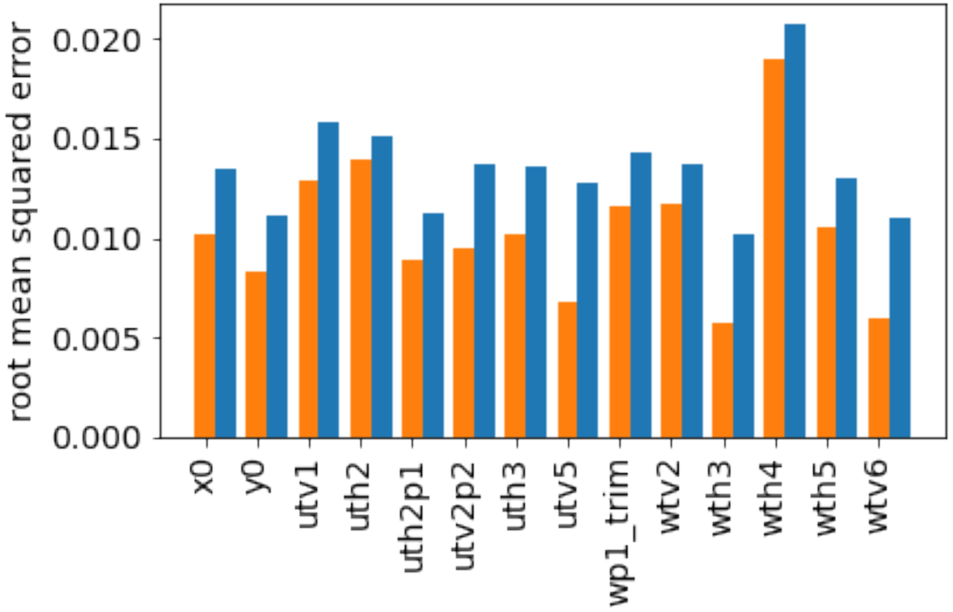
Transfer Line Simulation Studies



Transfer Line Simulation Studies

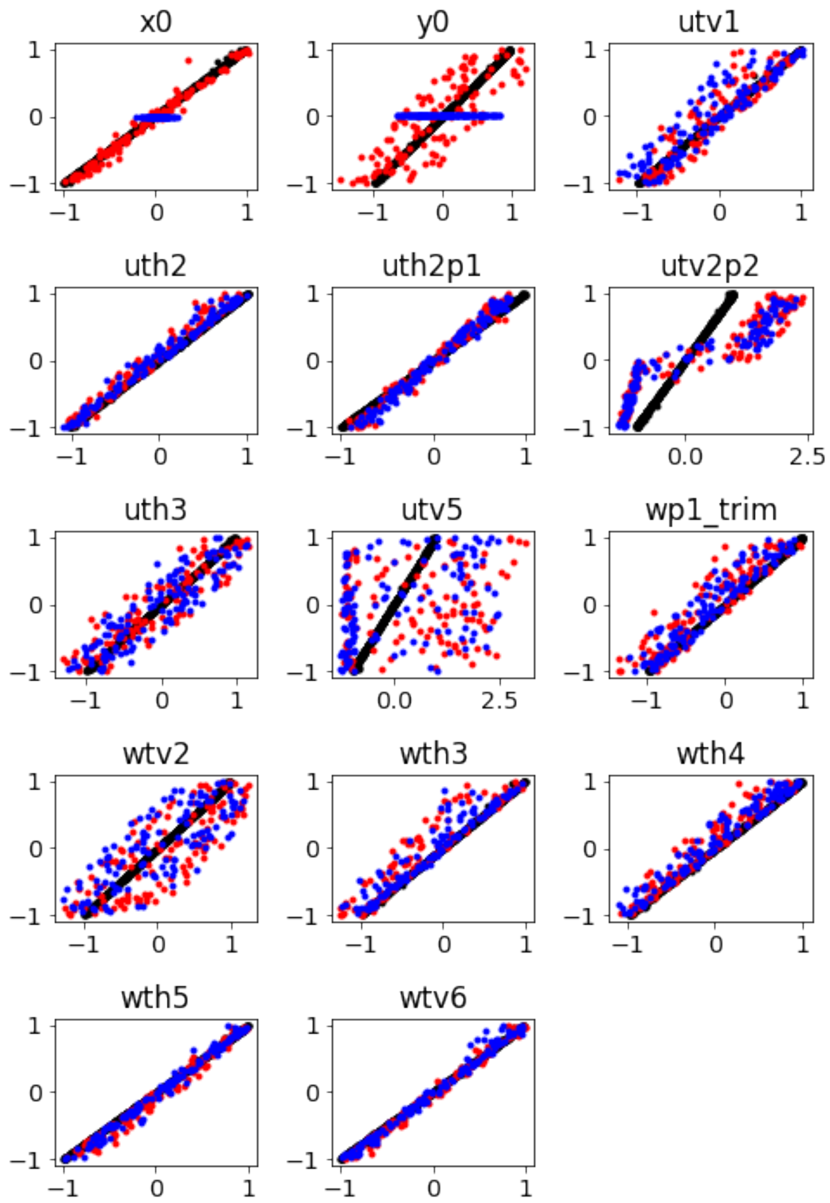
- Inverse model trained using 5000 samples, randomly varying the corrector strengths and beam initial positions.
- Removed four correctors (utv4, uth6, utv7, and wth1) from the inverse model due to degeneracy issues.
  - In future work we will address this issue
- Model / Training Parameters:
  - For this study the data were split into 80% training and 20% validation
  - 5 dense layers with 45 nodes each
  - Gaussian noise for regularization
  - Rectified linear units for the activation functions





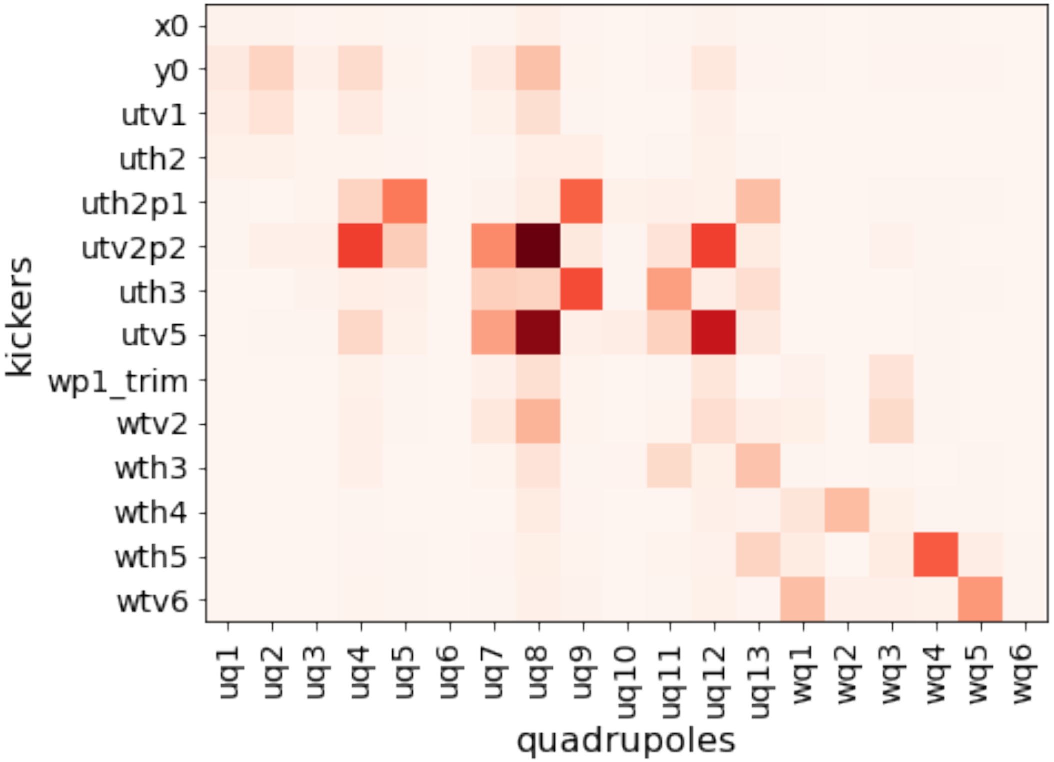
Transfer Line Simulation Studies

- Two configurations were used: one where the initial positions were also varied randomly and one where the initial positions were not varied.
- Right: Predicted corrector settings vs the ground truth for the validation set
  - Black: without quadrupole errors
  - Red: a single quadrupole error and random initial position errors
  - Blue: a single quadrupole error without initial position errors



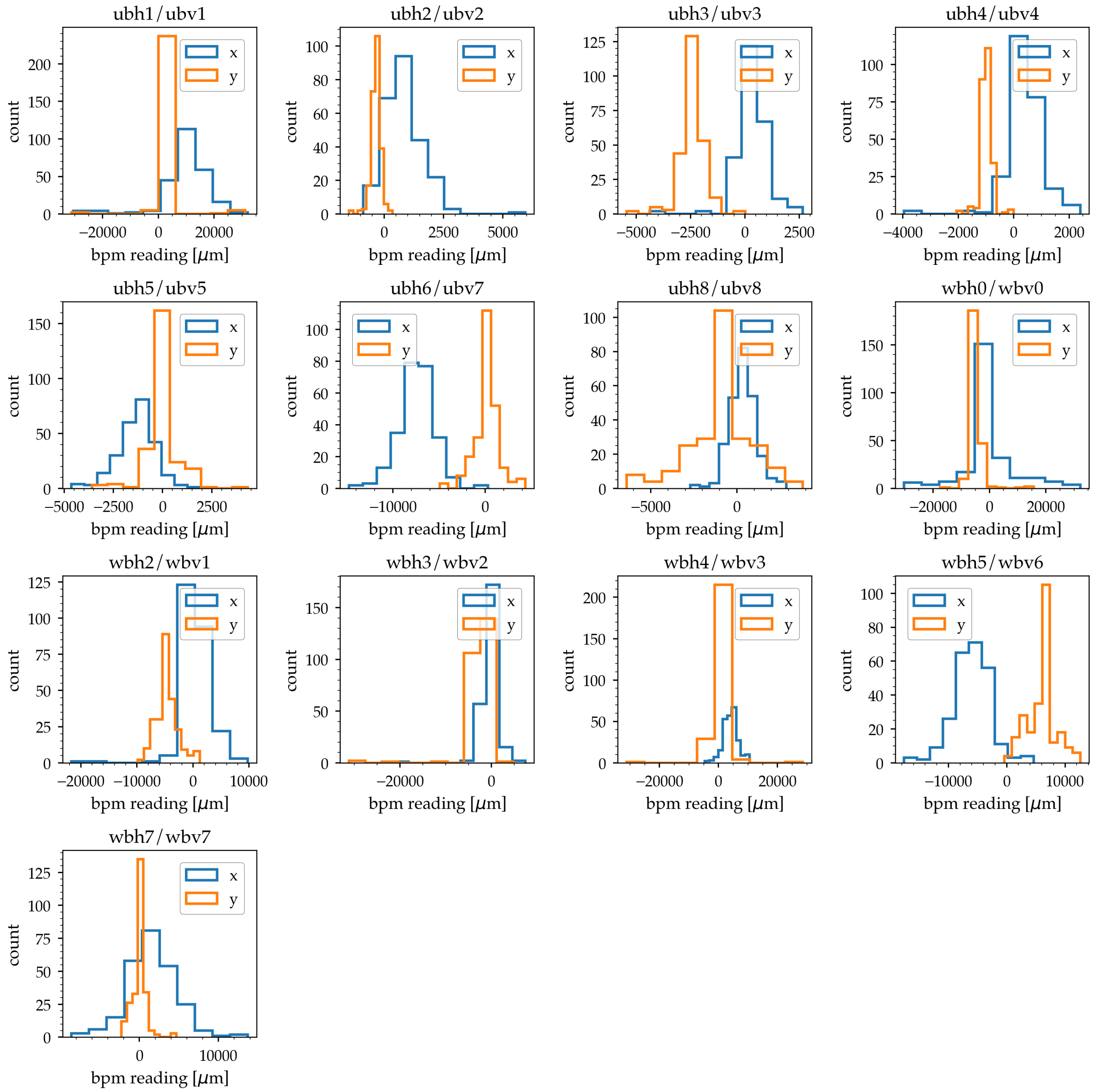
Transfer Line Simulation Studies

- Sensitivity of each corrector prediction to a particular quadrupole
  - Unique signatures for each quadrupole
  - The model clearly identifies errors in these magnets without any explicit knowledge of their existence



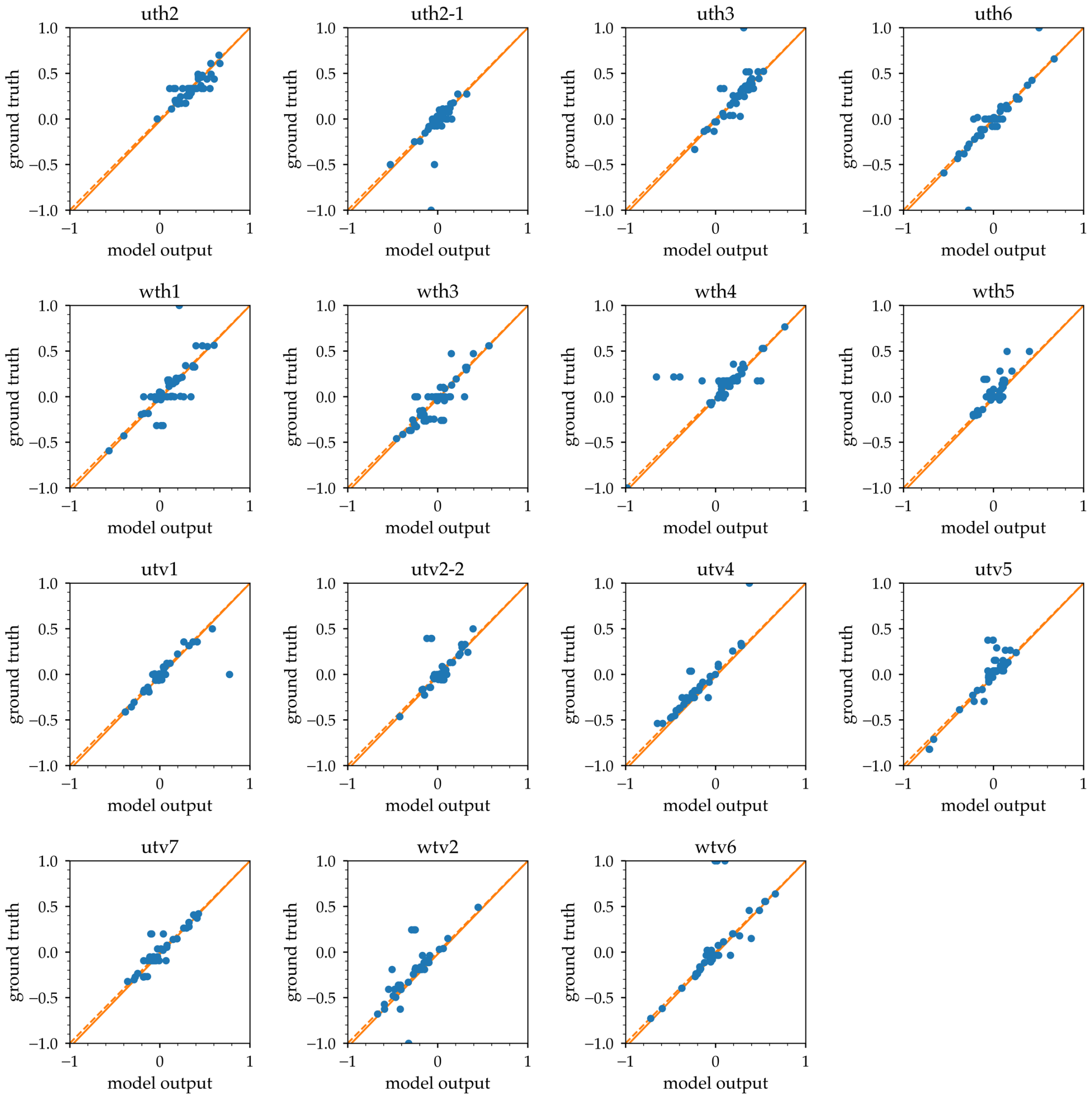
AGS to RHIC Beam Studies

- Collected BPM and corrector data for the nominal machine configuration
  - 1) learn how much data do we need to train an inverse model for the transfer line and
  - 2) establish the feasibility of a neural network based inverse model for detecting quadrupole errors in the ATR line.



AGS to RHIC Model

- Predicted corrector settings vs. ground truth for the validation set
  - The solid orange line is the linear fit between the ground truth and the model output
  - The dashed line is the ideal fit should the model accurately reconstruct the corrector settings from the BPMs
- Model performance is good overall
  - Correctors wth1, wth3, and wth4 perform the worst. Note wth1 was removed from the simulation data
  - Neural network trained with relatively few data points



Conclusions

- Inverse models were used to detect errors in quadrupole strengths using BPM and corrector data
  - Initial success with the FODO toy problem
  - Scaled to the UW line on the ATR at RHIC
  - Inverse models can identify quadrupole errors by comparing the predicted corrector setting to actual corrector settings
  - Each quadruple strength error yields a unique model error signature

- Developing ML models using measurements from the UW line

- Future work
  - Use signatures to predict unknown quadrupole errors
  - Use model errors to tune out quadrupole errors
  - Test on the UW line

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