August 31th 2020

2021 Snowmass Letter of Interest: High bandwidth adaptive control systems for particle accelerators

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High-precision science requires high precision controls. The next generation of particle accelerators for high energy physics and beyond will generate TeV-scale particle beams in large, multi-Km size machines which would collide high brightness beams with nanometer scale spot sizes at the interaction point. Tuning energy, timing and position of the beam will require controls at the limit of today's technology performance, see [1] for an overview of future requirements and recent developments in advanced controls and ML for accelerators.

The extended size of future machines demands at the same time a centralized, global optimization procedure, which could analyze and control the system behavior with a holistic view, and local nodes acting directly on the specific subsystem. For global optimization, new methods can learn optimal feedback control laws for time-varying systems directly from data [2]. Local feedbacks, such as FPGA-based RF field controllers must be placed as close to the controlled components as possible to minimize signal delay because the feedback gain K of a simple proportional feedback is (to 1st order) limited to ~1/D, where D is the signal delay.

Depending on machine type, superconducting radio frequency (SRF)-based accelerating cavities or high-peak power/high frequency warm cavities will form the backbone of the particle accelerators, posing challenges in the control of amplitude and phase (very narrowband resonant structures the first, high frequency electronics, short RF pulses in the second case). SRF based controls are especially challenging for closely spaced and extremely intense bunches whose transient fields excite higher order modes that will have a deleterious effect on trailing bunch quality as they are spaced closer and closer together. Furthermore, the extremely narrow bandwidth of SRF cavities limits the speed of amplitude and phase adjustment relative to a fixed RF power source and their control could greatly benefit from predictive controls [3,4]. Lower Q, faster cavities will be required for precise controls of beams close to the interaction point, which include measurement and stabilization requirements of beam position with «100 nm resolution and must have minimal signal delay to enable the use of as high feedback gain as possible [5].

As machines grow in size and complexity, automated failure detection is also important for a centralized global control system communicating with multiple individual feedback nodes. As the number of high impact individual components grows, ML-based methods will become more important to predict or identify failures almost instantly and respond by shutting off devices to prevent damage or by adjusting nearby functioning devices to make up for the loss of a few individuals, which requires a global coordination between all of the components. Preliminary work towards ML-based automated fault detection includes SRF cavity fault classification at Jefferson Laboratory [6] and for BPM fault detection at CERN [7].

For Laser-Plasma Accelerators (LPAs), advanced controls and feedback systems will be part of the solution towards achieving higher beam quality. One promising path is to coherently combine hundreds of parallelly amplified ultrafast fiber laser pulses temporally, spatially and spectrally, in order to meet the requirement of multi-kHz, high efficiency, Joules of pulse energy and femtosecond pulse-width driving laser for each of ~100 LPA stages of a future collider [11] that is in US DOE's long term strategy. Preliminary results show the potential of deep learning models in helping to process the large amount of information for real time active coherence stabilization. Spatial combination of 81 channels as been achieved at LBNL using pre-trained deep learning models and model-free deep reinforcement online-learning.

The next generation of accelerators, including compact high repetition rate Ultrafast Electron diffraction (UED) setups [8][9] and Free Electron Lasers, require improvements in the precision of controls and require adaptive controls that compensate for un-modeled time variation and disturbances. The need to handle time variation requires the combination of model-independent adaptive feedback, AI, and physics-informed models. A first of its kind adaptive ML-based fs-resolution longitudinal phase space control of the LCLS electron beam was recently demonstrated [10]. Such work needs to be extended to larger parameter range values and larger sets of coupled parameters for existing and future machines. Figure 1 shows a schematic of a possible adaptive ML-based control system.

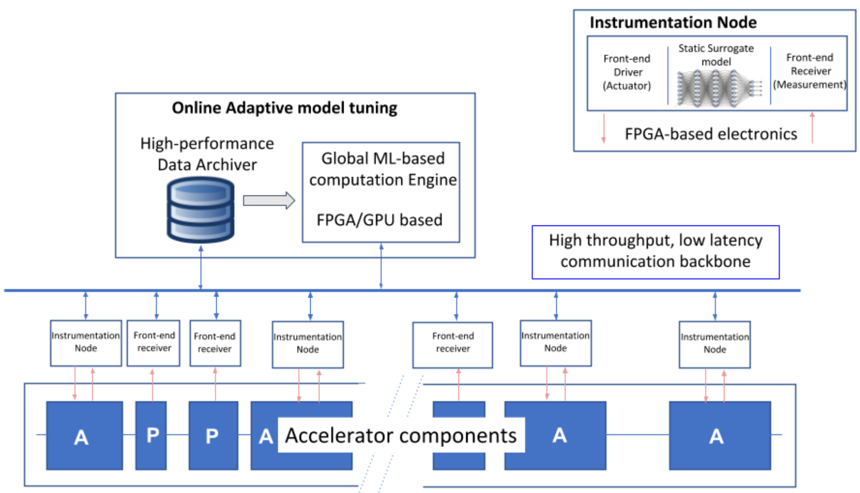

Figure 1: Possible scheme of a real-time control network for a particle accelerator.

High-bandwidth and global-scale control requirements are driving the design approach above:

- Signals are digitized either by direct sampling or after down-conversion depending on the bandwidth and the noise figure required.
- The signal is used on a local feedback to keep the system locked to a setpoint
- Data is time-stamped and sent to the individual nodes to generate the new setpoints via a Neural Network-based surrogate model of the machine, and to the archiver.
- A global Machine-Learning-based engine uses the archived data to test, train and refine the surrogate model. New models are constantly pushed to the instrumentation nodes, catching time-dependent beamline behaviors.

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