Adaptive Machine Learning for Time Varying Systems: Noninvasive Diagnostics and Automatic Control for Short Intense Bunches

Alexander Scheinker[1, a)] and Spencer Gessner[2, b)]
[1)]*Los Alamos National Laboratory, Los Alamos, NM 87544, USA*
[2)]*SLAC National Accelerator Laboratory, Menlo Park, CA 94025, USA*

(Dated: 18 August 2020)

Abstract: Particle accelerators are large complex systems composed of hundreds-thousands of interconnected electromagnetic components including radio frequency (RF) resonant accelerating structures for beam acceleration and longitudinal focusing and various magnets for beam steering and transverse focusing. Charged particle beams are themselves complex objects living in a six dimensional phase space. They undergo complex collective effects such as coherent synchrotron radiation and vary with time in unpredictable ways. Sources of variation include accelerator RF phase and amplitude jitter, and magnet current jitter, and time-varying laser intensities and photoemission at the beam source. As bunches become shorter and more intense, the effects of intra-bunch collective interactions such as space charge forces and bunch-to-bunch influences such as wakefields also increase. Short, intense bunches are extremely difficult to accurately image because their dimensions are beyond the resolution of existing diagnostics and they may be destructive to intercepting diagnostics. Adaptive machine learning methods designed for time-varying systems have the potential to aid in the diagnostics and control of high-intensity, ultrashort beams by interfacing online models with real time non-invasive beam data, providing a detailed virtual view of intense bunch dynamics.

Motivation

A major challenge faced by advanced accelerators and in particular by those important to high energy physics (HEP), such as wakefield acceleration (WFA) experiments, is the ability to precisely generate and control the acceleration of extremely compressed (few fs/μm), high charge (few nC), high peak current (>200 kA) electron bunches with low energy-spread and tailored current profiles. In order to control the position-energy (z,E) 2D longitudinal phase space (LPS) of intense ultra-short bunches at high energy (>10 GeV) requires the ability to non-invasively measure their 2D LPS distributions at high resolution (< fs/μm). Furthermore, once they are generated, in order to precisely accelerate trains of closely spaced (ns) intense bunches requires the development of novel algorithms for sub-ns control of the electromagnetic fields of radio frequency (RF) accelerating cavities. Intense closely spaced bunches create strong wakefields in RF accelerating structures spoiling the emittance and acceleration of trailing bunches. This issue is particularly challenging for high-Q cryogenically cooled copper (C^3) or superconducting accelerating structures, which are extremely efficient and narrow bandwidth. The precise control of ultra-short, intense, and closely spaced bunches in particle accelerators requires new adaptive machine learning (ML) algorithms for controls and non-invasive diagnostics.

The 2019-20 HEP general accelerator R&D accelerator and beam physics (ABP) workshops identified the following four grand challenges which we view as an interdependent system and are the motivation for this work:
1). Beam Intensity: *How do we increase beam intensities by orders of magnitude?* This requires the development of low emittance sources of high intensity particle bunches, whose development would be greatly aided by more accurate diagnostics.
2). Beam Prediction: *How do we develop predictive "virtual particle accelerators"?* As bunch intensity increases, we need a combination of adaptive model-based non-invasive diagnostics coupled to real-time data from existing diagnostics to provide a virtual view of the 6D (x,p_x,y,p_y,z,p_z) phase space of intense charged particle bunches. These diagnostics can then inform the design and development of higher intensity sources.
3). Beam Control: *How do we control the beam distribution down to the level of individual particles?* Utilizing a detailed virtual view of the beam, we can develop adaptive controls that automatically manipulate the 6D particle distribution. As beam control becomes more precise, it aids the development of new and more accurate virtual diagnostics by providing, for example, a very precise known distribution at a certain accelerator location that can be used as input to a high quality physics-based model for further predictions along the accelerator.
4). Beam Quality: *How do we increase beam phase-space density by orders of magnitude, towards quantum degeneracy limit?* Once we have diagnostics and controls we can work on improving the beam quality (preserving low emittance through higher levels of bunch compression) with active real-time adaptive feedback, and higher quality more predictable beams are in turn easier to control and to predict at higher energies downstream.

WFA techniques have the potential to accelerate beams within a few meters to the same energies that would require kilometers of traditional RF acceleration. WFAs can potentially serve as energy upgrades for an ILC, enable compact ILC designs, can be used to study extremely high-intensity and high-energy nonlinear beam dynamics, and have the potential to enable compact free

[a)]ascheink@lanl.gov
[b)]sgess@slac.stanford.edu

electron lasers (FEL). For example, the Facility for Advanced Accelerator Experimental Tests (FACET) at SLAC has demonstrated acceleration of electrons[1] as well as positrons[2] to high energies within one meter of plasma. The AWAKE experiment at CERN uses transversely-focused ($\sim 200\mu$m), high-intensity (3×10^{11}), high-energy (400 GeV) protons from CERN's Super Proton Synchrotron (SPS) accelerator to drive wakefields in a 10 meter-long plasma and accelerate electron bunches with MeV energy up to energies of 2 GeV[3]. FACET-II is currently being commissioned with the goal of providing custom tailored current profiles for various experiments with bunch lengths as low as (1 μm or $\sim$3 fs) and high peak currents (20 - 200 kA)[4].

The WFA process is extremely sensitive to the detailed longitudinal current profiles of these bunches and it would be of great benefit to have precise control over these profiles. However, the dynamics of extremely short and intense charged particle beams are difficult to control and quickly/accurately model due to collective effects such as space charge forces and wakefields. Furthermore, diagnostics are extremely limited for such high-current, high-energy, and short electron bunches. Even if lengthy, detailed measurements of beams are made and used as input into the models, due to uncertain and time-varying components and settings, the predictive power of the models drifts with time and quickly degrades. Therefore, currently WFA methods cannot produce beams that match the quality (such as emittance, energy spread, and reproducibility) of conventional accelerators.

Proposed Innovation: Adaptive Virtual Diagnostics (Virtual TCAV) and Adaptive Feedback Controls

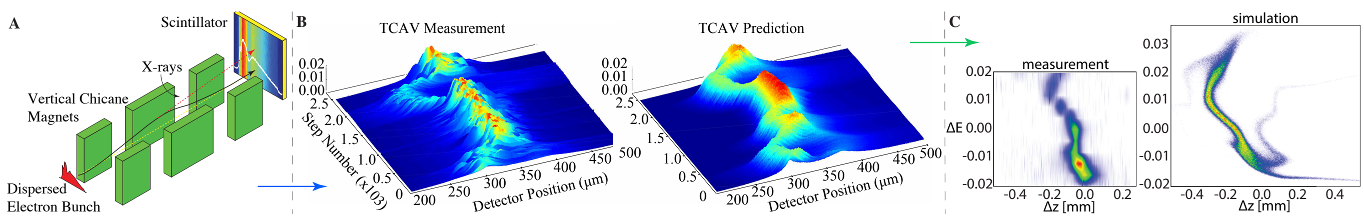

FIG. 1. Adaptive virtual diagnostic demonstrated at FACET. **A:** Online model adaptively tuned to match energy spread spectrum prediction to non-invasive measurement. **B:** TCAV measurements predicted as the beam changes with time. **C:** Virtual view of longitudinal phase space[5].

Machine learning (ML) methods can be used to learn complex relationships between coupled parameters and beam properties. Because both accelerator components and beams change with time, ML alone is not sufficient and requires the addition of adaptive feedback to automatically compensate for un-modeled disturbances and changes.

We propose that adaptive ML techniques can be extremely useful for developing adaptive virtual diagnostics and adaptive feedback controls for shorter, more intense charged particle beams that are of importance to HEP science. Our goal is to couple model-independent adaptive feedback techniques from nonlinear feedback control theory that are by design robust to changes, nonlinearities, and external disturbances that cannot be accurately modeled[6–8].

The development of virtual diagnostics for WFA were first demonstrated at FACET[5], as shown in Figure 1, where an online model was adaptively tuned based on non-invasive diagnostics to provide a virtual TCAV measurement of the beam's longitudinal phase space (LPS). The ability of the virtual non-invasive diagnostic to track the beam's LPS was confirmed by simultaneously running a destructive TCAV measurement. Preliminary results towards developing an adaptive ML approach were first demonstrated at the LCLS free electron laser where a neural network was trained to give instant estimates of parameter setting required for achieving a desired LPS distribution as measured by the TCAV following the undulator and then adaptive model-independent feedback was used to fine tune parameters and zoom in on and track the desired LPS distribution despite time-varying beam and accelerator parameters[9]. The use of adaptive model-independent feedback control for automatic multi-objective optimization of the AWAKE electron beam line for simultaneous orbit control and transverse emittance minimization was also recently demonstrated at CERN[10].

Various ML methods for particle accelerator applications are now being developed at facilities around the world. An ML method has been developed to directly map accelerator parameter settings to LPS predictions[11], ML techniques have been developed to optimize FEL performance[12], a novel ghost imaging approach has been developed to map the time-varying quantum efficiency of photocathodes[13], multi-objective Gaussian process optimization has been applied to the nonlinear storage ring dynamics of SPEAR3[14], and various ML algorithms for identifying faulty beam position monitors and for optics corrections have been tested at CERN[15–17].

A broad overview of recent developments and the state of the art in adaptive controls and machine learning for particle accelerators can be found in the proceedings of the 2019 Advanced Control Methods for Particle Accelerators (ACM4PA) workshop[18].

In future work, the goal is to develop coupled adaptive ML-based controls and ML-based online diagnostics[19] that can utilize recently developed model-independent methods for the optimal control of unknown systems, such as accelerators and their beams[20], based on virtual diagnostics. The use of virtual diagnostics to guide automatic LPS control was recently studied in simulation for FACET-II[21].

References

[1]M. Litos, E. Adli, W. An, C. Clarke, C. Clayton, S. Corde, J. Delahaye, R. England, A. Fisher, J. Frederico, *et al.*, “High-efficiency acceleration of an electron beam in a plasma wakefield accelerator,” Nature **515**, 92 (2014), https://www.nature.com/articles/nature13882.

[2]S. Corde, E. Adli, J. Allen, W. An, C. Clarke, C. Clayton, J. Delahaye, J. Frederico, S. Gessner, S. Green, *et al.*, “Multi-gigaelectronvolt acceleration of positrons in a self-loaded plasma wakefield,” Nature **524**, 442 (2015), https://www.nature.com/articles/nature14890.

[3]E. Adli, A. Ahuja, O. Apsimon, R. Apsimon, A.-M. Bachmann, D. Barrientos, F. Batsch, J. Bauche, V. B. Olsen, M. Bernardini, *et al.*, “Acceleration of electrons in the plasma wakefield of a proton bunch,” Nature **561**, 363–367 (2018), https://www.nature.com/articles/s41586-018-0485-4;.

[4]C. Joshi, E. Adli, W. An, C. E. Clayton, S. Corde, S. Gessner, M. J. Hogan, M. Litos, W. Lu, K. A. Marsh, *et al.*, “Plasma wakefield acceleration experiments at FACET II,” Plasma Physics and Controlled Fusion **60**, 034001 (2018), https://iopscience.iop.org/article/10.1088/1361-6587/aaa2e3/meta.

[5]A. Scheinker and S. Gessner, “Adaptive method for electron bunch profile prediction,” Physical Review Special Topics-Accelerators and Beams **18**, 102801 (2015), https://doi.org/10.1103/PhysRevSTAB.18.102801.

[6]A. Scheinker, “Model independent beam tuning,” in *Int. Partile Accelerator Conf.(IPAC’13), Shanghai, China, 19-24 May 2013* (JACOW Publishing, Geneva, Switzerland, 2013) pp. 1862–1864, http://accelconf.web.cern.ch/AccelConf/IPAC2013/papers/tupwa068.pdf?n=IPAC2013/papers/tupwa068.pdf.

[7]A. Scheinker and D. Scheinker, “Bounded extremum seeking with discontinuous dithers,” Automatica **69**, 250–257 (2016), https://doi.org/10.1016/j.automatica.2016.02.023.

[8]A. Scheinker and D. Scheinker, “Constrained extremum seeking stabilization of systems not affine in control,” International Journal of Robust and Nonlinear Control **28**, 568–581 (2018), https://doi.org/10.1002/rnc.3886.

[9]A. Scheinker, A. Edelen, D. Bohler, C. Emma, and A. Lutman, “Demonstration of model-independent control of the longitudinal phase space of electron beams in the linac-coherent light source with femtosecond resolution,” Physical review letters **121**, 044801 (2018), https://doi.org/10.1103/PhysRevLett.121.044801.

[10]A. Scheinker, S. Hirlaender, F. M. Velotti, S. Gessner, G. Z. Della Porta, V. Kain, B. Goddard, and R. Ramjiawan, “Online multi-objective particle accelerator optimization of the awake electron beam line for simultaneous emittance and orbit control,” AIP Advances **10**, 055320 (2020), https://doi.org/10.1063/5.0003423.

[11]C. Emma, A. Edelen, M. Hogan, B. O’Shea, G. White, and V. Yakimenko, “Machine learning-based longitudinal phase space prediction of particle accelerators,” Physical Review Accelerators and Beams **21**, 112802 (2018), https://doi.org/10.1103/PhysRevAccelBeams.21.112802.

[12]J. Duris, D. Kennedy, A. Hanuka, J. Shtalenkova, A. Edelen, P. Baxevanis, A. Egger, T. Cope, M. McIntire, S. Ermon, *et al.*, “Bayesian optimization of a free-electron laser,” Physical Review Letters **124**, 124801 (2020), https://doi.org/10.1103/PhysRevLett.124.124801.

[13]K. Kabra, S. Li, F. Cropp, T. J. Lane, P. Musumeci, and D. Ratner, “Mapping photocathode quantum efficiency with ghost imaging,” Physical Review Accelerators and Beams **23**, 022803 (2020), https://doi.org/10.1103/PhysRevAccelBeams.23.022803.

[14]M. Song, X. Huang, L. Spentzouris, and Z. Zhang, “Storage ring nonlinear dynamics optimization with multi-objective multi-generation gaussian process optimizer,” Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment , 164273 (2020), https://doi.org/10.1016/j.nima.2020.164273.

[15]E. Fol, *Evaluation of machine learning methods for LHC optics measurements and corrections software*, Ph.D. thesis, Hochschule, Eng. Econ., Karlsruhe (2017), http://cds.cern.ch/record/2309558/files/CERN-THESIS-2017-336.pdf?version=1.

[16]E. Fol, J. M. Coello de Portugal, and R. Tomás, “Jacow: Application of machine learning to beam diagnostics,” (2019), http://cds.cern.ch/record/2716703/files/tuoa02.pdf?version=1.

[17]E. Fol, J. C. de Portugal, G. Franchetti, and R. Tomás, “Optics corrections using machine learning in the lhc,” in *Proceedings of the 2019 International Particle Accelerator Conference, Melbourne, Australia* (2019) https://accelconf.web.cern.ch/ipac2019/papers/thprb077.pdf.

[18]A. Scheinker, C. Emma, A. Edelen, and S. Gessner, “Advanced control methods for particle accelerators (acm4pa) 2019,” Tech. Rep. (Los Alamos National Lab.(LANL), Los Alamos, NM (United States), 2019) https://permalink.lanl.gov/object/tr?what=info:lanl-repo/lareport/LA-UR-19-32526.

[19]A. Edelen, N. Neveu, M. Frey, Y. Huber, C. Mayes, and A. Adelmann, “Machine learning for orders of magnitude speedup in multiobjective optimization of particle accelerator systems,” Physical Review Accelerators and Beams **23**, 044601 (2020).

[20]A. Scheinker and D. Scheinker, “Extremum seeking for optimal control problems with unknown time-varying systems and unknown objective functions,” International Journal of Adaptive Control and Signal Processing (2020), https://doi.org/10.1002/acs.3097.

[21]A. Scheinker, S. Gessner, C. Emma, and A. L. Edelen, “Adaptive model tuning studies for non-invasive diagnostics and feedback control of plasma wakefield acceleration at FACET-II,” Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment , 163902 (2020), https://doi.org/10.1016/j.nima.2020.163902.

[22]S. Gessner, E. Adli, J. M. Allen, W. An, C. I. Clarke, C. E. Clayton, S. Corde, J. Delahaye, J. Frederico, S. Z. Green, *et al.*, “Demonstration of a positron beam-driven hollow channel plasma wakefield accelerator,” Nature communications **7**, 1–6 (2016), https://www.nature.com/articles/ncomms11785?origin=ppub.

[23]S. J. Gessner, “Demonstration of the hollow channel plasma wakefield accelerator No. SLAC-R-1073,” Tech. Rep. (2016) https://www.slac.stanford.edu/cgi-bin/getdoc/slac-r-1073.pdf.