ISBN: 978-3-95450-184-7 doi:10.18429/JACoW-IPAC2018-THYGBE1

APPLYING ARTIFICIAL INTELLIGENCE TO ACCELERATORS*

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Abstract

Particle accelerators are being designed and operated over a wide range of complex beam phase space distributions. For example, the Linac Coherent Light Source (LCLS) upgrade, LCLS-II, is considering complex schemes such as two-color operation [1], while the plasma wakefield acceleration facility for advanced accelerator experimental tests (FACET) upgrade, FACET-II, is planning on providing custom tailored current profiles [2]. Because of uncertainty due to limited diagnostics and time varying performance, such as thermal drifts, as well as collective effects and the complex coupling of large numbers of components, it is impossible to use simple look up tables for parameter settings in order to quickly switch between widely varying operating ranges. Several forms of artificial intelligence are currently being investigated in order to enable accelerators to quickly and automatically re-adjust component settings without human intervention. In this work we discuss recent progress in applying neural networks and adaptive feedback algorithms to enable automatic accelerator tuning and optimization.

INTRODUCTION

Unlike traditional particle accelerators which are designed to run in one or a few static configurations for fixed beam properties, existing free electron lasers (FEL), such as the LCLS, and future machines such as the EuXFEL and the planned MaRIE, are all facing the extremely difficult challenge of quickly switching between various beam energies, bunch currents, pulse separation times, and repetition rates for various users. For example, LCLS provides users with photon energies ranging from 0.27 keV to 12 keV and bunch charge and pulse durations ranging from 20 pC at 3 fs to 1 nC at 300 fs. Reconfiguring the accelerator to a low charge mode in order to provide 3 fs bunches takes many hours.

Lowering accelerator tuning times concerns both existing and future particle accelerators in general (LANSCE, LHC, SNS, NLC) and FELs (FLASH, SACLA, LCLS, SwissFEL, PAL-XFEL, EuXFEL, LCLS-II) and plasma wakefield accelerators (FACET-II, AWA) in particular. Although existing and planned accelerators have automatic digital control systems, the systems are not well enough controlled to simply apply look up tables of parameter settings to quickly switch between different operating conditions [3]. Existing controls maintain components at fixed points, set based on desired beam and light properties. Analytic studies and simulations initially provide these set points. However, models are not perfect and component characteristics drift in noisy and time-varying environments. Tuning difficulties arise because exact physics-model based simulation and prediction of beam dynamics is practically impossible due to machine uncertainties, which include uncertain and time-varying phase space distribution of the beam, misalignments, hysteresis, thermal cycling, uncertain field profiles, time varying parameters, and collective effects in bunch compressors where extremely short and thereby high current bunches experience CSR and space charge forces. Therefore, even when local controllers maintain desired set points exactly, performance drifts. The result is that operators continuously tweak parameters to maintain steady state operation and spend hours tuning when large changes are required [3].

Such difficulties will only increase as existing and future light sources seek to provide brighter, shorter wavelength (0.05 nm at EuXFEL and 0.01 nm at MaRIE), more coherent light [4]. To achieve their performance goals, new machines face unique challenges, such as requiring extremely low electron beam emittance and energy spread [5, 6]. These factors have created an interest in artificial intelligence (AI) techniques including machine learning (ML) [7–10] and adaptive feedback. DESY has been developing an automatic tuning framework for applying various automated tuning algorithms [11]. Various feedback techniques exist, see for example [7] and references within. A recently developed feedback approach known as extremum seeking (ES) is particularly useful for particle accelerators because it is model independent, can tune many coupled parameters simultaneously, can handle time-variation and uncertainties, and extremely noisy measurements [12, 13].

AUTOMATIC TUNING

We consider two classes of automatic machine tuning: 1) model-based methods utilizing tools from ML and 2) model-independent real-time feedback methods.

The main strength of ML-based approaches is that they can be applied in a global sense to large, complex systems. A limitation of such ML-based approaches is that they require extremely large training sets which grow quickly with the number of parameters being tuned, are only accurate for beam properties which are close to the training data, and their performance suffers as the system for which they have been trained starts to change as parameters and their interconnections vary with time. Therefore, while an ML approach can theoretically automatically tune a machine to achieve close to desired beam properties quickly, over an extremely wide range of operating conditions, the match will only be approximate and will drift with time. Furthermore, it is likely that automatic re-training of the neural network will not be a sufficiently stable process to be fully relied upon in practice as a method of providing continuous feedback

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(particularly with the large number of inputs and outputs that would be used for a large machine model).

The main strength of adaptive/feedback-based model-independent methods such as extremum seeking (ES) is that they can also handle large complex systems with many coupled components, but with the additional benefit that they can handle very noisy data and unknown time-varying components [12, 13]. Therefore a real-time feedback tuning approach such as ES is able to zoom in on and track optimal machine settings in order to continuously provide desired beam properties despite the uncertainty and time variation of the accelerator's components. One limitation of a feedback-based approach such as ES is the possibility of being trapped in a local minimum when tasked with moving over too large of a range in parameter space. Such a limitation has to be explored on a case by case basis and depends on the nonlinearities of each specific system. We propose a combination of ML and ES-based feedback where initial coarse tuning is performed by ML, which is then followed by real time fine tuning by ES to zoom in on and maintain optimal settings despite uncertain time-variation of the system.

ML AND FEEDBACK EXAMPLES

1: ES for beam loading compensation at LANSCE [14].
2: A NN model has been designed to predict the resonant frequency of the RFQ in the PIP-II Injector Experiment (PXIE), to be used in a model predictive control scheme [8]. The predictive accuracy of the model is shown in Figure 1.

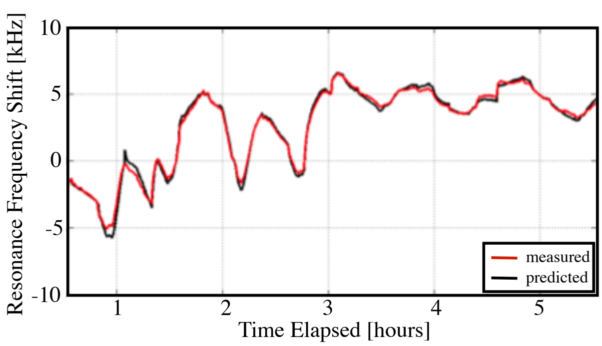

Figure 1: RFQ resonance frequency shift prediction.

3: Bayesian optimization, utilizing Gaussian processes has been utilized at LCLS via Ocelot to automatically tune quadrupole magnets to maximize pulse energy [15].
4: At the FERMI FEL, a novel quantitative method has been developed for non-destructively providing a quality index of the FEL spectrum, which can be utilized by various algorithms for spectrum optimization [16].
5: On-line optimization of various objective functions has been performed at the European XFEL using various algorithms such as a Nelder-Mead simplex method built via the OCELOT interface including: dispersion minimization, orbit distortion compensation, beam loss minimization, and photon pulse energy maximization [17].

6: ES was used to tune a model to match a non-destructive energy spread spectrum measurement to non-invasively predict the electron bunch length at FACET, as was verified by XTCAV measurements as shown in Figure 2 [18].

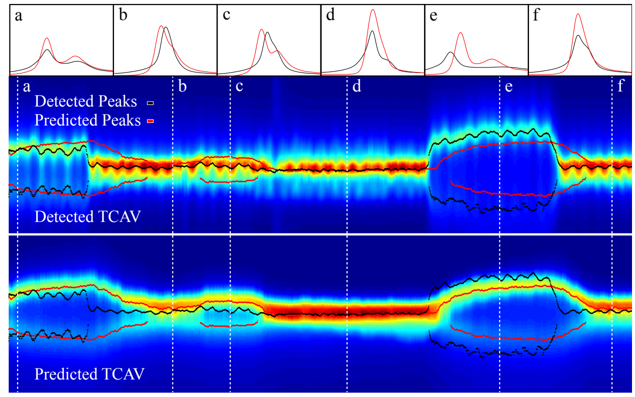

Figure 2: FACET bunch length prediction.

7: ES automatically tuned the magnetic field strengths and pulse widths of two kicker (K_1, K_2) and two skew quad (S_1, S_2) magnets to continuously minimize betatron oscillations in the injection/kicker system of the SPEAR3 electron beam while the field of a third kicker magnet (K_3) was quickly varied, as shown in Figure 3 [19].
8: ES matched desired longitudinal phase space distributions as measured by an XTCAV at the LCLS beam line by automatically adjusting the phase and energy set points of the RF acceleration and bunch compressors [20].
9: In a preliminary simulation study for a compact THz FEL, a NN control policy was trained to provide suggested machine settings to switch between desired electron beam energies while preserving the match into the undulator and a fast-executing surrogate model was also trained from PARMELA simulation results in order to facilitate the training of the control policy, as shown in Figure 4 [21].

CONCLUSIONS

One promising approach to accelerator tuning and optimization is a combination of ML and ES techniques, which is being explored in a collaboration between LCLS and LANL, as depicted in Figure 5. The goal is to initially use ML to get within a neighborhood of required machine settings for a given set of desired beam properties, after which an model-independent ES is activated to zoom in on and continuously track the actual, time-varying optimal settings.

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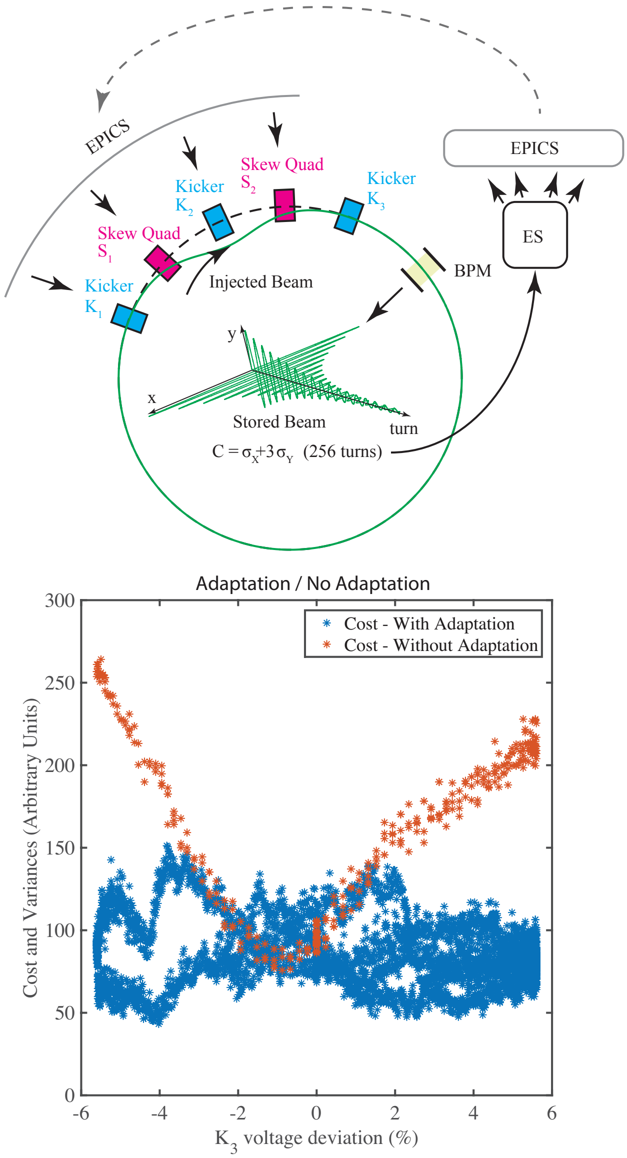

Figure 3: SPEAR3 adaptive feedback results.

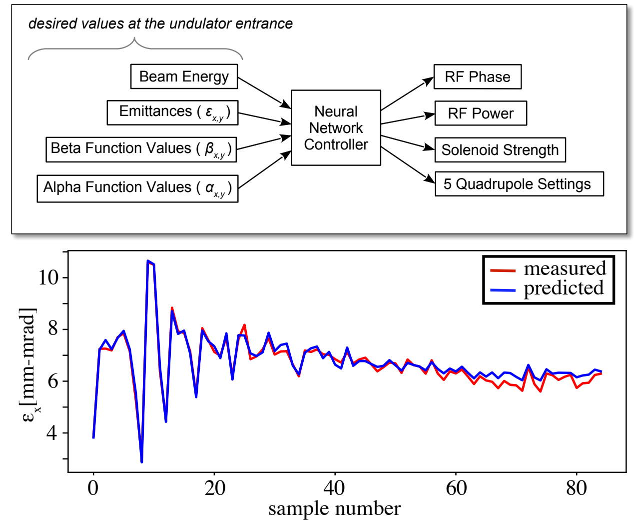

Figure 4: NN control policy for switching between operating conditions and predictions of surogate model.

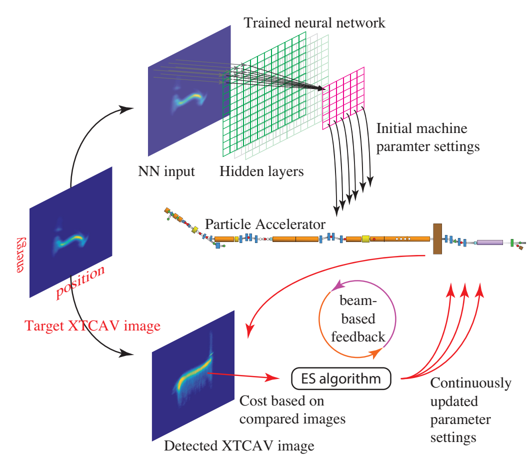

Figure 5: NN for fast tuning to a neighborhood of desired accelerator settings, followed by model-independent ES feedback to track time-varying unknown optimal parameters.

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