Machine Learning Experiments for Storage Rings at FAST

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Outline of the talk

Machine Learning in accelerators — what's been done already?

Leveraging what's been done — current machine learning projects at RadiaSoft

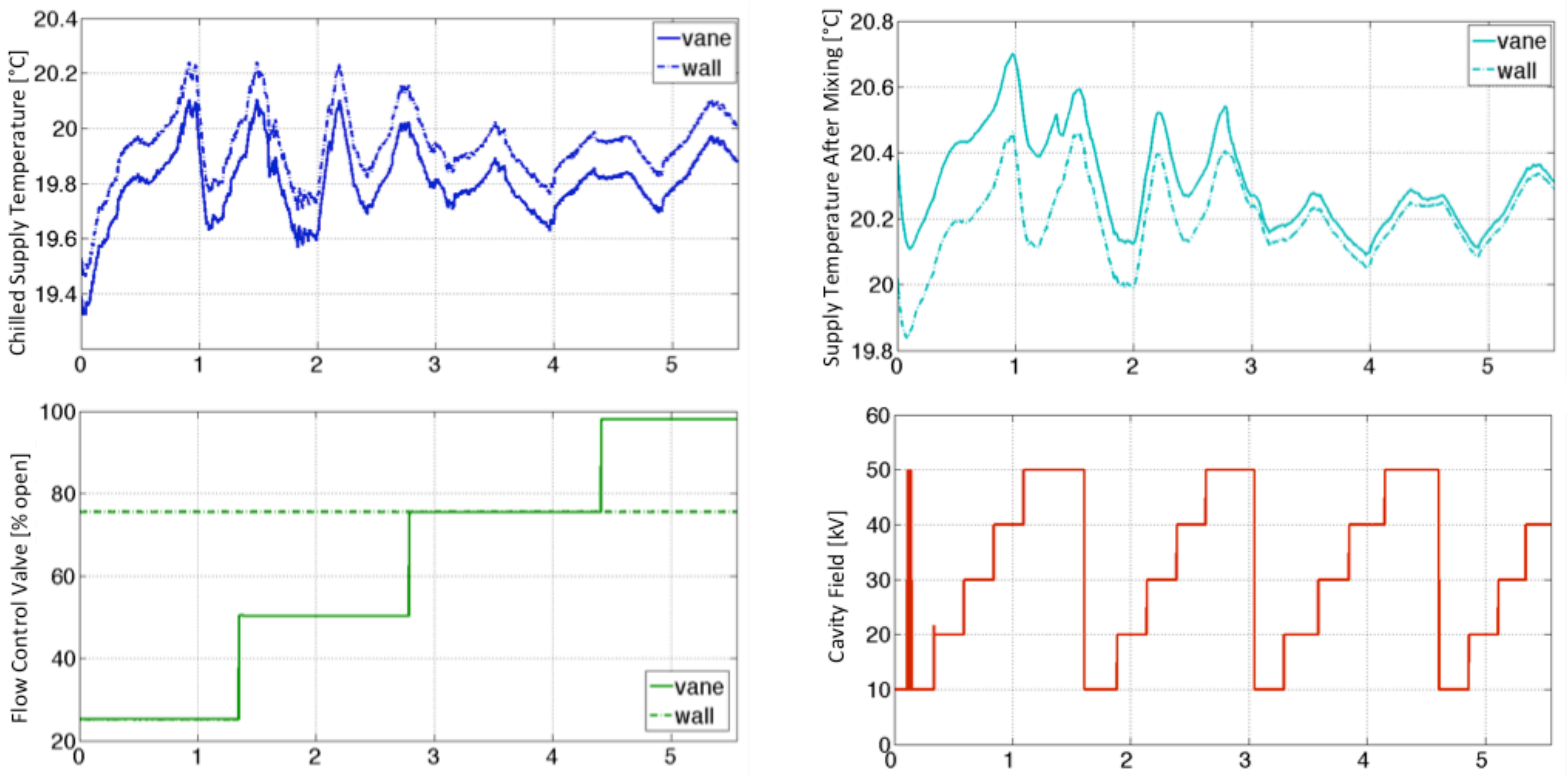
Proof-of-concept experiments for machine learning techniques in rings

Examples of Machine Learning in Accelerators

Modeling frequency shift with settings in the PXIE RFQ

The PXIE RFQ resonant frequency depends strongly on the temperature of the vanes and walls

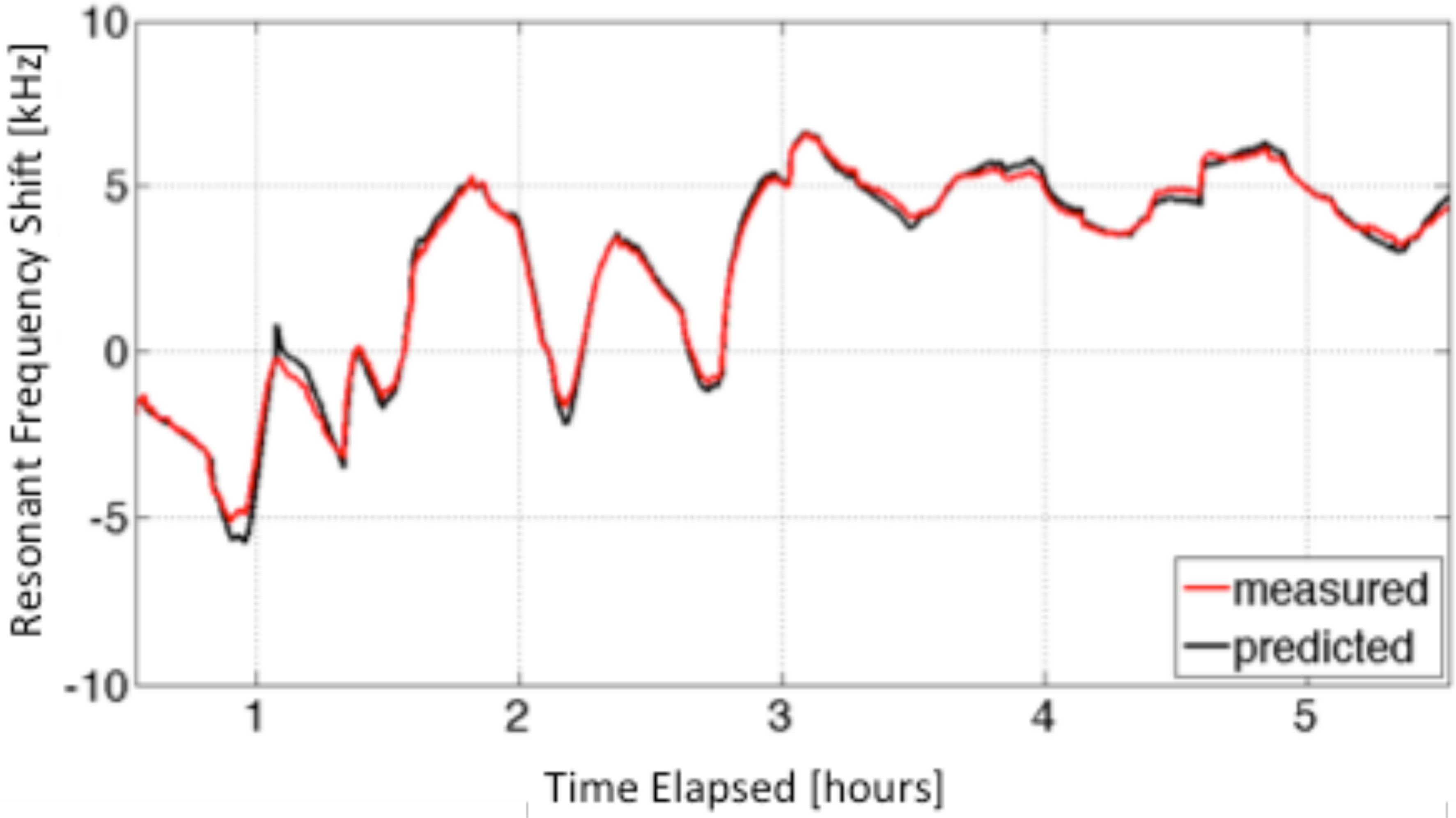
There are a number of parameters that influence the resonant frequency in a nonlinear way, such as flow control valve settings, water temperature, RF voltage, ambient temperature…



A. L. Edelen et al. "Neural Network Model of the PXIE RFQ Cooling System and Resonant Frequency Response", Proc. of IPAC '16.

Modeling frequency shift with settings in the PXIE RFQ

Training a neural network on these models enables accurate modeling of the resonant frequency shift due to these disparate parameters



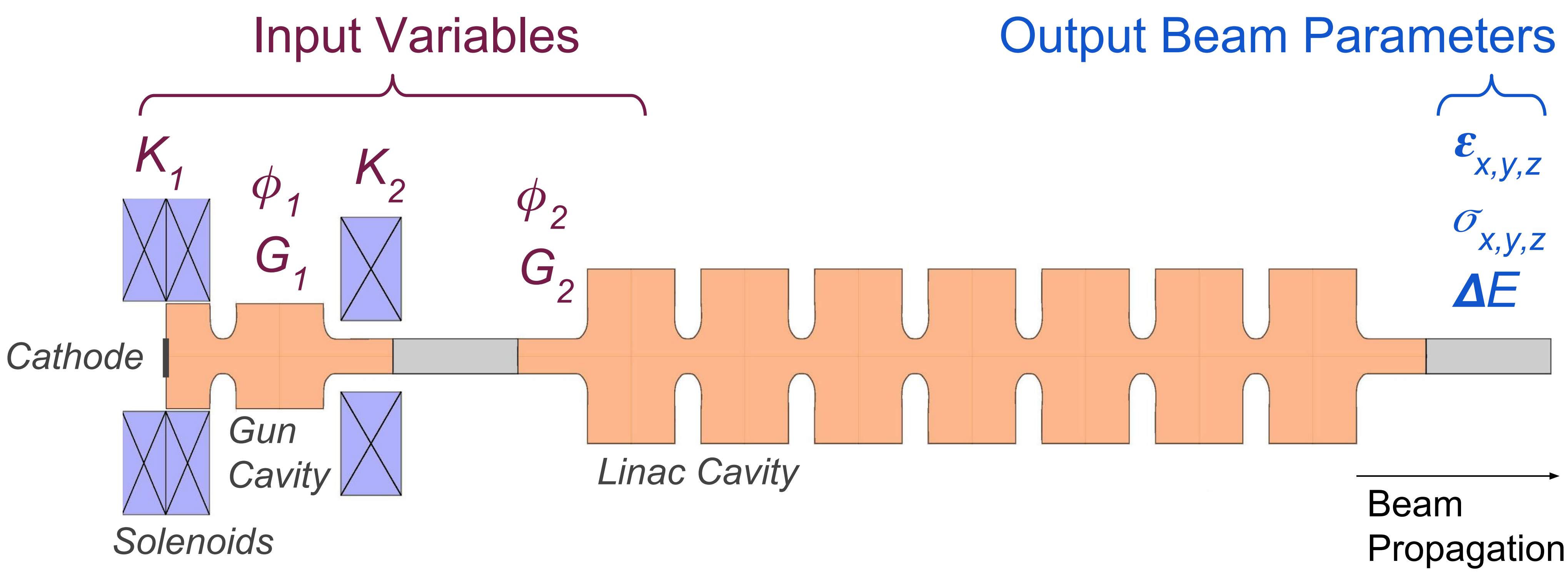
comparison of the frequency shift measured and predicted by the neural network model trained on data

A. L. Edelen et al. "Neural Network Model of the PXIE RFQ Cooling System and Resonant Frequency Response", Proc. of IPAC '16.

Surrogate Models are a fast model built on simulation and experimental data

Neural networks excel at modeling complex data sets, given enough data. Idea is to run a few hundred PIC simulations to train a network, then use that network for thousands+ "function evaluations"

Test Case: Modeling the Argonne Wakefield Accelerator

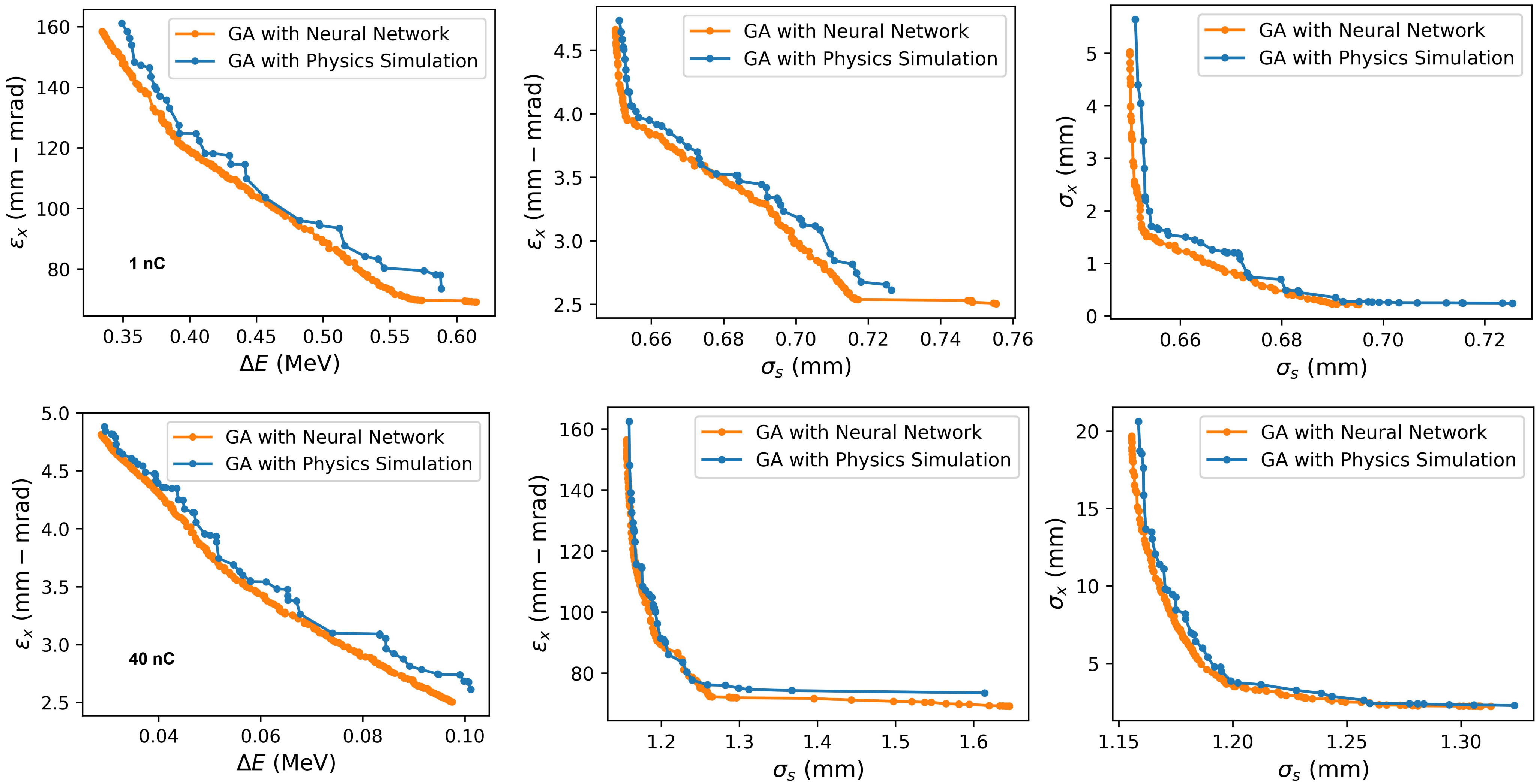


A. L. Edelen et al. "Machine Learning to Enable Orders of Magnitude Speedup in Multi-Objective Optimization of Particle Accelerator Systems", arXiv:1903.07759.

Surrogate models for fast optimization and online modeling

Running on-line optimization over the many parameters in an accelerator — magnet settings, rf phase, space charge effects — is computationally too expensive

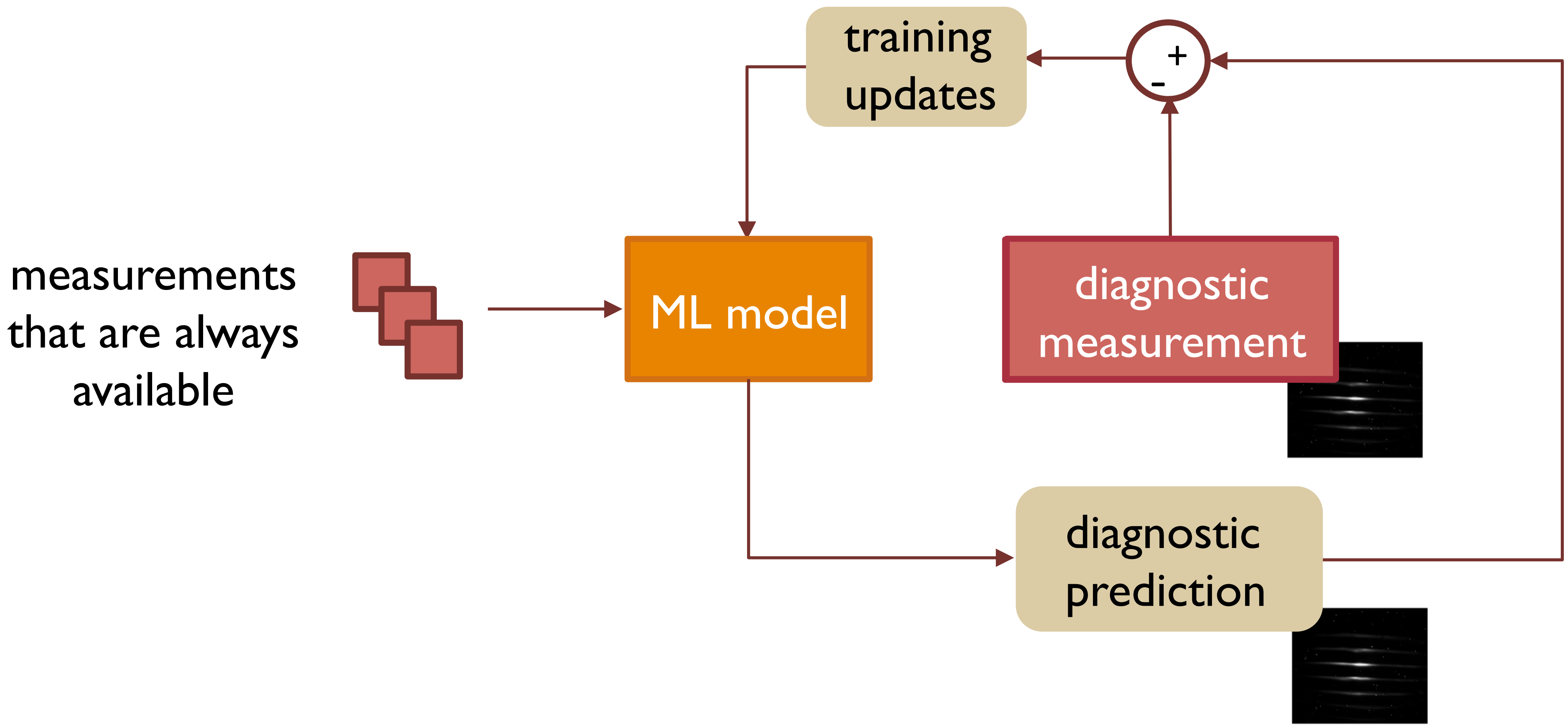
Training a neural network on PIC simulation data provides a 10^3–10^6 speedup to optimize the accelerator design



comparison of Pareto fronts obtained with OPAL simulations versus neural networks surrogate models at Argonne Wakefield Accelerator

A. L. Edelen et al. “Machine Learning to Enable Orders of Magnitude Speedup in Multi-Objective Optimization of Particle Accelerator Systems”, arXiv:1903.07759.

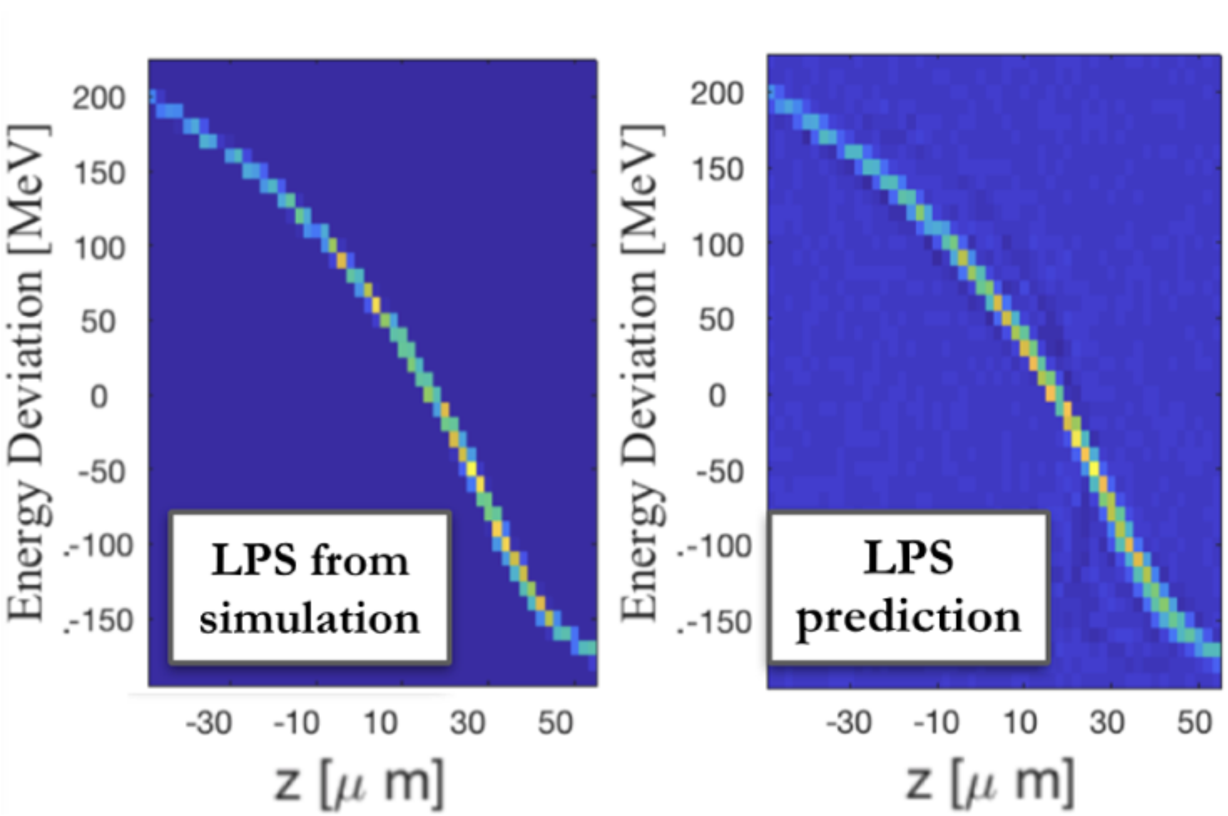
Virtual Diagnostics allow destructive diagnostic "measurements" during normal operation



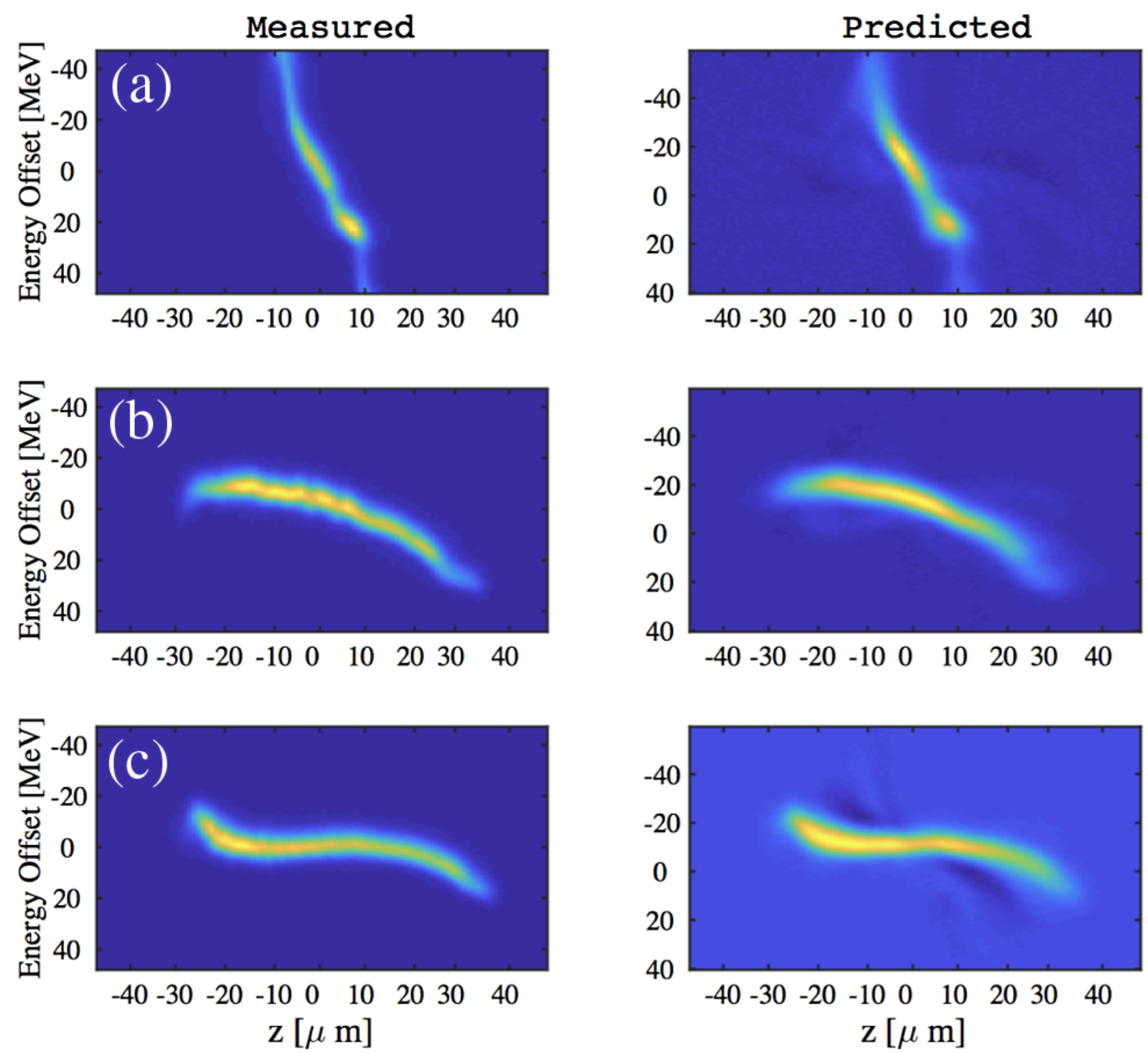
Longitudinal phase space measurements for FACET-II

Want to know the shot-to-shot longitudinal phase space going into the plasma channel at FACET-II, which is an intercepting diagnostic

Trained a perceptron neural network on simulation or actual transverse deflecting cavity data



FACET-II LPS from OPAL simulations (left) and neural network trained on simulation data(right)



LCLS LPS from transverse deflecting cavity measurements (left) and neural network trained on transverse deflecting cavity data (right)

C. Emma, A. Edelen, et al., "Machine learning-based longitudinal phase space prediction of particle accelerators", Phys. Rev. Acc. Beams **21**, 112802 (2018).

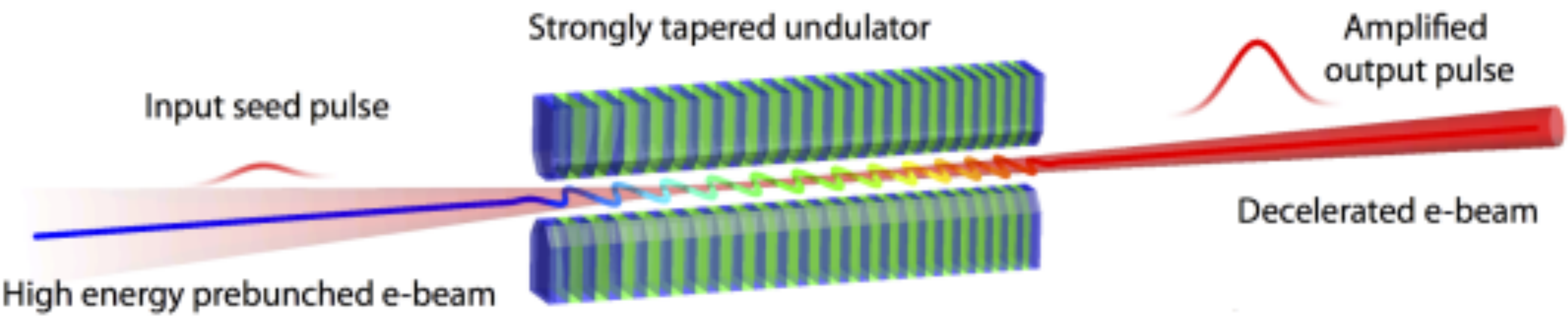
RadiaSoft Active Projects with Machine Learning for Accelerators

Develop simulation tools and toolboxes for implementing a virtual transverse deflecting cavity to support high-efficiency FEL experiments

Develop and test a browser based toolbox for applying machine learning to accelerators

TESSA-266 Experiment: An Ultra-High-Efficiency Free-Electron Laser

*in collaboration with Argonne National Laboratory, UCLA, and RadiaBeam

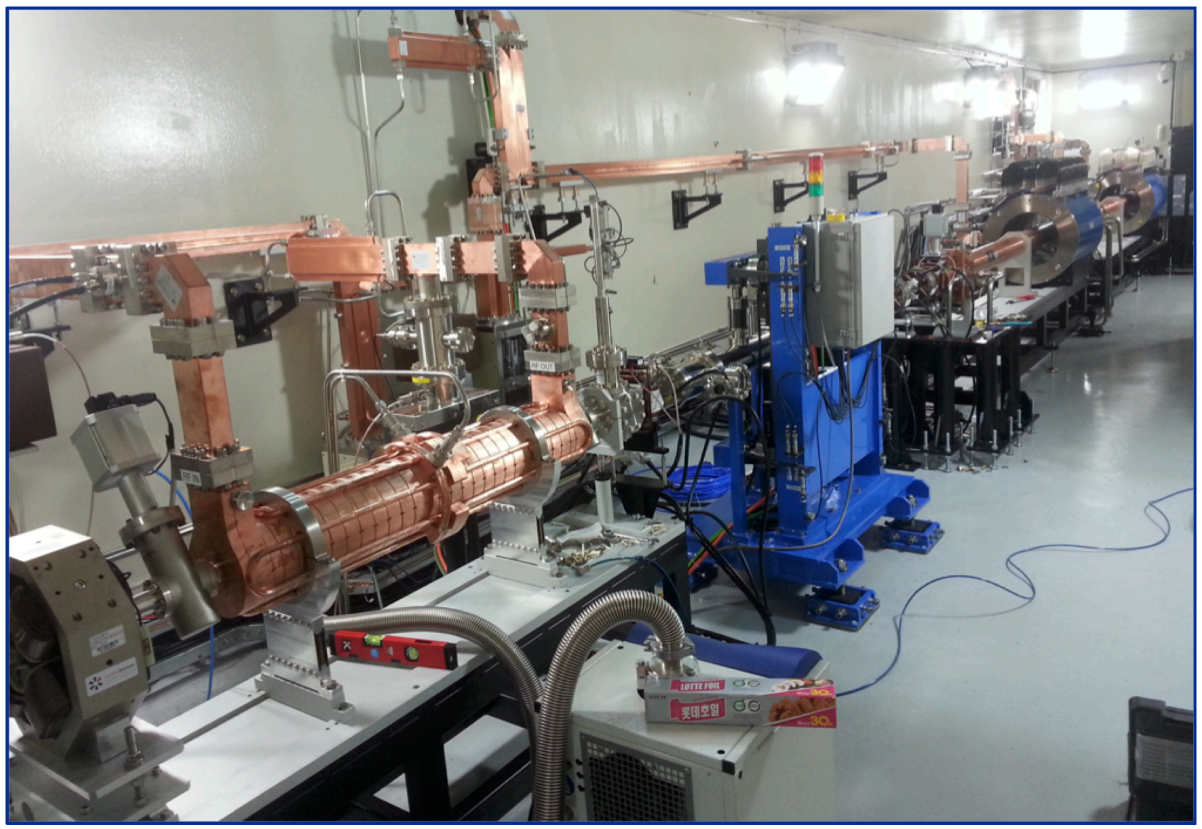


J. Duris et al. "Tapering enhanced stimulated superradiant amplification", New J. Phys. (2015).

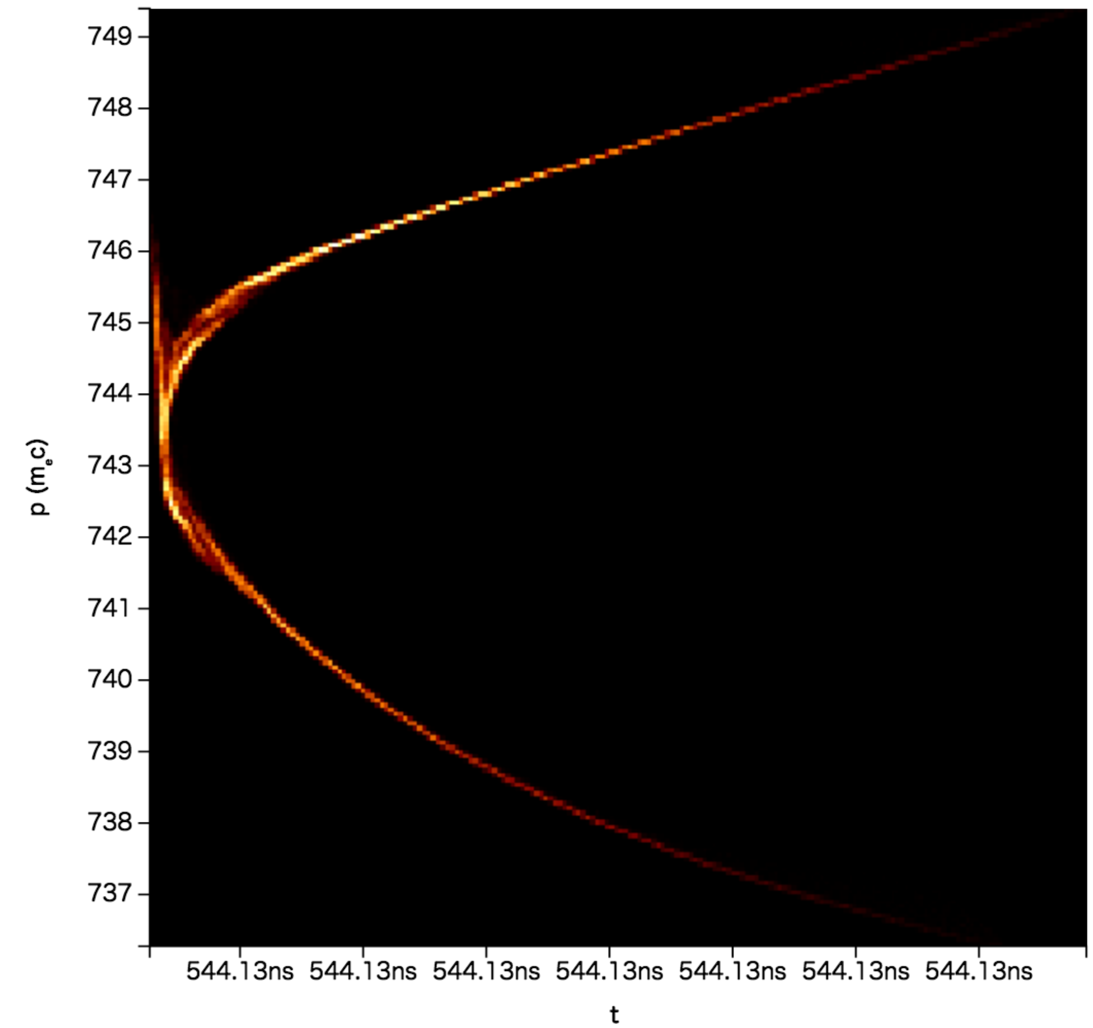
Longitudinal phase space measurement for high-efficiency free-electron laser

*in collaboration with Argonne National Laboratory, UCLA, and RadiaBeam

We want to know the shot-to-shot longitudinal phase space going into the tapered TESSA undulator, which is an intercepting diagnostic



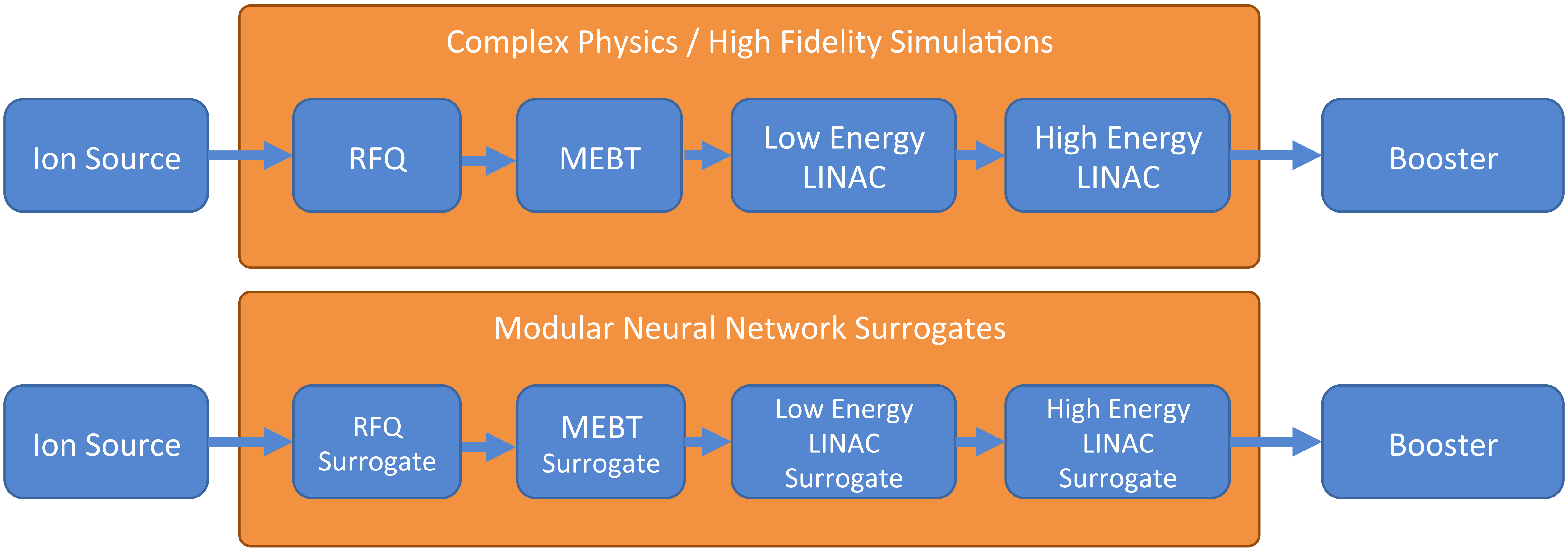
RadiaBeam transverse deflecting cavity



LEA beamline has CSR, wake fields, and longitudinal space charge, which can cause shot to shot variation in the LPS that we need to understand to analyze TESSA performance

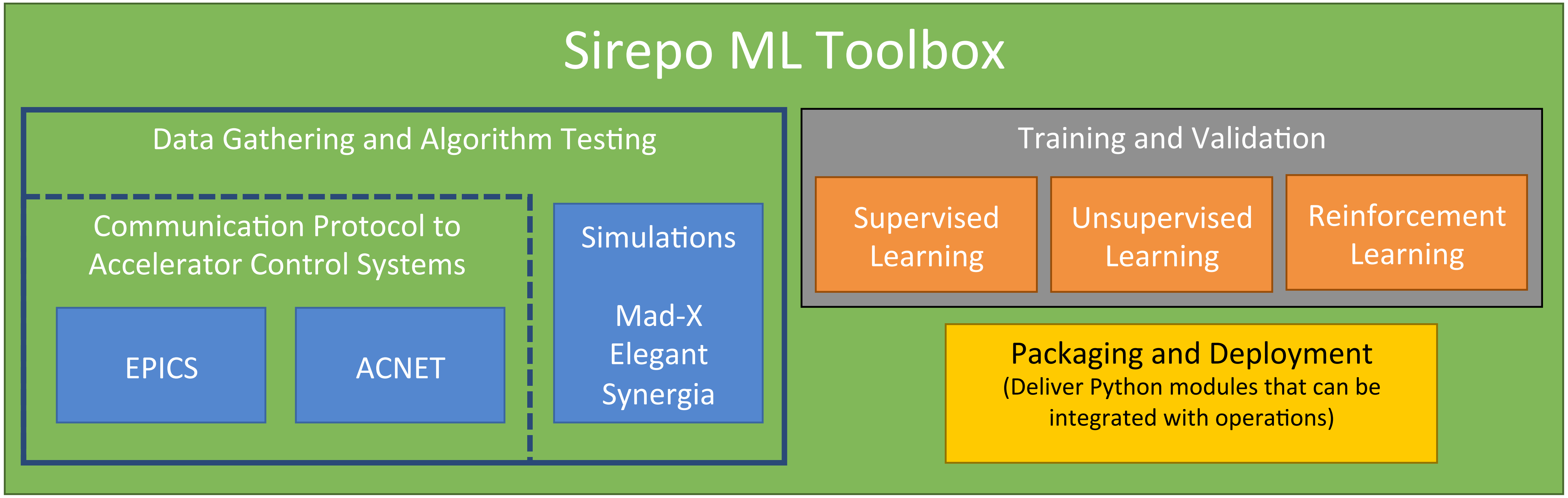
Effort supported with a Phase II SBIR by DOE Office of Science, Office of Basic Energy Science under contract no. DE-SC0018571.

Want to develop an online model of the Fermilab linac using surrogate models



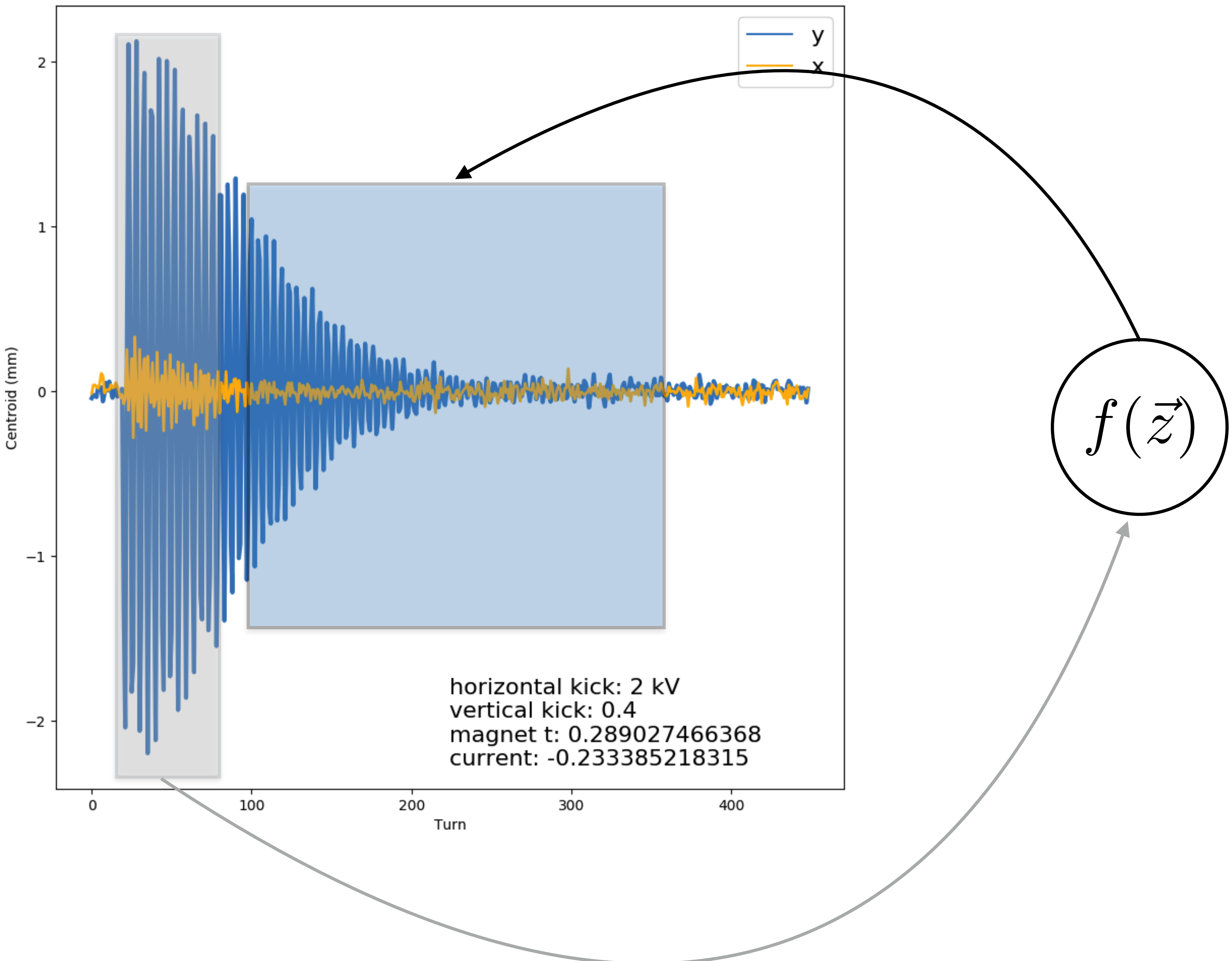
Modular surrogate models allows easy retraining for similar machines

Goal is to develop a machine learning toolbox in the Sirepo framework



General application to rings—
Can we predict long-term behavior from short-term data?

Can a neural network predict long-term BPM measurements from short time-series data?

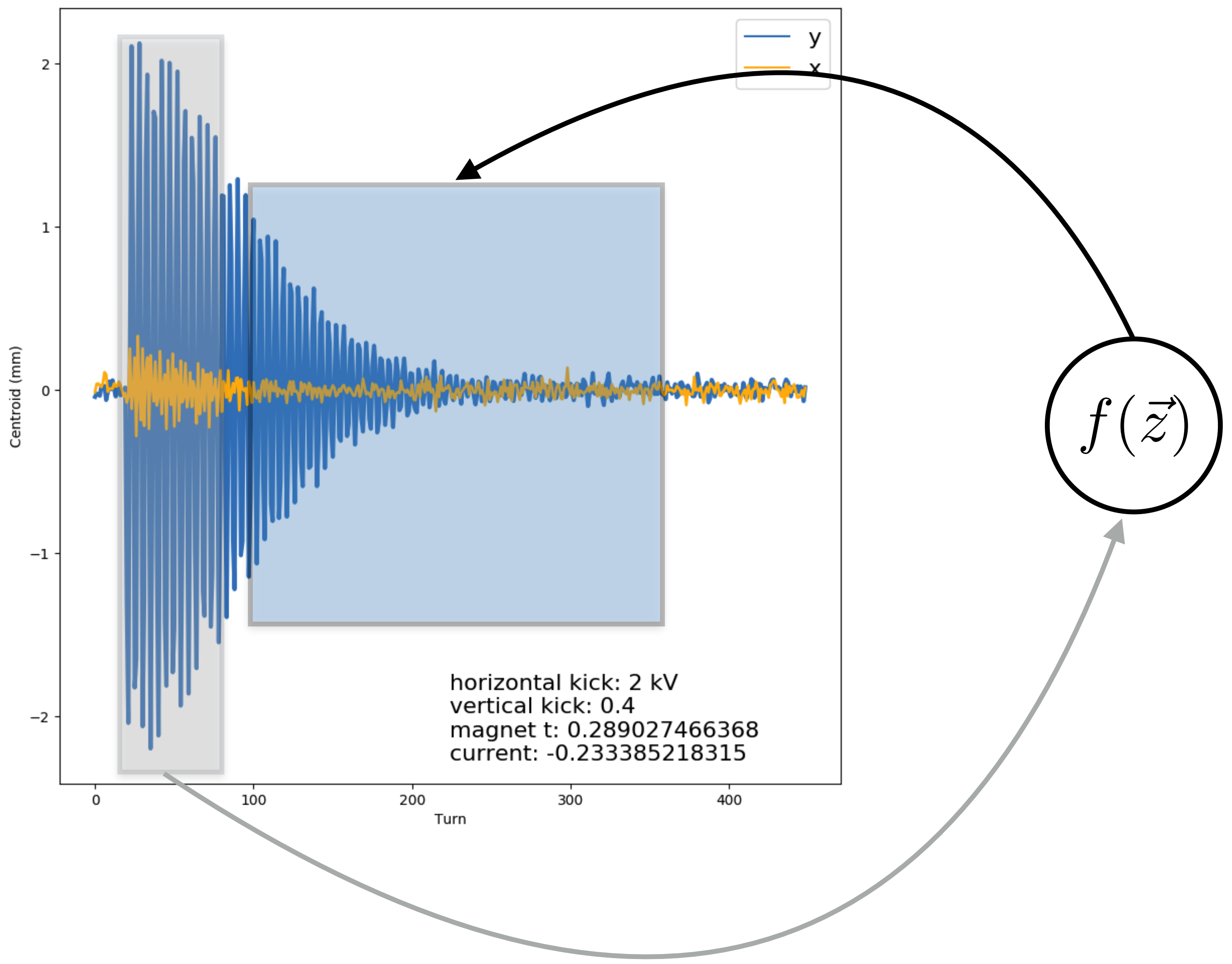


Can a neural network predict long-term BPM measurements from short time-series data?

For varying elliptic element strength, kick the beam transversely

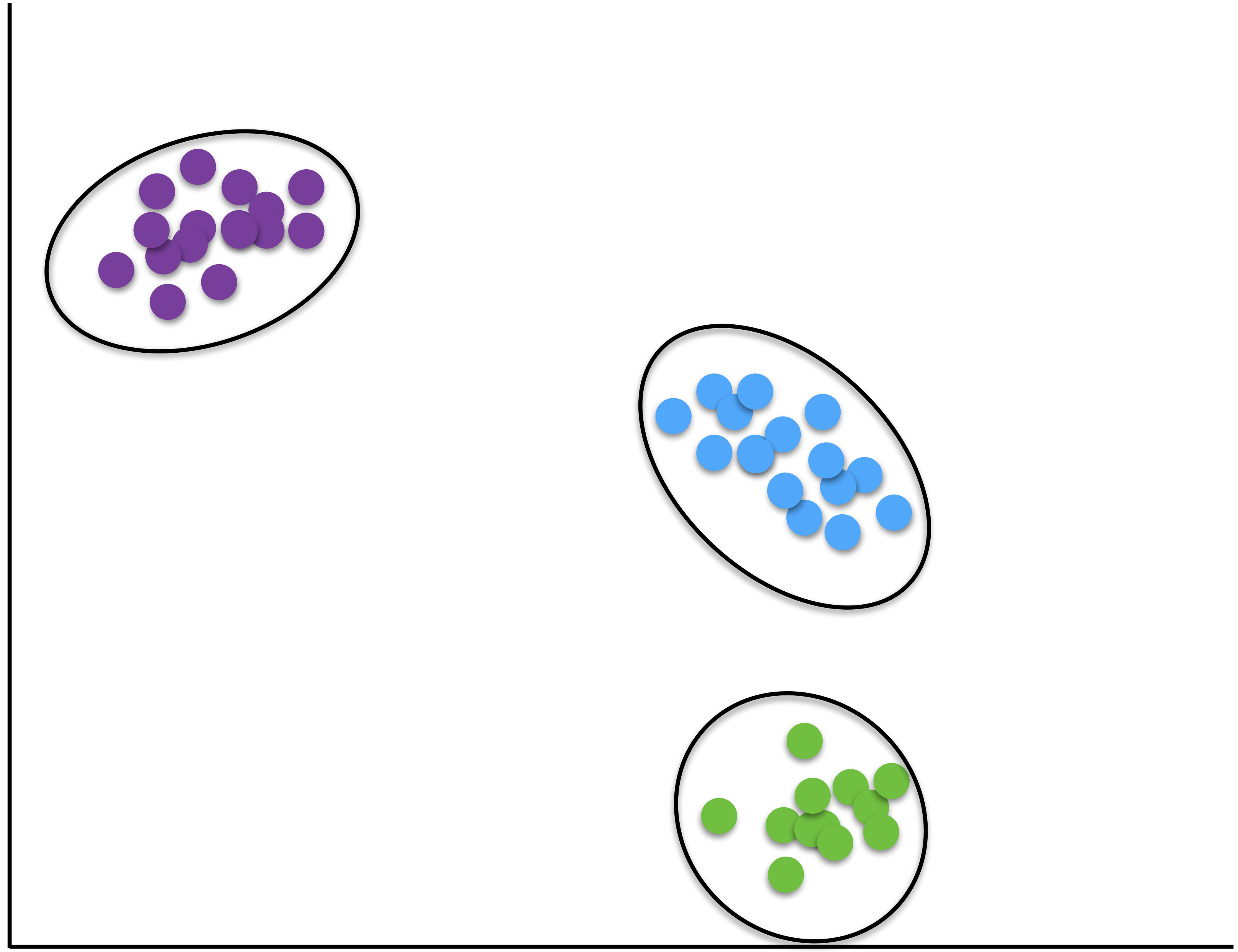
Determine how many turns worth of BPM data is required to reliably predict the next, much longer set of turns

First step towards proof-of-concept many-turn virtual diagnostics (replacement for gas jet diagnostic or phosphor screen, for example)

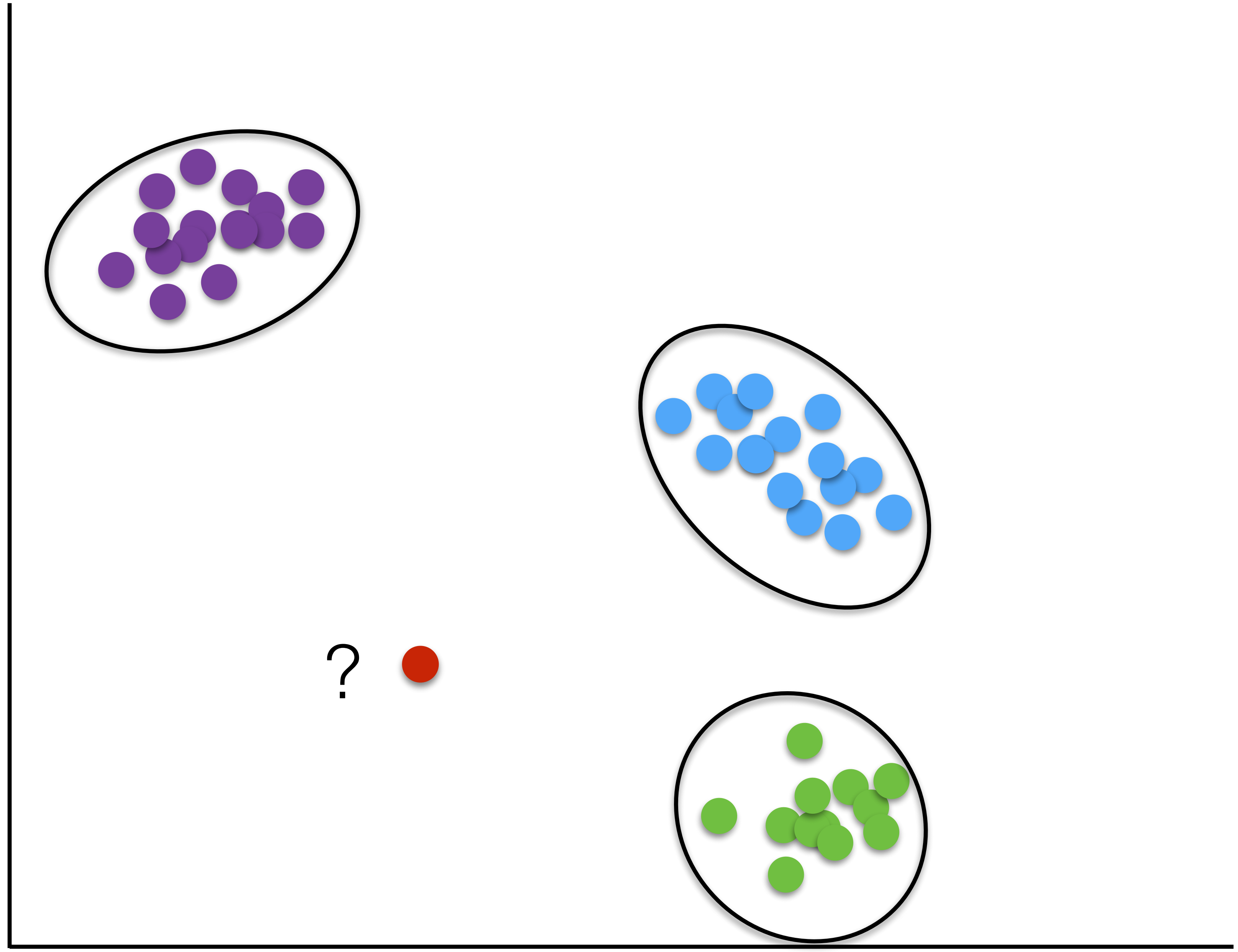


General application to rings—
Can we determine “bad” beam behavior from normal operation?

Clustering algorithms can classify distinct operating modes based on diagnostic data



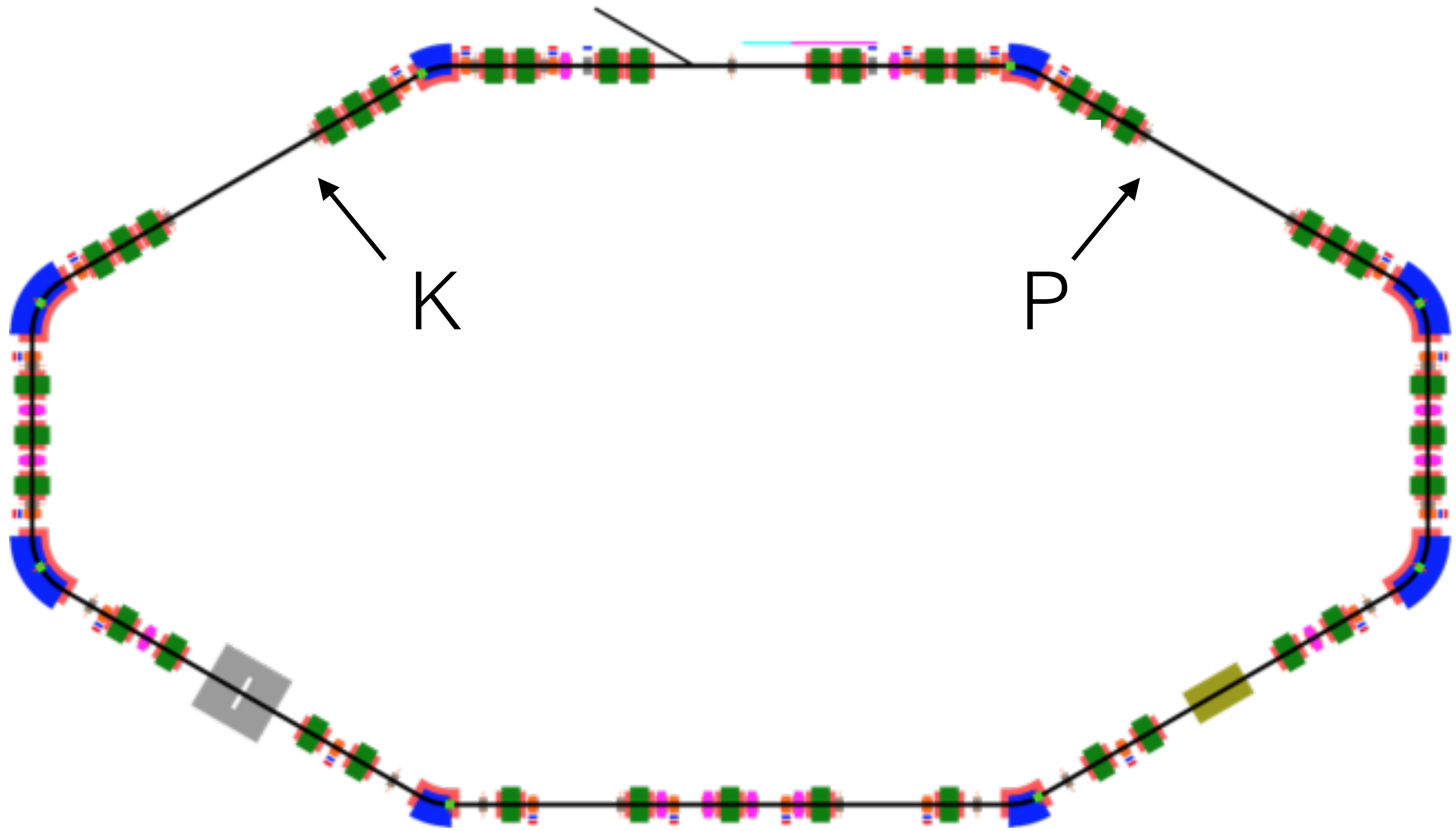
Anomaly detection looks for data points that "don't belong"



Can we then detect the onset of a slow instability using anomaly detection?

Can we use clustering and anomaly detection to determine if we've turned on the anti-damper?

How long does it take to detect that we've turned on the anti-damper?



Schematic of the IOTA ring with a pick-up [P] and kicker [K] for an anti-damper

E. Stern et al. "Suppression of Instabilities in Generated by an Anti-Damper with a Nonlinear Magnetic Element in IOTA", Proc. of IPAC '18.