

A Browser Based Toolkit for Improved Accelerator Controls

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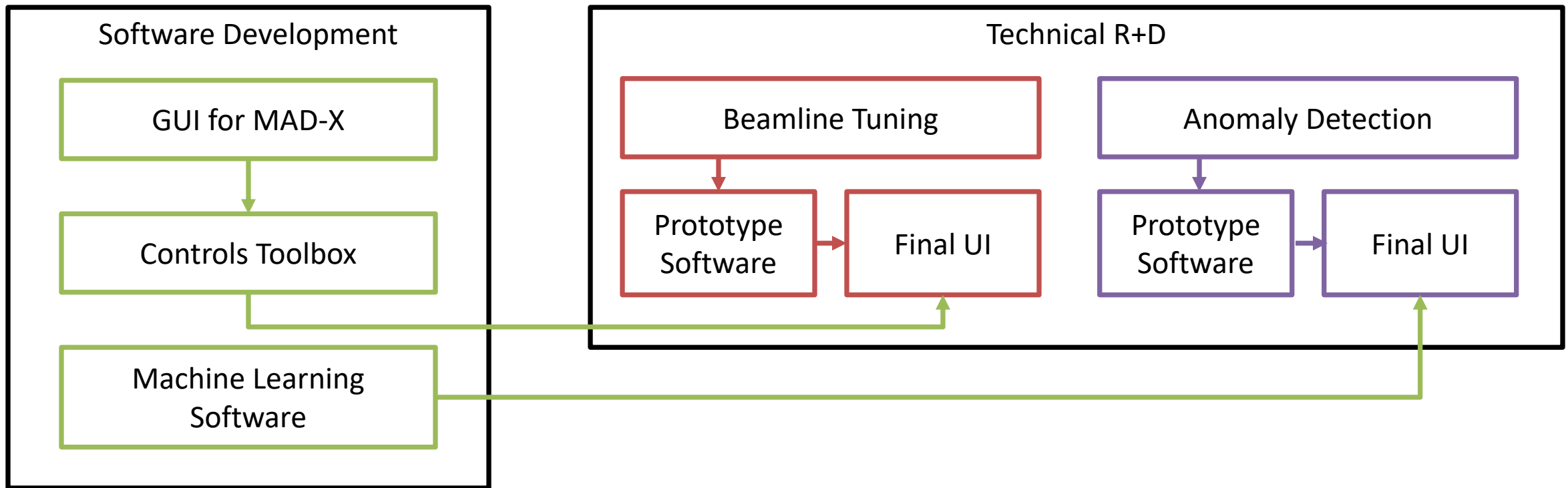
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Nuclear Physics Exchange Meeting: Virtual

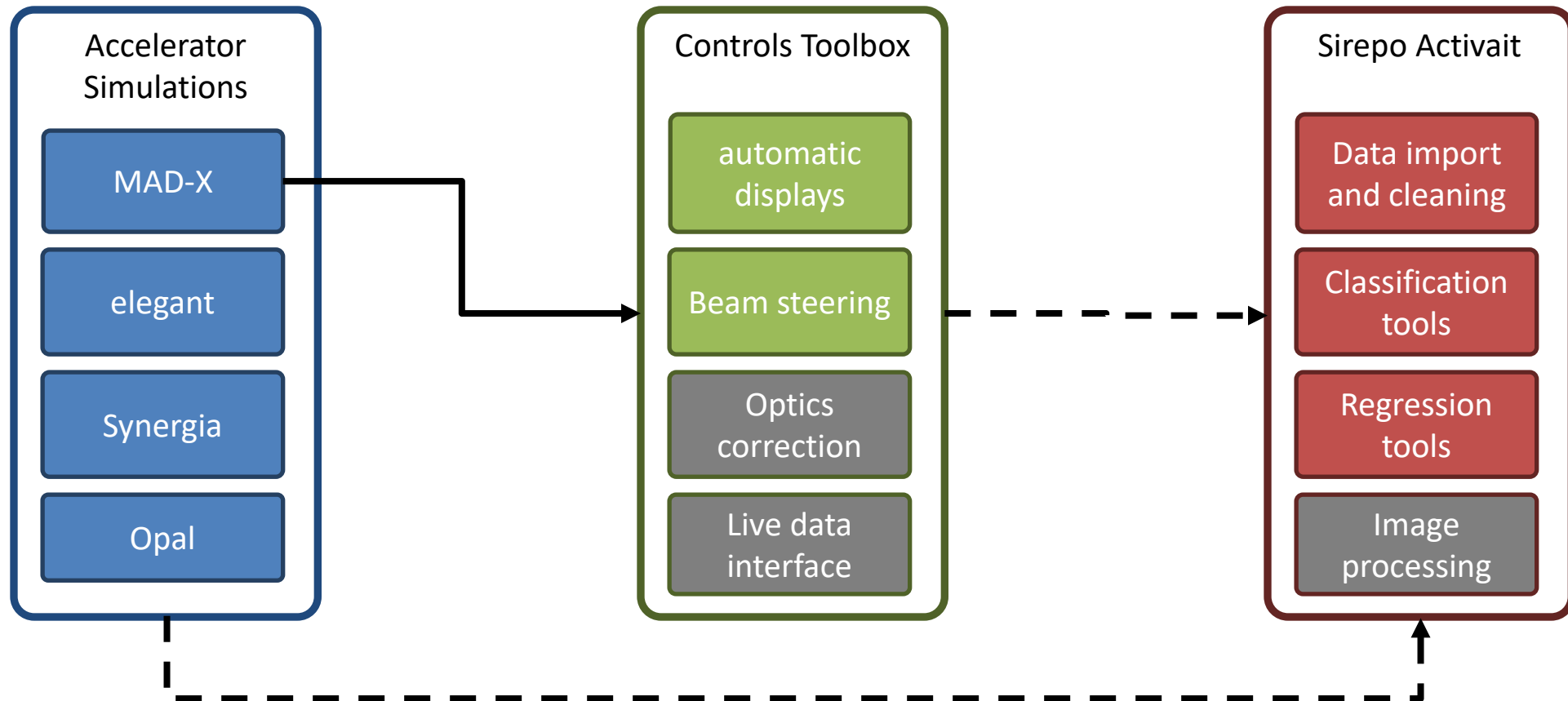
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Project objectives

- 1) Demonstrate the deployment of custom control interfaces using our web-based toolbox
- 2) Test rapid reconfiguration of the BNL ATR Line between 5 and 10 GeV/u
- 3) Test a machine-learning based smart-alarm system at the CEBAF polarized electron source

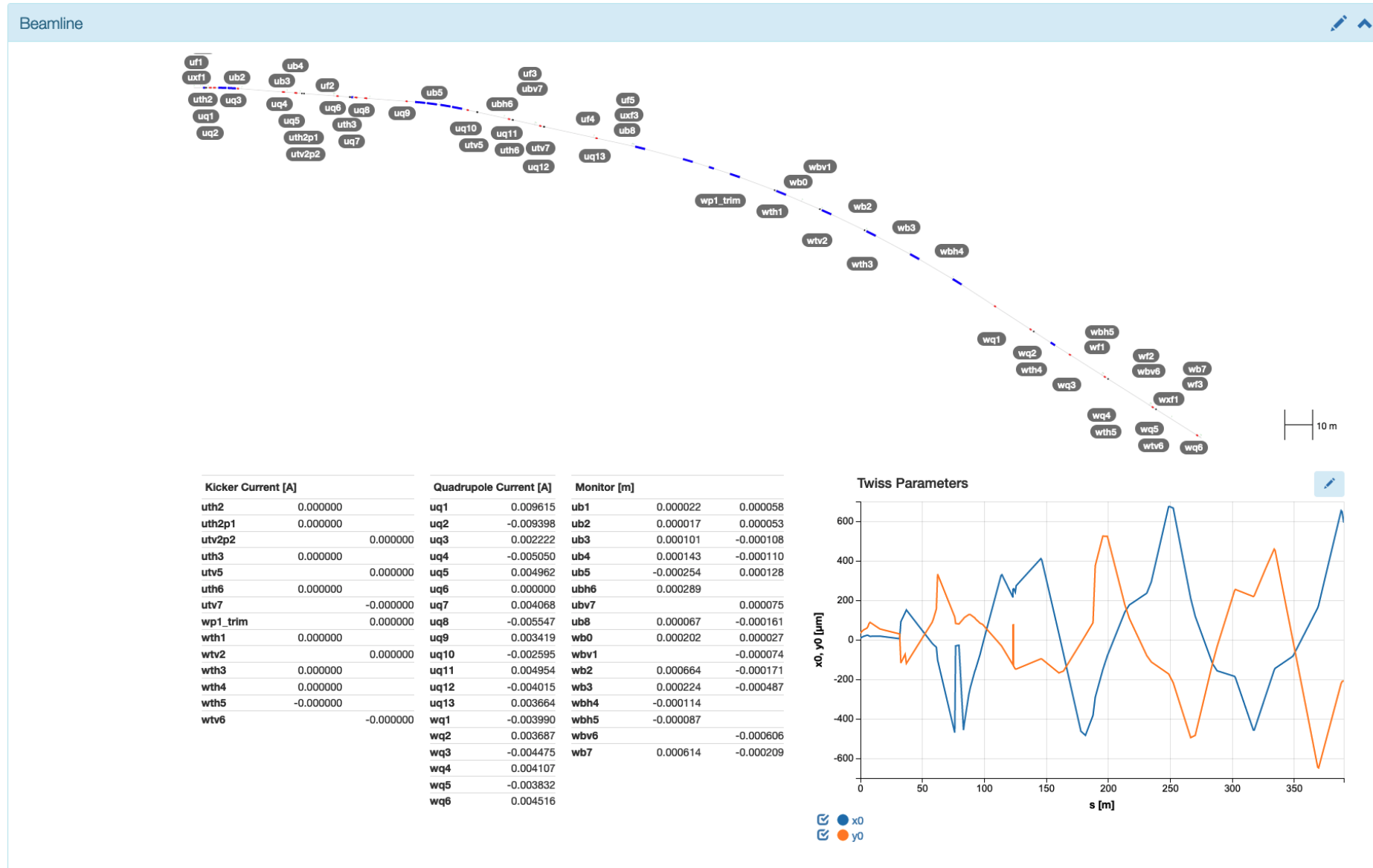


A Browser Based workflow for Accelerator Controls



Automated creation of control room displays

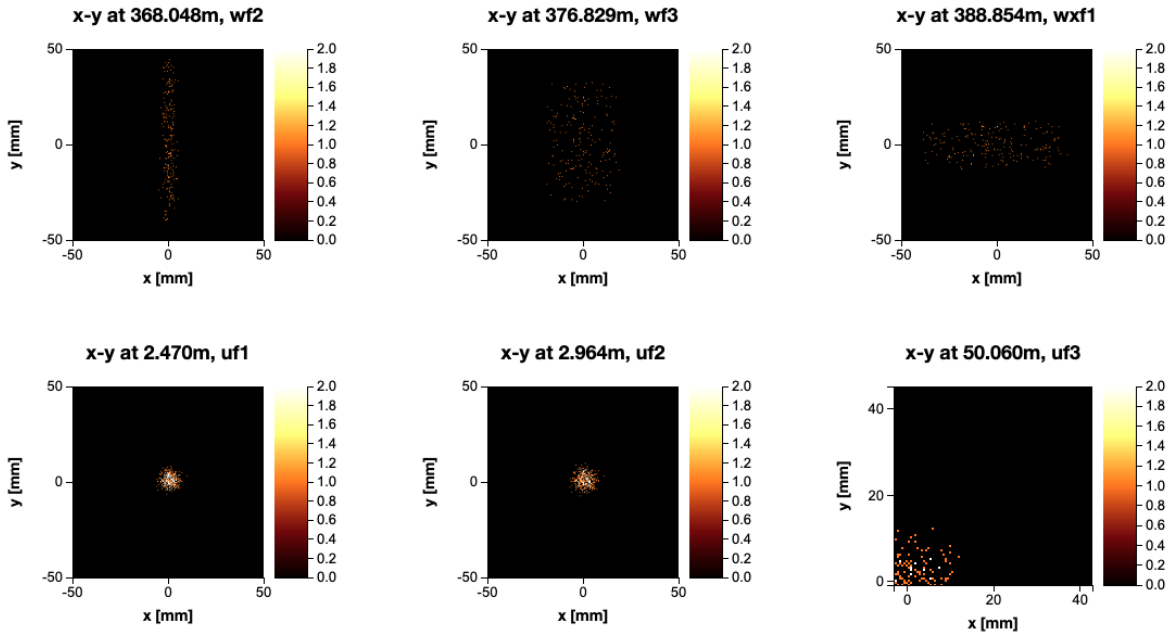
- Build a lattice in MAD-X and use our controls application for optimization
 - Controls display is generated automatically
 - Provides scalar settings and readings
 - Magnet transfer maps can be specified via upload of a CSV file
- Magnet excitation curves used to compute currents
- Beam offset shown in the twiss parameter plot.
 - Online model capabilities are available



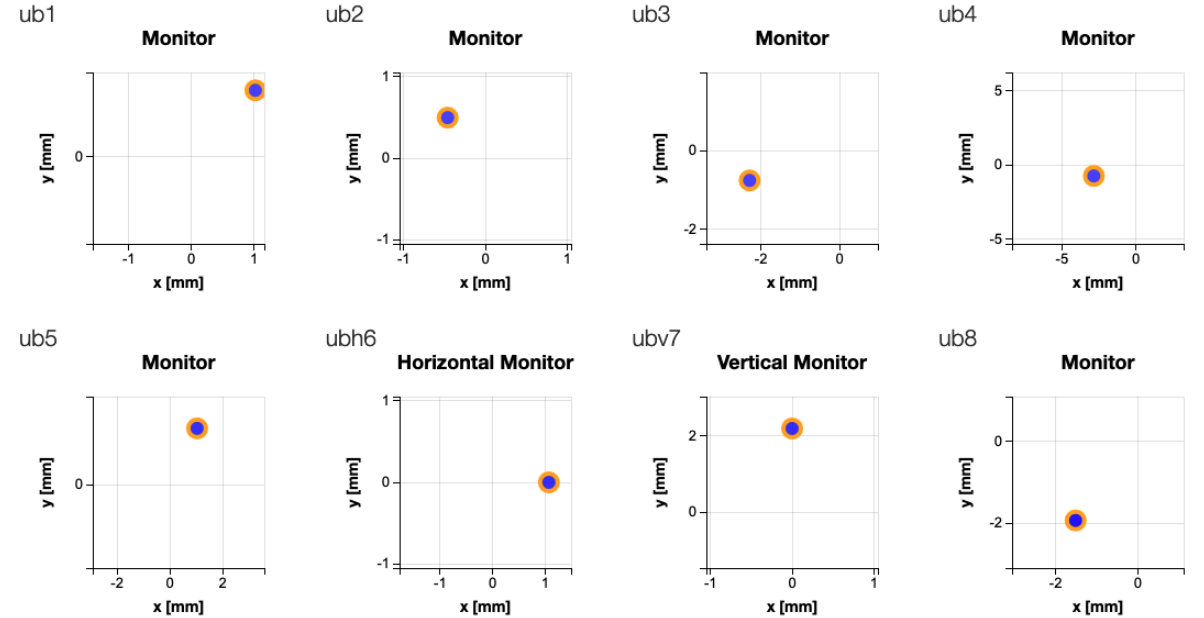
Diagnostic displays

- Diagnostic displays show the output from BPMs and from screens.
- Screens update live as the simulation is running or if it is getting data from the control system
- We have tested our ability to pull data from the control system and make settings from the browser
- Optimization setup can be used to optimize on a simulation or on data from the machine

Particle Plots

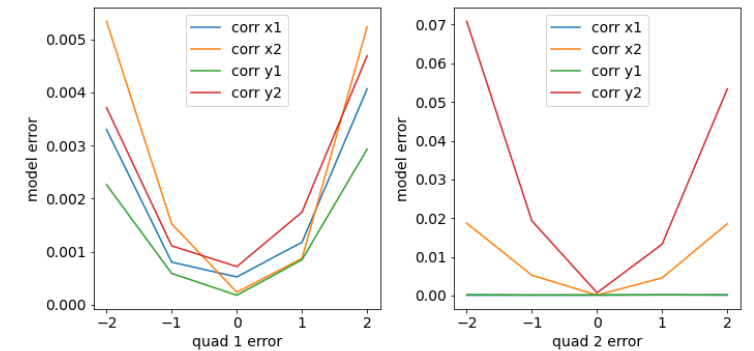
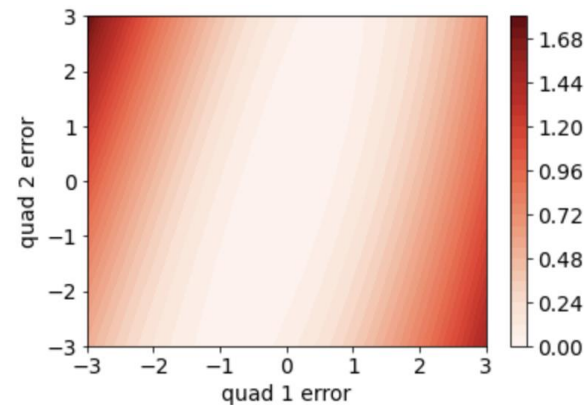
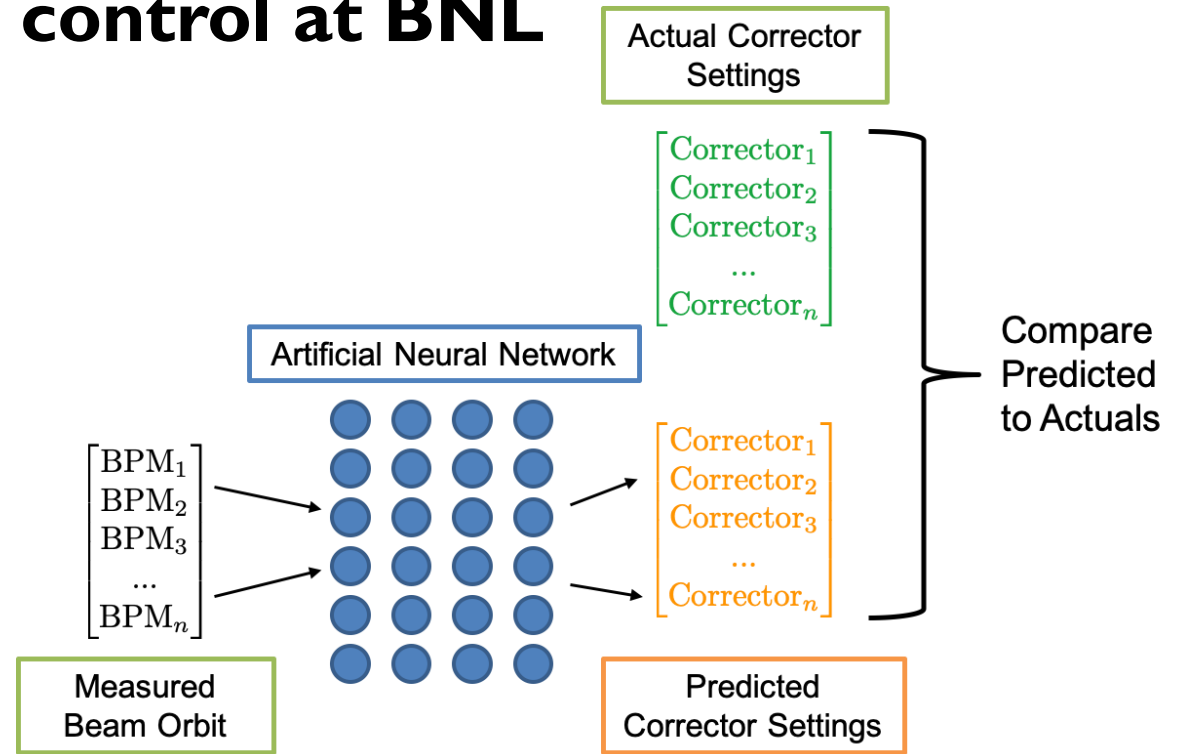


Monitors



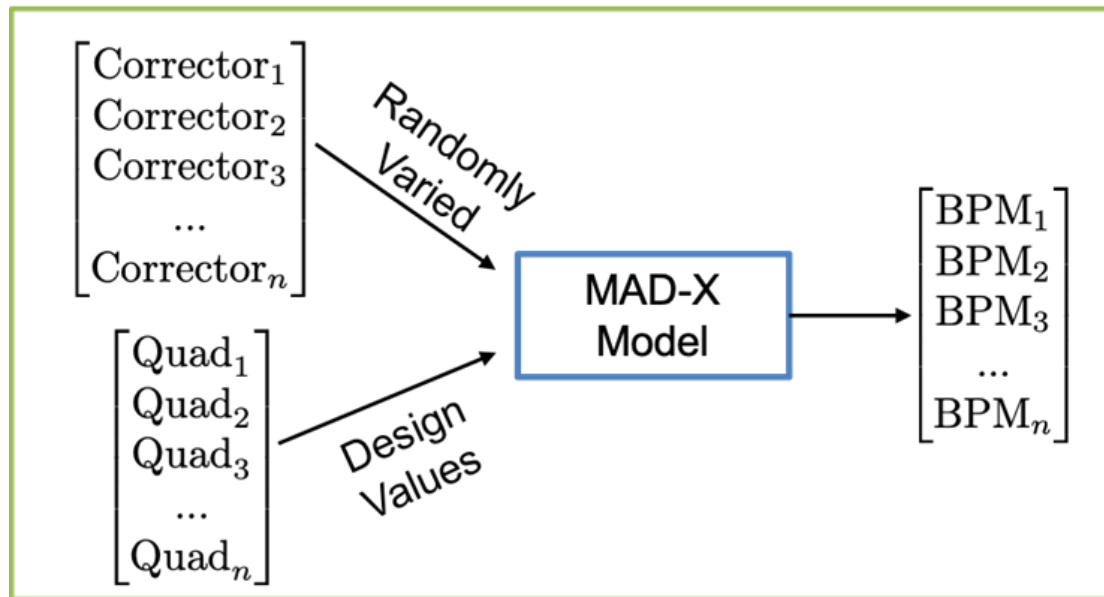
Inverse models for diagnostics and control at BNL

- 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
- Inverse models for tuning
 - Minimize error between predicted settings and actual settings by varying quads
 - Right: model error as a function of quad strength error

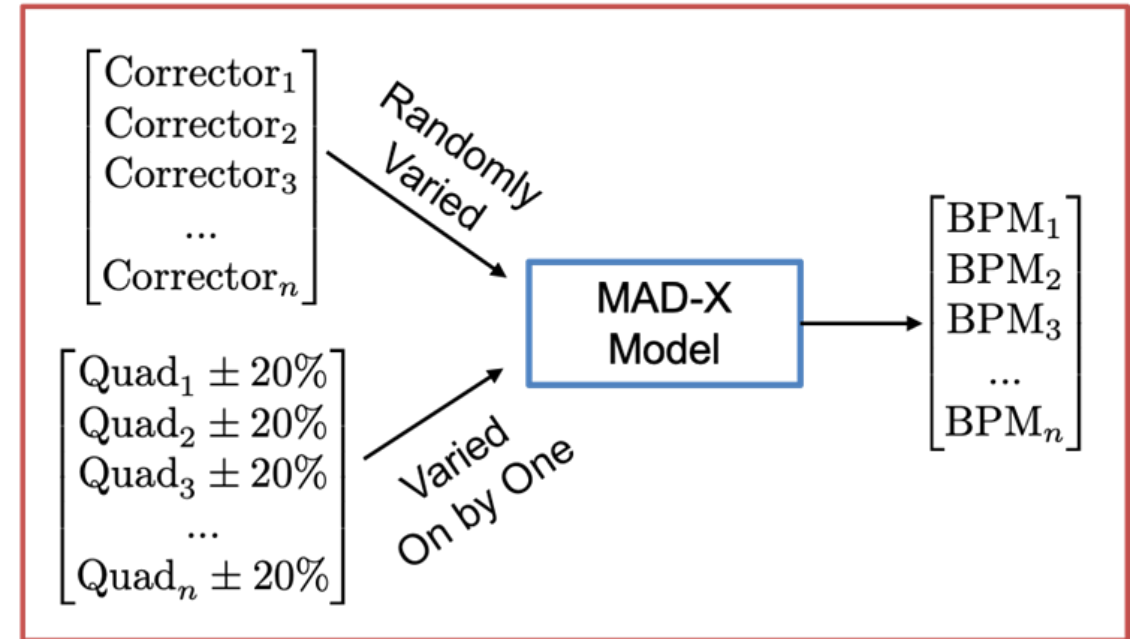


AGS to RHIC transfer line study

Training Data Generation

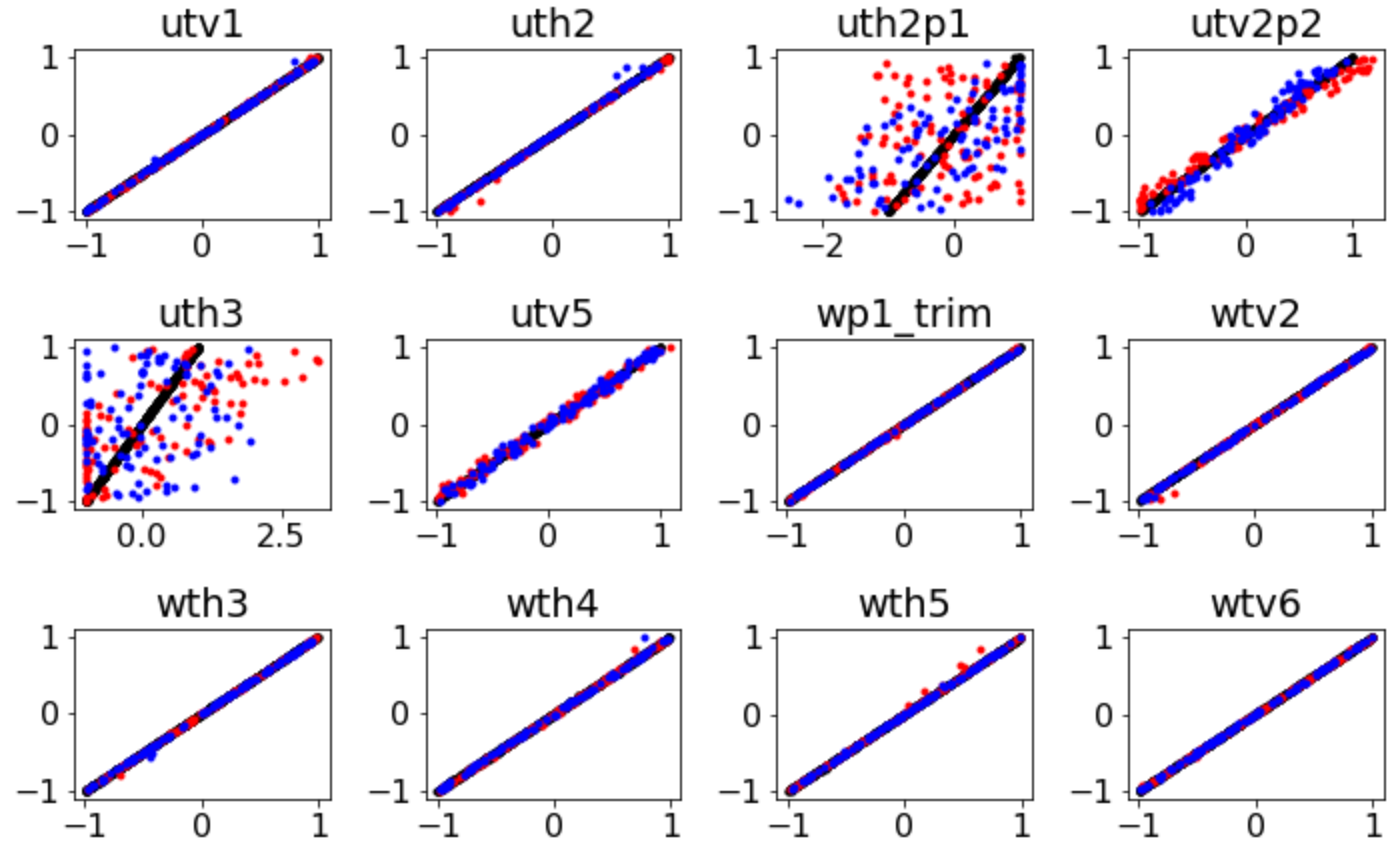


Test Data Generation



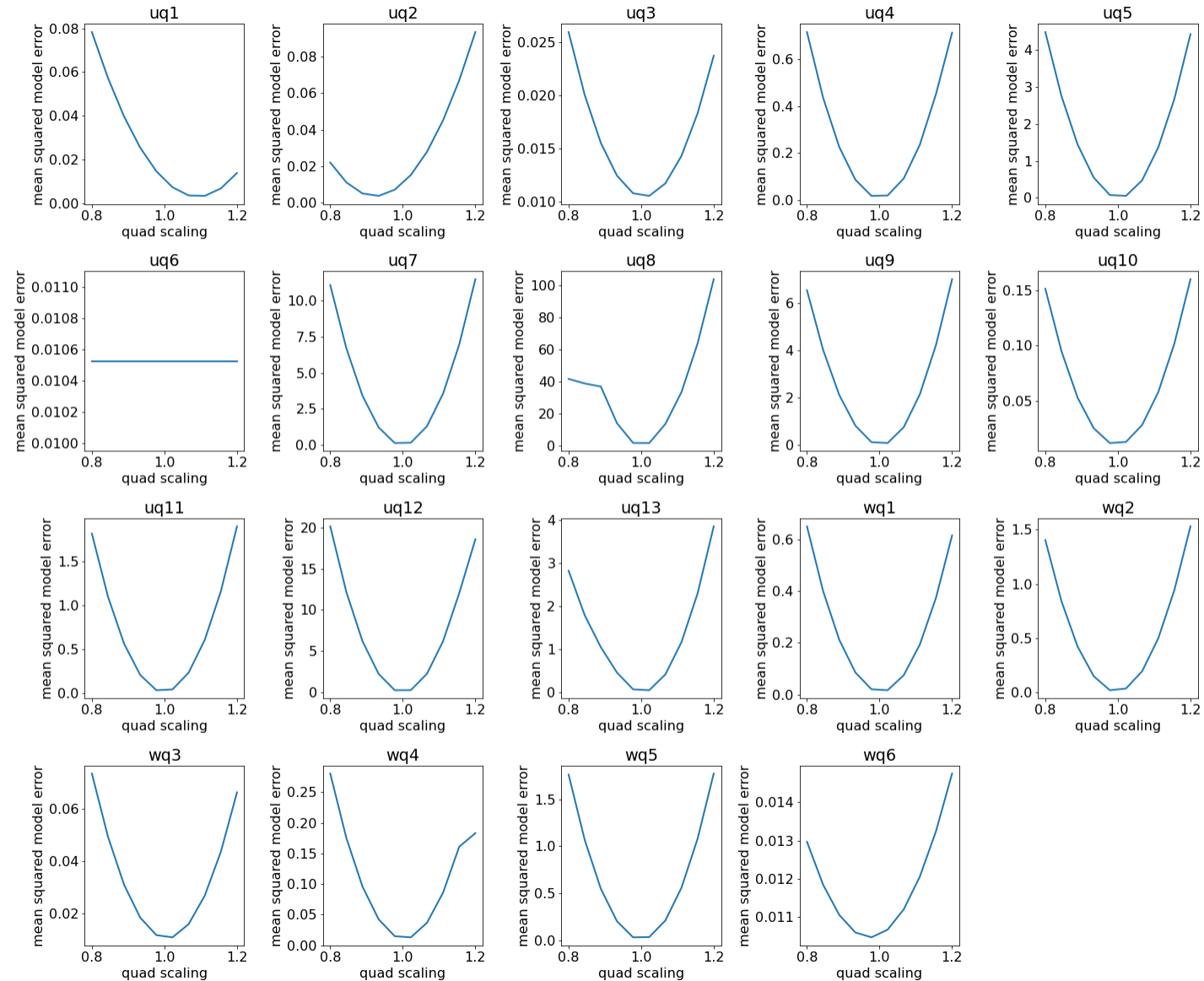
AGS to RHIC transfer line study

- Right: Predicted corrector settings vs the ground truth for the validation set
 - Black: without quadrupole errors
 - Red: a single quadrupole error of -20%
 - Blue: a single quadrupole error of +20%



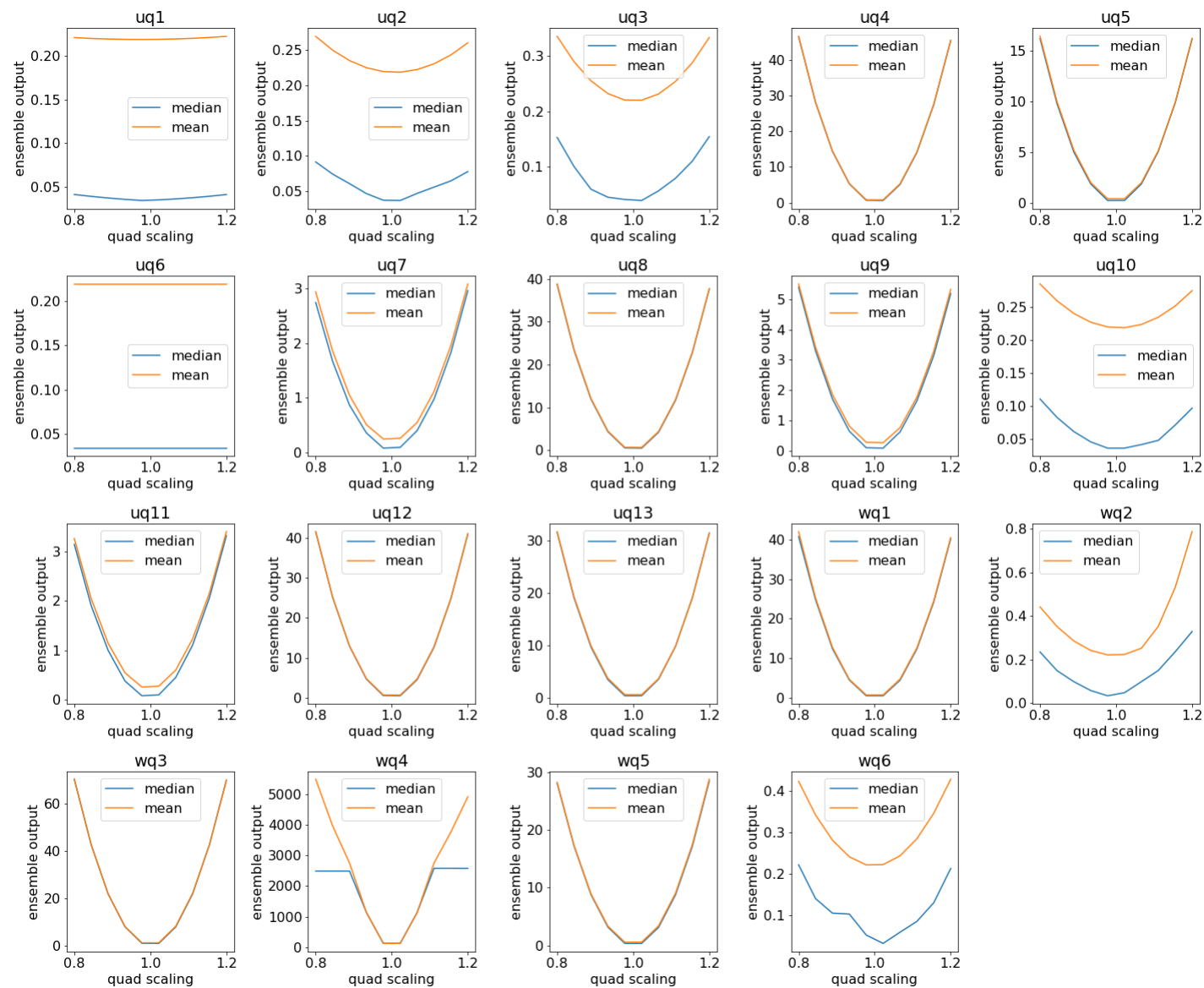
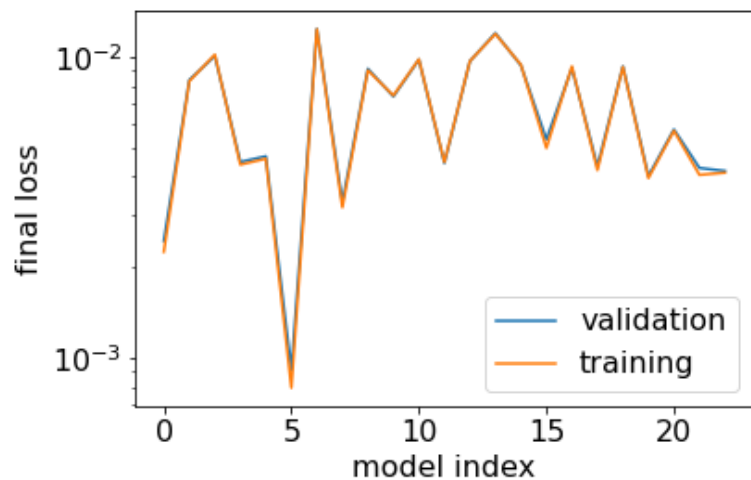
Computing the Model Loss as Quadrupoles are Varied

- Model trained for 100k epochs
- Individually varied the quads over a range of plus or minus 20% excitation
- All quads show sensitivity except uq6
- Many quads have minima at 1.0 with some offset
 - Longer training time can improve this
 - Ensemble methods may be more efficient



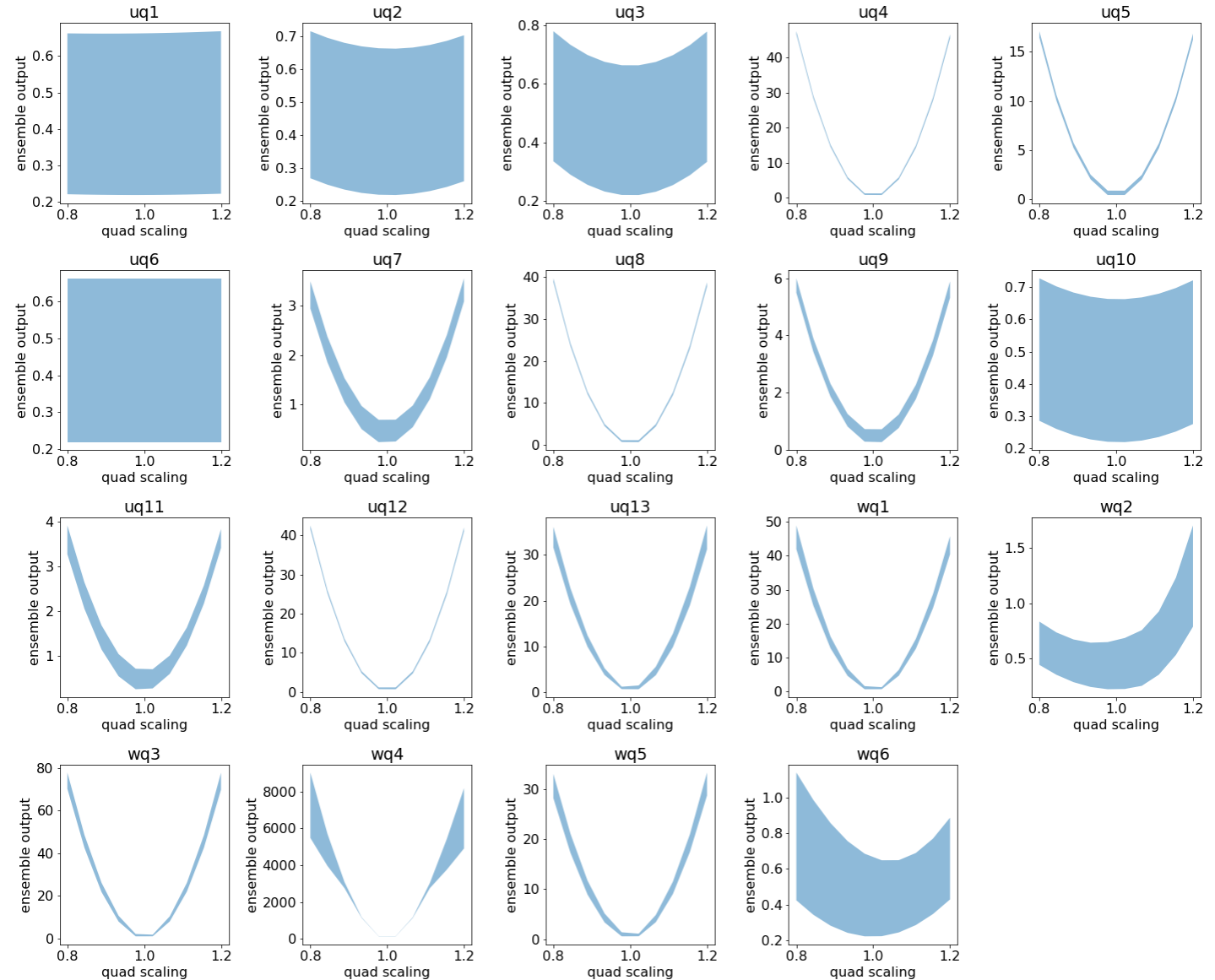
Consider an Ensemble of Models

- Trained 23 different models
 - Same training and validation data and architecture
 - Different random initializations
- Bottom: final training and validation loss for each model
- Consider median and mean for output of the ensemble
- Examine the ensemble output as you vary the quad strengths
- Right: Ensemble output as a function of quad strength variation
 - Note clearly defined minima at or very close to 1.0 for all cases except uq6
 - This is an improvement over slide 16 where some quads do not have well defined minima



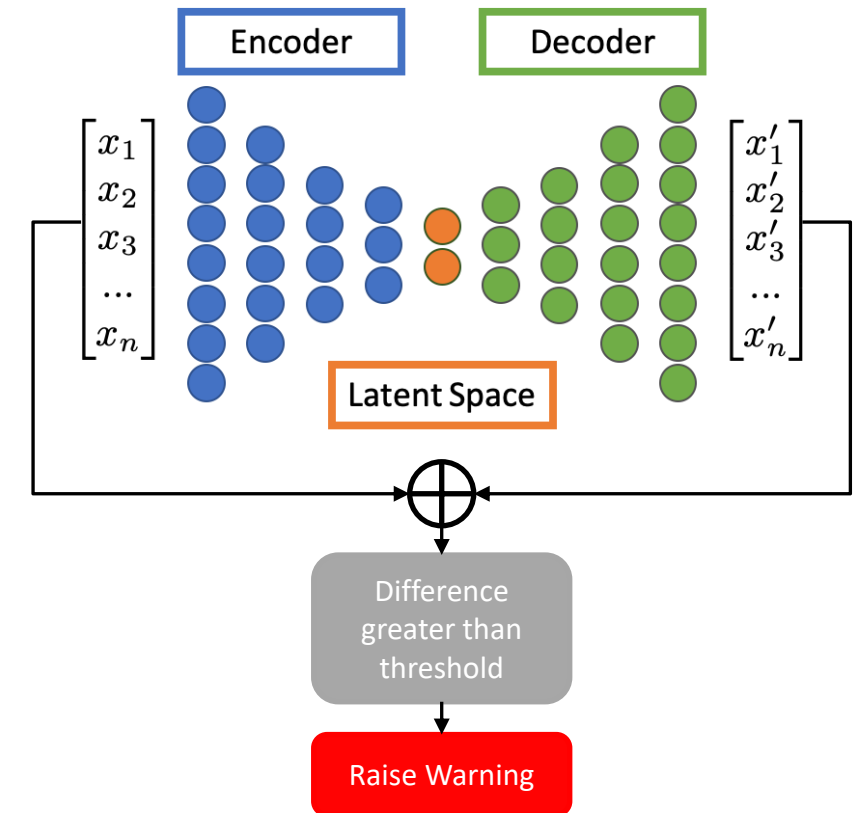
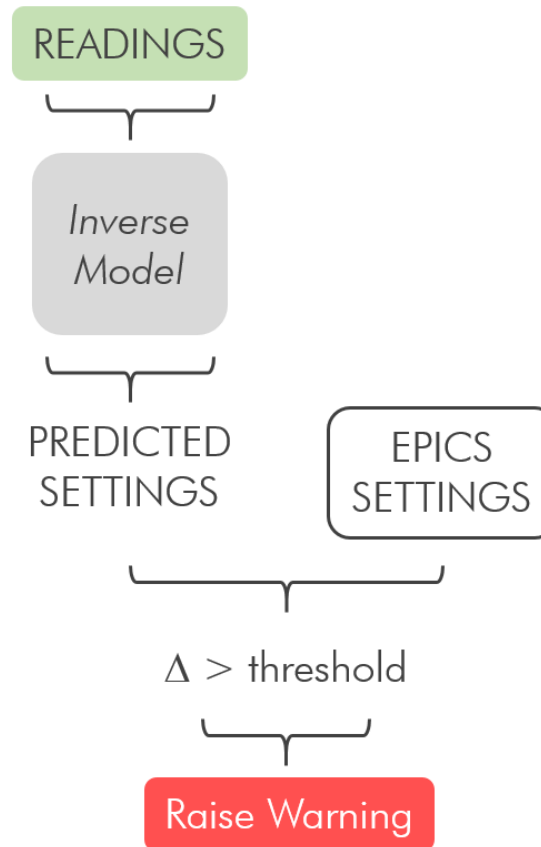
Consider an Ensemble of Models

- Consider median and mean for output of the ensemble
- Examine the ensemble output as you vary the quad strengths
- Right: Mean ensemble metric showing one standard deviation in the ensemble output
 - Note clearly defined minima at or very close to 1.0 for all cases except uq6
 - This is an improvement over slide 16 where some quads do not have well defined minima



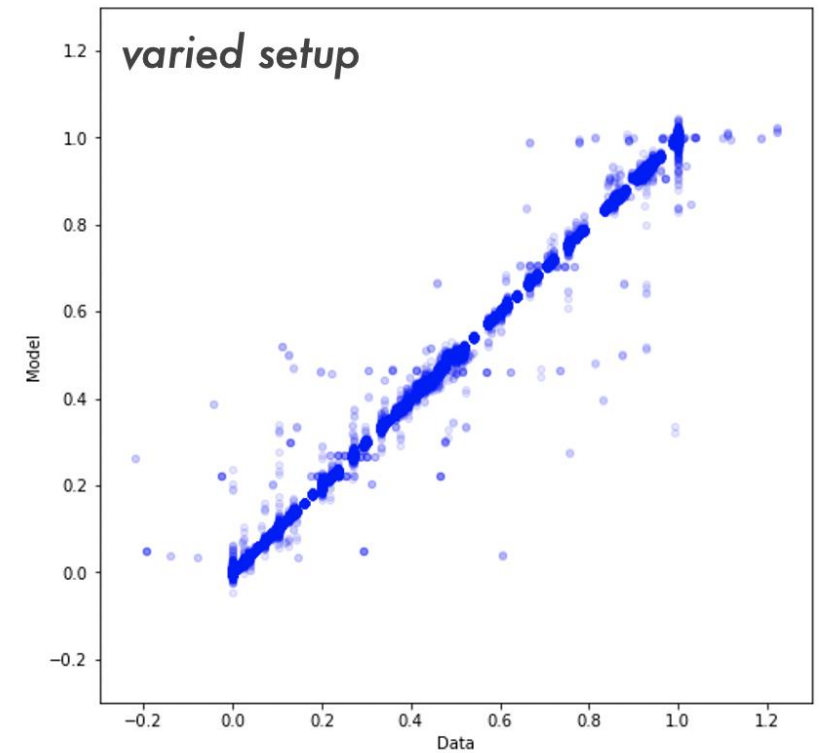
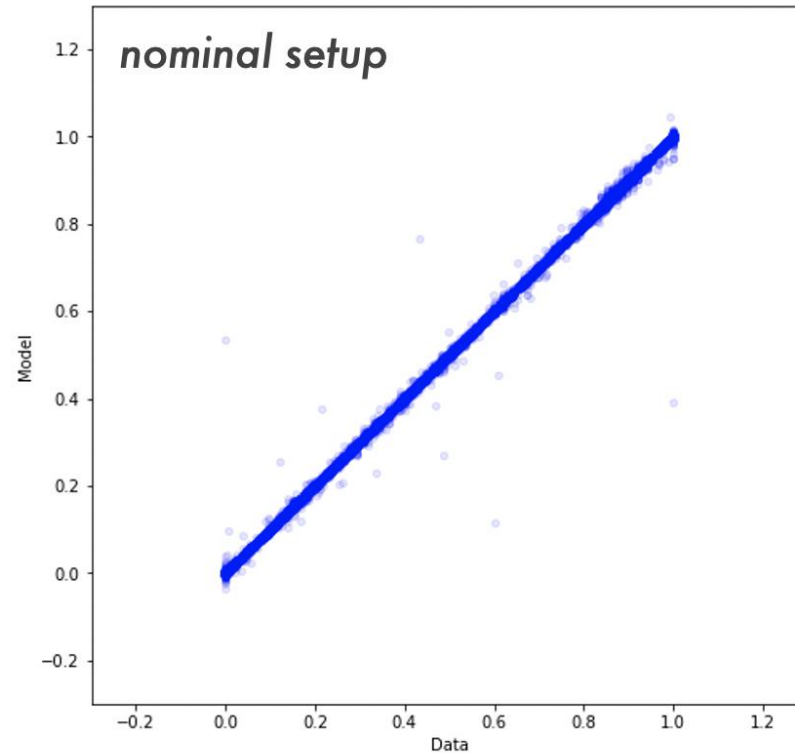
A Smart Alarm System for the CEBAF Injector

- Alarm systems typically alert operators when there is a problem with the beam
 - Often does not provide much information on what caused the alarm
 - Diagnosing the problems is time consuming for operators
- Use machine learning to automate the root-cause-analysis effort
 - Autoencoders quantify similarities or differences between machine states
 - Inverse models use actual measurements to predict settings



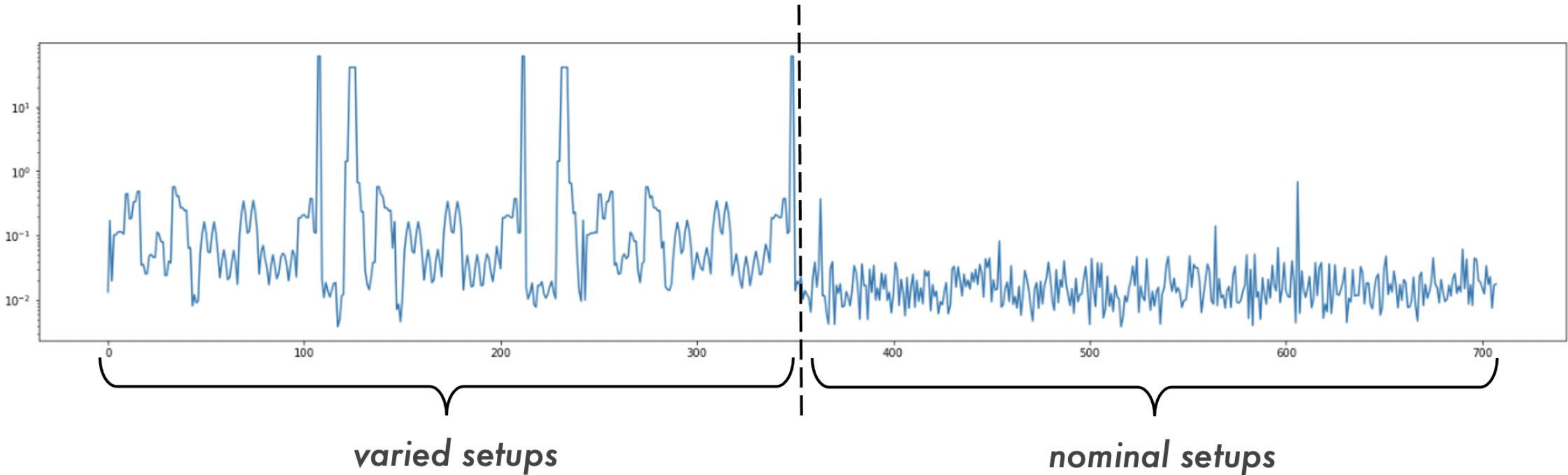
A Smart Alarm System for the CEBAF Injector

- Data collected during two different operational modes.
 - First during normal operations
 - Second during a dedicated machine study where parameters were varied
- Neural network inverse model is trained to predict settings from readings
 - Left: Model prediction vs the ground truth for the validation data from the nominal setup
 - Right: Model prediction vs the ground truth for the test data (study data)



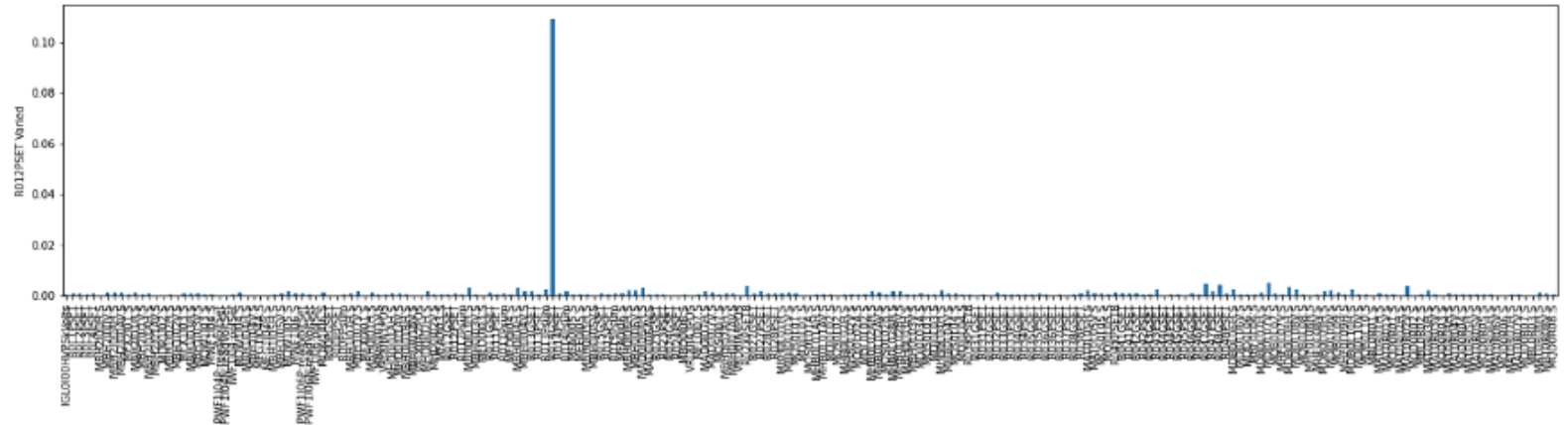
A Smart Alarm System for the CEBAF Injector

- RMS error of the predicted settings by parameter for the machine study (left) and the nominal setup (right).
- The difference is indicative of the model being able to detect variations in the machine state.

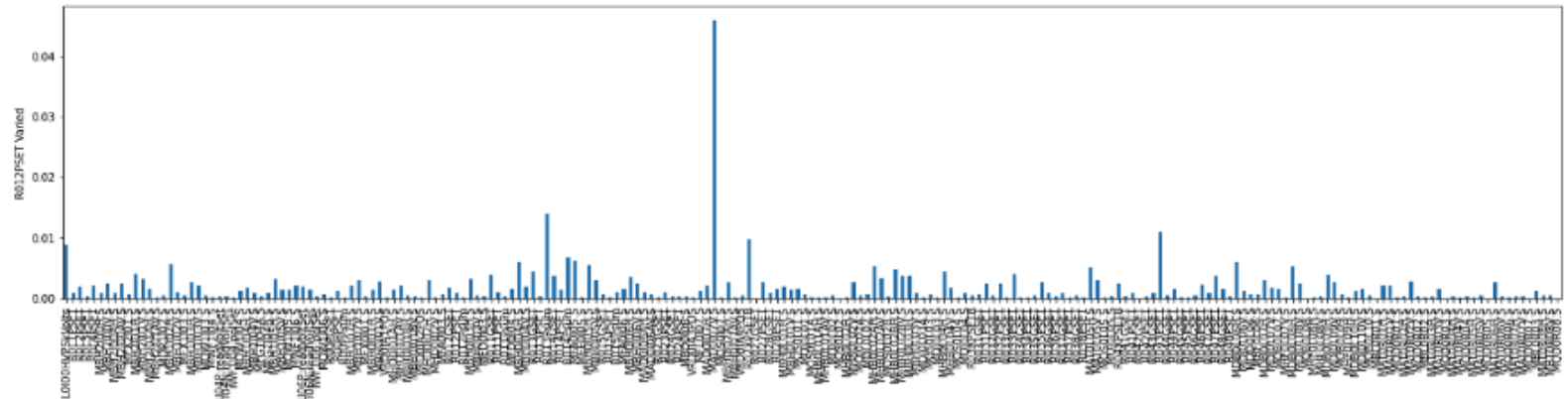


A Smart Alarm System for the CEBAF Injector

R014GSET → 28.28



MAD0107V.BDL → 20.9



- Identifying individual errors using the inverse model

- Top: model error is a maximum for R014GSET which is the parameter that changed
- Bottom: model error is maximum for MAD0107V which is the parameter that was changed

Conclusions / Future work

- **Smart alarm system at Jlab**
 - Algorithm development nearing completion, publication in preparation (Expected completion within the Phase II)
 - Next step: implementation for use during operations (Planned work for a Phase IIB proposal / other funding source)
 - Transfer techniques to other accelerators (Planned work for a Phase IIB proposal / other funding sources)
- **Beamline control algorithms at BNL**
 - Algorithm development nearing completion, publication in preparation (Expected completion within the Phase II)
 - Next step: test algorithm during dedicated machine studies, targeting the next operational cycle (Planned work for a Phase IIB proposal / other funding sources)
 - Transfer techniques to other accelerators and develop generalized formula for deploying this system (Planned work for a Phase IIB proposal / other funding sources)
- **Controls toolbox and GUIs**
 - GUI has been tested at BNL without beam
 - Next step is to test the GUI during a beam study (Planned work for a Phase IIB proposal / other funding sources)
 - Incorporate GUIs into regular operations (Planned work for a Phase IIB proposal / other funding sources)

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