Particle Accelerator Self-Evaluation by Machine Learning

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Proposal title: Particle Accelerator Self-Evaluation by Machine Learning

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Other Investigators: Timur Shaftan (NSLS-II), Thomas Robertazzi (Stony Brook), Natalie Isenberg (CSI), Yuan Gao (C-AD), Vincent Schoefer (C-AD), Yongjun Li (NSLS-II), Reid Smith (NSLS-II), David Sagan (Cornell)

Indicate if this is a cross-directorate proposal. Yes _X_ No___

If yes, identify other directorates/organizations: C-AD, NSLS-II, CSI, Cornell, SBU

Program: Specify which program: Multiprogram

Proposal Term: From: 10/01/22 To: 09/30/25

Total funding per year in FY23, FY24 and FY25: 2.6FTE per year

Brookhaven National Laboratory

Context

- Large accelerators have thousands of measured parameters that describe their state, e.g., field strength, magnet alignments, etc.

- These parameters are used to make a virtual accelerator model (VAM). An accurate model is needed for operations, e.g., to run feedback systems, to optimize luminosity.

- Today, human intervention and dedicated beam study times are often required to find system parameters.

➔ Time consuming dedicated studies

➔ Sensitivity to human errors.

- An accurate VAM (existing or from ML) can provide a digital twin to the control system that controls the twin just like the physical accelerator. Prototypes (CBETA-V & CESR-V) have led to enormous operational simplifications and optimizations, to virtual detectors, and to early fault detection.

Main Goal

- Provide a control system procedure that evaluates the main parameters of an accelerator automatically and parasitically to user operation.

- As a first example, establish this procedure initially by means of the Orbit Response Matrix. Afterwards add other measurables, e.g., parasitically evaluate injection oscillations.

The ORM method:

- N corrector magnets produce beam orbit changes at M beam-position monitors.
- These N*M values can be used to determine many of the accelerator's parameters, e.g., magnets strength and alignments.

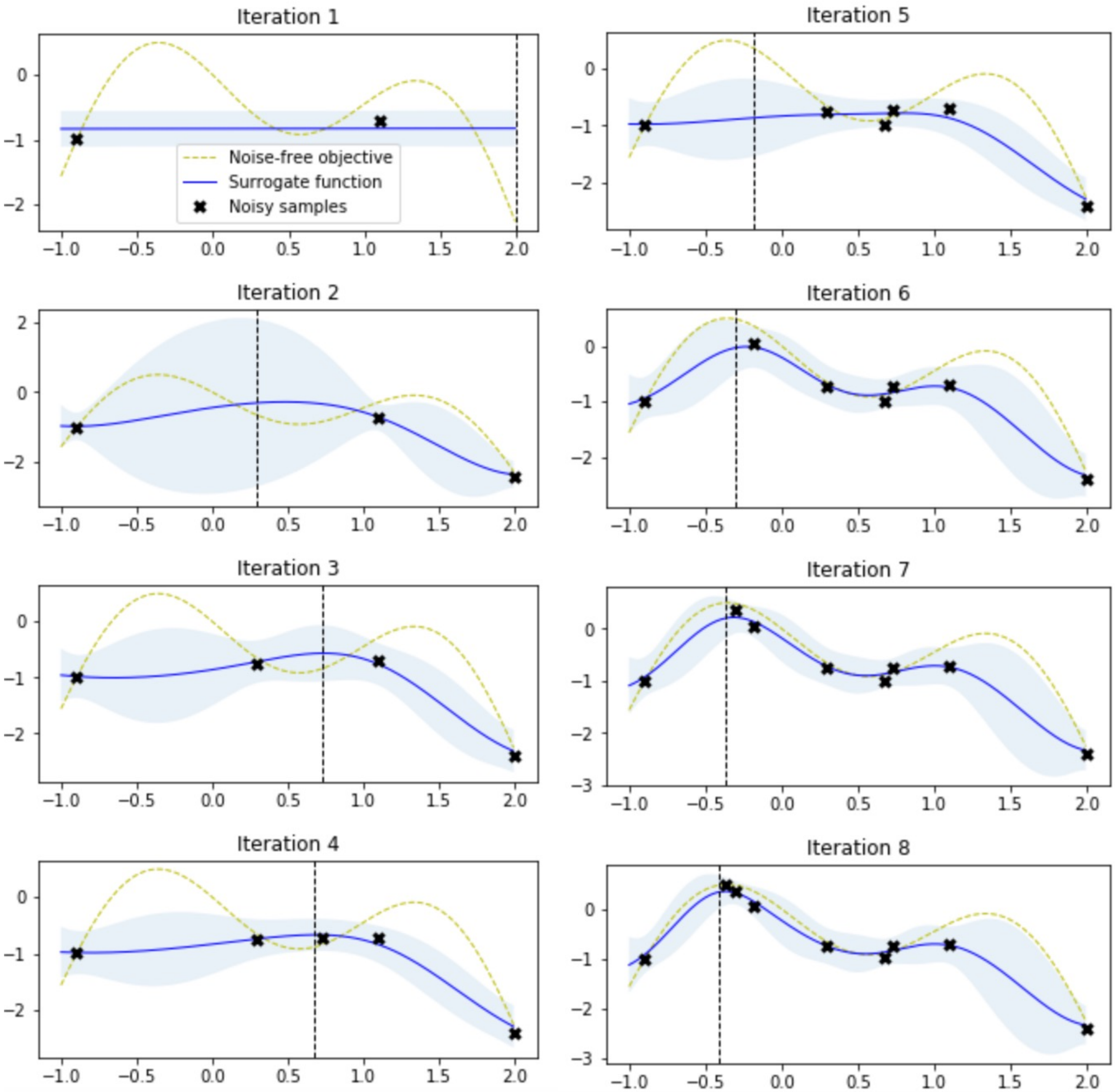
- 1st Goal: Establish the ORM automatically and parasitically, without dedicated study time in the AGS, RHIC, and NSLS-II.

Deliverables

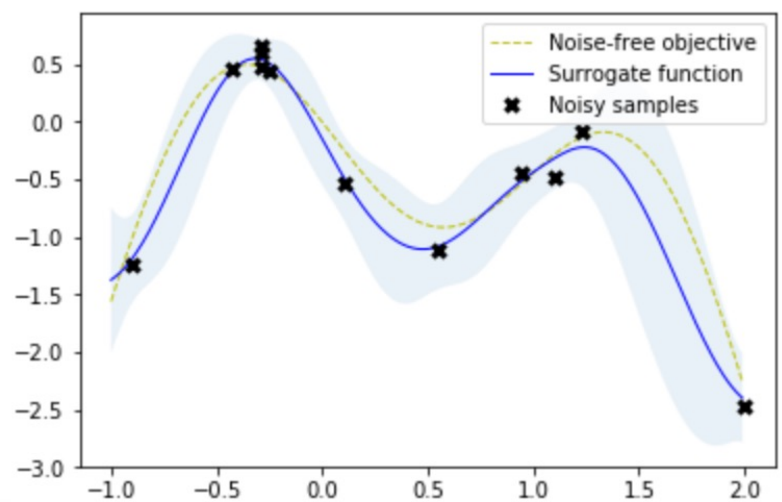
- Machine Learning routines, connected to the control systems, that provide the ORM and other dynamic accelerator functions automatically and parasitically during accelerator operation for AGS, RHIC, and NSLS-II.
- Determine accelerator parameters from the ORM.
- Provide a virtual accelerator model with these parameters.
- Make these routines generic so they can easily be transferred to other ring accelerators.
- Connect the virtual accelerator model to the control system to form a full digital twin.

Methods to achieve the goals

Bayesian optimization

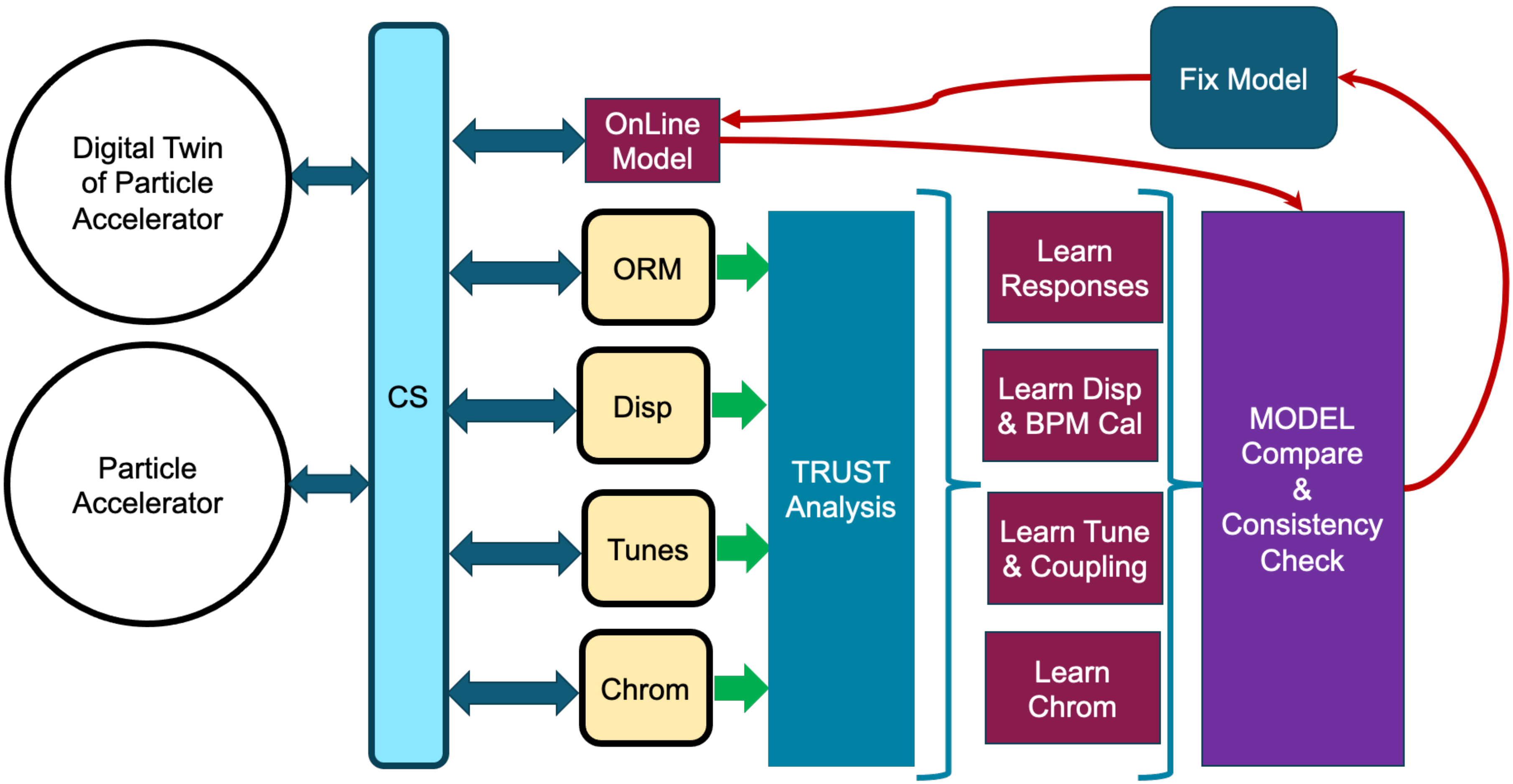


- Functions are successively approximated, with diminishing uncertainty.
- Detector noise can be included.



Methods to achieve the goals

Control system implementation and the Digital Twin



The Digital Twin is based on the Virtual Accelerator Model and can be addressed from the control system just like the physical accelerator.

Personnel involved

Georg Hoffstaetter (C-AD and Cornell) – Accelerator physics

Kevin Brown (C-AD and Stony Brook) – Controls implementation

Timur Shaftan (NSLS-II) – NSLS-II implementation

Natalie Isenberg (CSI) - ML with uncertainties

Yuan Gao (C-AD) – ML applications

Vincent Schoefer (C-AD) – Controls implementation

Yongjun Li (NSLS-II) - Operation implementation

Reid Smith (NSLS-II) – Operation implementation

Thomas Robertazzi (Stony Brook) – ML with uncertainties

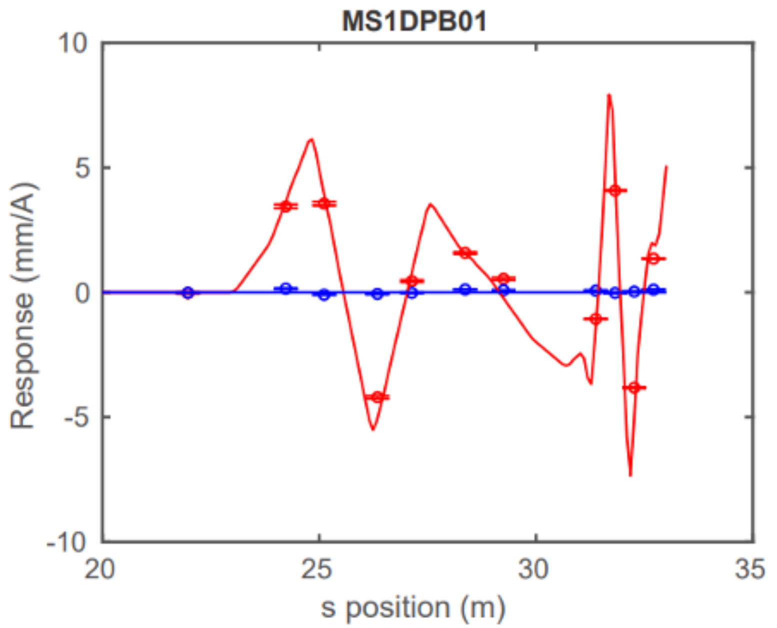
David Sagan (Cornell) – Bmad accelerator modeling

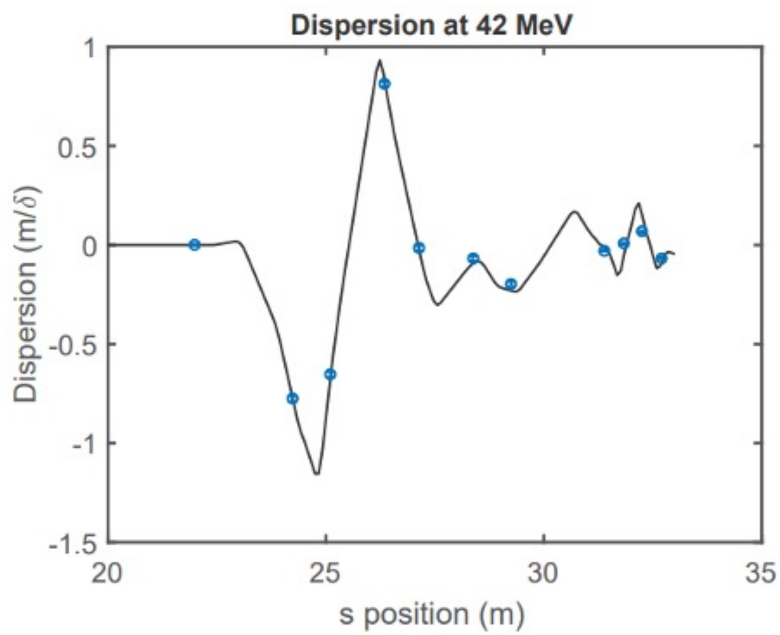
Required procurements

- Computational tools and control system interfaces are available.
- No procurements are needed.

Potential Benefits

- Continuous update of the virtual accelerator model.
- Savings in dedicated study time.
- Early warnings about component deterioration.
- Confidence estimates for detectors.
- Availability of a VAM for feedbacks and optimizations.
- Virtual detectors from the digital twin.
- Ease of operation and controls developments.





Selection criteria

- Intellectual merit
  - Accelerator applications of Bayesian optimization, Neural Networks, and AI/ML.
  - A new paradigm for accelerator control.
  - Quantitative confidence analysis on predictions with ML.
  - Construction of digital twins for a large accelerator control system.

- Return on Investment
  - Savings in costly accelerator study time.
  - Reduction of human error in dedicated data taking.

- The broader impacts on the Laboratory
  - Improved operation at the AGS, RHIC, and NSLS-II.
  - Flexible implementation that can be used for EIC rings and beyond.
  - Extendibility to BNL's linacs.

Summary

- Accelerator optimization and feedback systems need an accurate accelerator model.
- Obtaining the parameters for that model often requires human interaction and dedicated study time.
- AI/ML provides techniques to successively improve the knowledge of accelerator parameters during user operation.
- The Virtual Accelerator Model can therefore be continuously updated, providing: (a) accurate optimizations and feedback, (b) early fault detection, (c) virtual diagnostics.

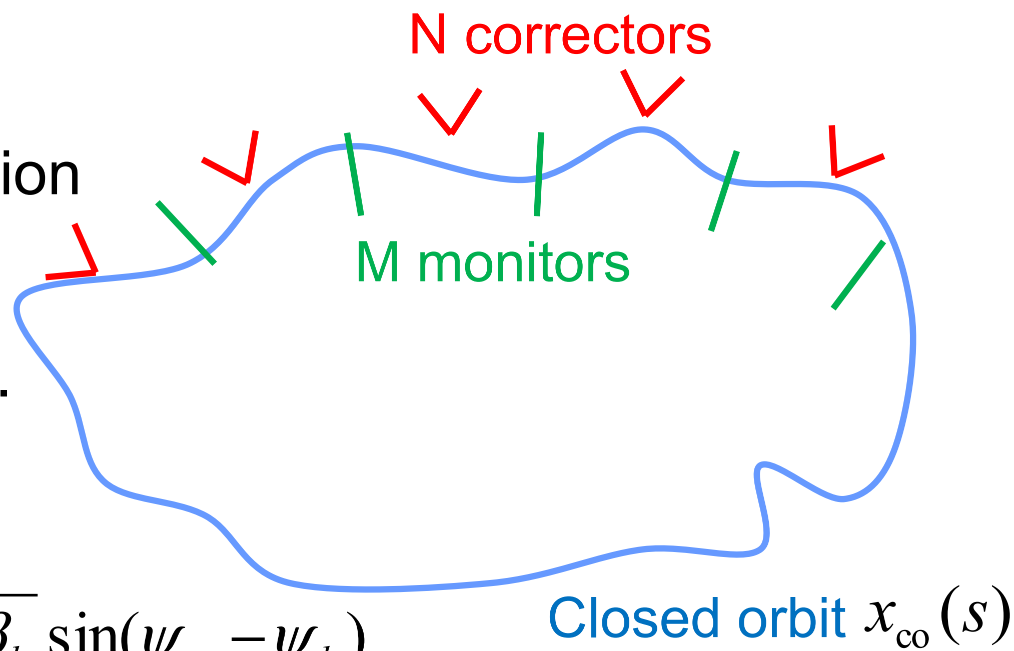
Why it has to be supported ?

  - There is large and growing interest in AI/ML applications in accelerators, manifested in papers and invited presentations.
  - All BNL accelerators will benefit, as well as new international accelerators.
  - The investment will be returned amply in reduced accelerator study times.

Methods to achieve the goals

The Orbit Response Matrix

- Each monitor reading is a function of N corrector coils.
- Bayesian optimization can successively learn this function.



$$x_{\rm co}^{\rm new}(s_m) = x_{\rm co}^{\rm old}(s_m) + \sum_k \Delta\vartheta_k \sqrt{\beta_m \beta_k}\,\sin(\psi_m - \psi_k)$$

$$= x_{\rm co}^{\rm old}(s_m) + \sum_k O_{mk} \Delta\vartheta_k$$

$$\vec{x}_{\rm co}^{\rm new} = \vec{x}_{\rm co}^{\rm old} + \underline{O}\Delta\vec{\vartheta}$$

$$\boxed{\Delta\vec{\vartheta} = -\underline{O}^{-1}\vec{x}_{\rm co}^{\rm old} \quad \Rightarrow \quad \vec{x}_{\rm co}^{\rm new} = 0}$$

The N*M ORM data can be used to

- Measure the optics functions (β, ψ).
- Determine quadrupole strength, sextupole alignments, etc.
- Direct closed orbit control.