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# ADAPTIVE FEEDBACK AND MACHINE LEARNING FOR PARTICLE ACCELERATORS *

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*Abstract*

The precise control of charged particle beams, such as an electron beam's longitudinal phase space as well as the maximization of the output power of a free electron laser (FEL), or the minimization of beam loss in accelerators, are challenging tasks. For example, even when all FEL parameter set points are held constant both the beam phase space and the output power have high variance because of the uncertainty and time-variation of thousands of coupled parameters and of the electron distribution coming off of the photo cathode. Similarly, all large accelerators face challenges due to time variation, leading to beam losses and changing behavior even when all accelerator parameters are held fixed. We present recent efforts towards developing machine learning methods along with automatic, model-independent feedback for automatic tuning of charge particle beams in particle accelerators. We present experimental results from the LANSCE linear accelerator at LANL, the EuXFEL, AWAKE at CERN, FACET-II and the LCLS.

## INTRODUCTION

Particle accelerators are complex systems with many coupled components including hundreds of radio frequency (RF) accelerating cavities and their RF amplifiers as well as thousands of magnets for steering and focusing charged particle beams and their power sources. Accelerator designs are initially optimized by utilizing analytical beam physics knowledge and simulation studies. Once accelerators are built their performance does not exactly match the theory and models on which their design is based.

The differences between actual and designed systems are due to factors including idealized analytical studies that make simplifying assumptions and misalignment of accelerator components. Beyond not matching their designs, accelerator components and their beams drift unpredictably with time: 1). RF and magnet system amplifiers, power sources, and reference signals drift with temperature and suffer random perturbations from the noise within the electrical grid; 2). The initial 6D $(x, y, z, p_x, p_y, p_z)$ phase space distribution of the beams entering accelerators from ion sources or photo cathodes drift and change unpredictably with time.

Most existing diagnostics are either destructive in nature or only provide beam-averaged measurements. Transverse deflecting cavities (TCAV), which can measure the longitudinal phase space (LPS) of relativistic electron bunches, destroy those bunches in the measurement process [1]. Beam position monitors (BPM) are non-invasive but only provide bunch-averaged position measurements and beam loss monitors provide no beam data beyond specifying a rough estimate of beam loss within a large region of an accelerator.

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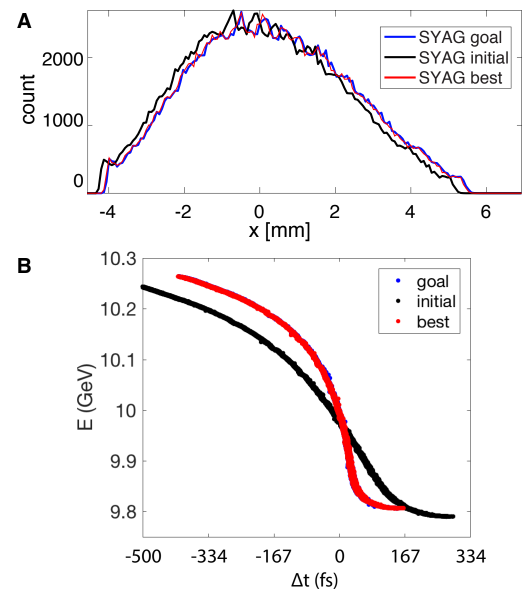


Figure 1: The adaptive model is tuned to match SYAG-based measurements of energy spread spectra (A). Once the modeled (red) and measured (blue) spectra converge the LPS of the measured beam is predicted almost exactly (B).

Because accelerators are uncertain and time-varying systems tuning and optimization require many hours of manual tuning. Tuning is especially challenging at older facilities with limited diagnostics such as the LANSCE linear accelerator at LANL [2], at facilities that must generate extremely short and intense beams such as FACET-II [3], and at facilities which require complex and precisely aligned interactions between multiple beams such as AWAKE [4]. Even the latest and most advanced facilities, especially when making large configuration changes to accommodate various experiment setups such as what must routinely take place at advanced FEL facilities such as the LCLS [5], LCLS-II [6], EuXFEL [7], PALFEL [8], and the SwissFEL [9].

Adaptive feedback and machine learning (ML) approaches are growing in popularity for particle accelerator for magnet tuning [10], non-invasive TCAV LPS diagnostics based on adaptive models at FACET [11], LPS diagnostics based on neural networks (NN) at SLAC [12], FEL light output power maximization at the LCLS and at the EuXFEL [13], surrogate modeling [14], detecting faulty BPMs and for optics corrections at the LHC at CERN by utilizing isolation forest techniques and NNs [15, 16], beam tuning at the SPEAR3 light source via Gaussian processes [17], and

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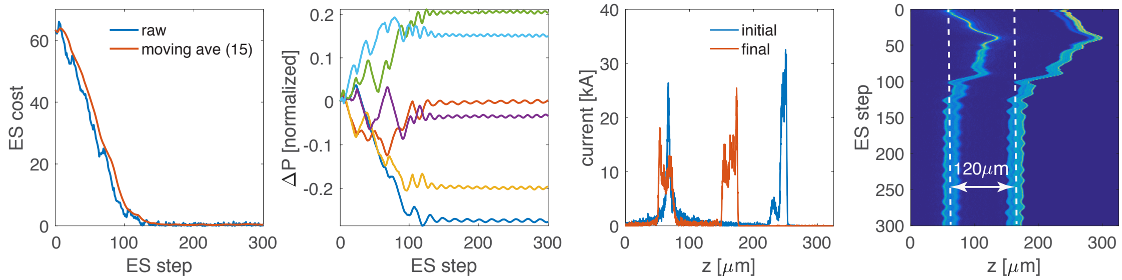

Figure 2: The 3D CNN's output is used as the initial condition for ES tuning.

multiobjective optimization for simultaneous orbit control and emittance minimization at AWAKE [18], .

## NON-INVASIVE DIAGNOSTICS

The FACET-II electron bunches are going to be extremely intense with nC charges and few fs bunch lengths. It is challenging to measure the detailed current profiles of intense bunches which damage or destroy intercepting diagnostics and because their few fs bunch lengths are shorter than the resolution of existing TCAV measurements which are limited to ~3fs for highly relativistic bunches. Non-invasive LPS diagnostics for intense, short beams would be useful for most FELs and in particular for particle driven plasma wakefield accelerators (PWA) such as FACET-II in order to enable more precise control of bunch profiles. A first of its kind demonstration of an adaptive non-invasive TCAV LPS diagnostic was developed and tested at FACET to accurately track and predict time varying LPS measurements based only on passive energy spread spectrum measurements [11]. Recently, we have begun developing such adaptive model tuning-based non-invasive diagnostics for the FACET-II beam [19]. Preliminary simulation results are shown in Figure 1 where matching the beam's energy spread spectrum resulted in an exact prediction of the LPS. Once such a diagnostic is up and running, it can enable automated feedback-based control and tuning of the LPS distribution of the FACET-II electron bunch, as shown in Figure 2.

## ACCELERATOR TUNING AND CONTROL

### *Pulse Energy Maximization at LCLS and EuXFEL*

At the LCLS and the EuXFEL we have applied an adaptive model-independent feedback control algorithm for automatic maximization of FEL output power [13]. The main strengths of this approach are its ability to handle multiple coupled components simultaneously and tune them based only on noisy measurements of analytically unknown functions.

### *Beam Loss Minimization at LANSCE*

LANSCE simultaneously accelerates intense space charge dominated beams of $H^+$ and $H^-$ ions and is especially challenging to tune because of very limited diagnostics (few BPMs, mostly beam loss monitors). We applied adaptive feedback to minimize multiple beam loss monitors in various sections of LANSCE simultaneously by tuning 6 parameters

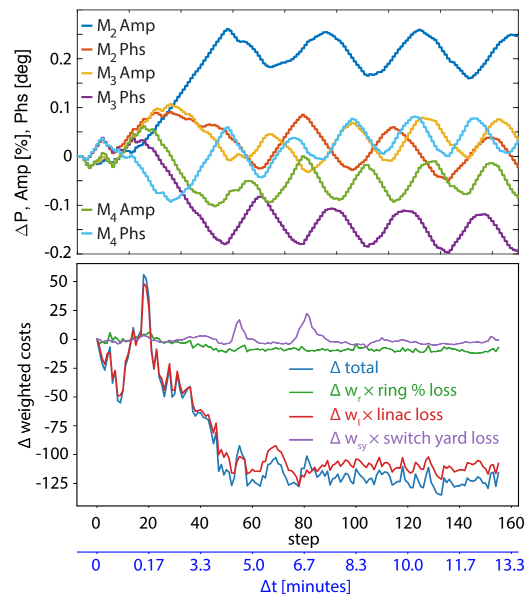

Figure 3: Beam losses and RF module settings.

simultaneously; the amplitude and phase set points of the first three digitally controlled RF modules $M_2 - M_4$. The strength of this algorithm was demonstrated when following a facility wide power glitch the beam came back on with high losses throughout the machine and the adaptive feedback was able to minimize them within ~5 minutes as shown in Figure 3, a task that could have taken up 1 hour of time if an operator had to iteratively tune all 6 knobs one at a time.

### *Multi-objective Optimization at AWAKE*

At the AWAKE PWA facility at CERN the electron beam line provides a tightly focused beam lined up with the 400 GeV proton beam for proton-driven PWA of electrons. Due to coupling, when an effort was made to minimize emittance growth by adjusting two solenoid and three quadrupole magnets directly following the injector, unwanted changes were seen in the beam's trajectory. Therefore we ran two adaptive feedbacks simultaneously, the first slowly adjusted 2 solenoids and 3 quads to minimize emittance growth, while the second adjusted 10 steering magnets at a 3× higher rate to maintain a desired trajectory, resulting in simultaneous emittance minimization and trajectory control via 15 parameter multiobjective optimization, as shown in Figure 4.

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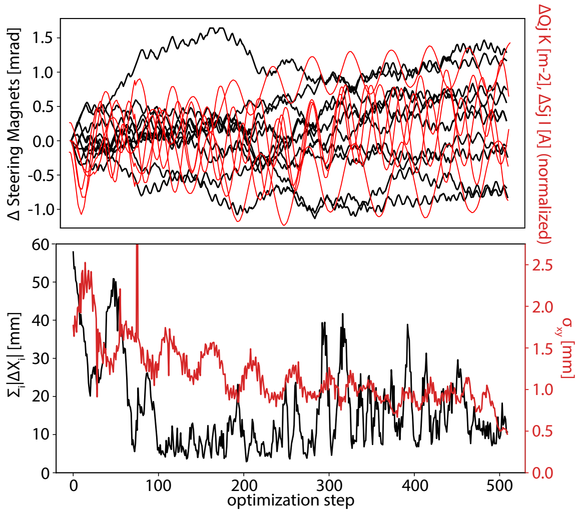


Figure 4: Tuning 15 components at AWAKE.

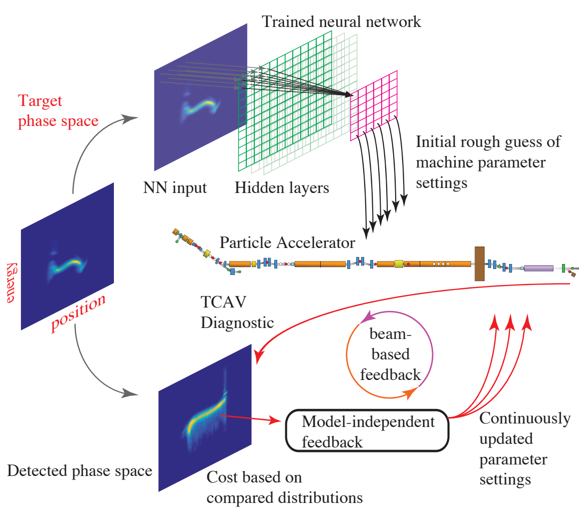


Figure 5: CNN output used as initial guess for ES tuning.

## ADAPTIVE MACHINE LEARNING FOR TIME VARYING SYSTEMS

### *Longitudinal Phase Space Control at the LCLS*

One limitation of standard ML-based approaches which use machine or simulation data in order to learn a representation of an accelerator is the fact that their performance drifts as accelerator beams and components change with time. Recently, an adaptive ML approach has been developed for time varying systems, as shown in Figure 5, and has been applied at the LCLS to automatically control the longitudinal phase space of the electron beam [20].

### *Transfer Learning and Domain Transfer*

Additional ways to enable the use of ML for changing systems are transfer learning and domain transfer. A NN can be trained on simulation data and then made more accurate for application to an actual accelerator by utilizing a much smaller set of machine data. This can also update a model for a changing accelerator over time. A recent demonstration of transfer learning and domain transfer trained a convolutional neural network (CNN) to map electron backscatter diffraction (EBSD) measurements to crystal orientations [21]. The CNN was first trained using >200,000 simulations, the last few layers were then retrained using only 1000 experimental measurements. However CNN accuracy was still limited due to noise and significant differences between experimental and simulated measurements. As an additional step domain transfer was applied in the form of training a U-net using 1000 experimental measurements, which pre-filtered experimental data and fed it to the CNN. Transfer learning together with domain transfer created a CNN for mapping EBSD measurements to crystal orientations >1000× faster than existing state of the art EBSD reconstruction methods.

## CONCLUSIONS

ML and adaptive feedback control methods are being developed by accelerator facilities around the world and new adaptive machine learning methods are enabling the control and optimization of complex time varying systems.

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