Coupling Experiment to Accelerator Control

November 13, 2024

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Abstract: A long term goal of accelerator-based experimental physics is to integrate the goals of the experiment with the detector response and, ultimately, control of the accelerator itself to achieve optimal measurements. This project aims to couple real-time calibration+reconstruction with fast analysis as feedback to beam controls in order to minimize measurement uncertainties. Uncertainty estimates based on real-time analysis of the data will be used as input to an AI/ML system that adjusts beam parameters in order to optimize the experiment for a given run time. The project will target two complementary experiments that will provide a cross-validation of the system. One will be a set of cross-section measurements made by large complex detectors (CLAS12 and GlueX) with a modest number of beam parameters. The other will be an asymmetry measurement with simpler detector systems (MOLLER) and a larger number of beam parameters. Each will provide actionable statistics on a short time scale ($\leq$ 1 hour for cross-sections or few minutes for asymmetry). Each will ensure an end-to-end closure test of the AI/ML control system.

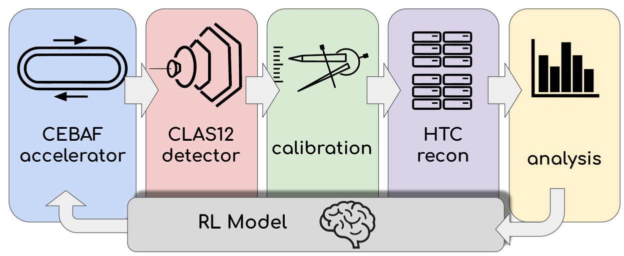

Figure 1: Real-time accelerator control based on experimental physics goals with CLAS12.

Fully self-driving NP experiments will require tight coupling between the physics goals of the experiment, the detector performance, and the accelerator beam conditions. Historically, the best approach to coupling such complex systems is to break them into independently manageable parts. The interface between the systems then becomes rigid and the systems are designed to work with the interface. This has been a very successful strategy and has largely been limited only by the experience and knowledge of the experimenters on how to adjust the system on one side of the interface in order to optimize the system on the other side. A primary example of this is the beam intensity in the *accelerator* system being adjusted to maximize the rate of the *detector* system, but only to the point that it operates well for achieving the *physics goals* (accelerator/detector/physics).

Typically, the physics goals of an experiment reduce to measuring a set of observables with the smallest achievable uncertainties. These uncertainties come in the form of statistical and systematic errors. The ideal self-driving experiment would make real-time estimates of these errors and feed this back to the detector and accelerator systems so they could be adjusted to minimize them. For example, in event-based measurements the reconstruction efficiency (ϵ_{ff}) is a function of the detector occupancy which itself depends on beam intensity. Therefore, the statistical uncertainty on the physics observable has positive and negative contributions from event rate and ϵ_{ff} leading to a minimum. Systematic uncertainties also depend on ϵ_{ff} of the channel of interest. The minimum of the total uncertainty curve will shift as the experiment objectives, detector response, or beam conditions change.

Objectives: Implement real-time calibration, reconstruction, and analysis of a continuous detector data stream with a quality sufficient to accurately estimate statistical and systematic errors within a limited time period (e.g. <1 hour). Use estimated uncertainties as part of the observation space for an AI-based control system (e.g. Deep Reinforcement Learning) whose action adjusts one or more accelerator parameters to minimize errors on the physics measurement. Target both a **cross-section** measurement using a high channel count detector such as CLAS12 or GlueX, and an **asymmetry** measurement using a low channel count detector (MOLLER). The number of beam parameters controlled will be more (less) for when the detector channel count is less (more).

Technical Approaches: CLAS12 and GlueX

Considerable work has been done in the past to apply AI/ML to specific areas in the execution and analysis of experiments for both CLAS12 and GlueX. The current project will include processing of the full data stream in real-time. This will require combining existing AI/ML solutions and developing new ones in appropriate, critical areas. Four stages of data processing are needed to estimate the uncertainty of an observable. These are:

1. Event Stream Filtering: Early studies of such a system with GlueX using **Boosted Decision Trees** were promising. Level-3 triggering will be used here, with AI/ML inference on hardware accelerators expected to play a role (e.g. ML-on-FPGAs).

2. Calibration: The AIEC project has successfully developed a combination of **AI-based** and **algorithmic techniques** to determine calibrations for the GlueX drift chamber detectors using environmental conditions.

3. Fast Reconstruction: NP experiments such as CLAS12/GlueX have reconstruction time dominated by charged particle tracking. CLAS12 has successfully applied **AI/ML noise hit filtering** in production. Work has been done to implement AI/ML methods to track fitting in both CLAS12 and GlueX systems.

4. Uncertainty Estimation: Systematic uncertainties will depend on track and calorimeter reconstruction efficiencies which, in turn, will depend on the kinematics and multiplicities of the reaction channel(s) of interest. Well-known reaction channels will be used to determine this via missing momentum/missing mass (e.g. single π^0 production for the calorimeters and $ep \to e'p\pi(\pi)$ for tracking). Mapping this to continuous accelerator operation will be done using **Deep Reinforcement Learning**.

Technical Approaches: MOLLER

Asymmetry measurements that use integration detectors such as MOLLER are very sensitive to multiple beam conditions. The beam parameters have inter-dependencies that affect the uncertainty in the asymmetry measurement in non-trivial ways making AI/ML a suitable tool for dynamic adjustments. Beam conditions that will affect the measurement include the following:

1. Background in Compton Polarimeter: Narrow apertures in the laser cavity or upstream beamline introduce backgrounds influenced by beam position in the Compton chicane, beam optics tuning, laser pulse phase relative to the accelerating RF, and injector parameters.

2. Beam Size: To prevent damage to target windows or density fluctuations (target boiling), the intrinsic (unrastered) beam size must remain within the specified limit of $\sigma \approx 200\,\mu m$.

3. Orthogonality of the Beam Modulation Calibration System: Calibration relies on beam modulation via air-core corrector magnets to span the beam phase space. This is highly sensitive to the beamline optics configuration.

4. Position Feedback Correction Slopes: Precise control of beam position differences involves feedback on small average helicity-correlated position differences using Pockels cell gradient-steering voltages or helicity-correlated corrector magnets in the injector. Changes in beam optics may alter the transfer function between the low-energy injector and the high-energy hall.

5. Halo: Halo is sensitive to factors like the transfer function from the electron source to the hall, laser pulse phase, and bunching.

6. Beam Energy: Accelerator adjustments may not alter the net beam energy beyond 5×10^{-5}.

Required Resources: In addition to labor, existing High Throughput Computing (HTC) and network resources will be needed for brief periods. Two hour reservations of up to 5k cores of the JLab SciComp farm will be needed bi-weekly for the second year of the project. A dedicated 2 days of beam time in the experimental halls will be needed for the final exercise.

	Name	Institution	Year 1	Year 2	Total
Lead PI	David Lawrence	Jefferson Lab	$1,214k	$1,205k	$2,419k
Co-PI	Kent Paschke	University of Virginia	$203k	$212k	$415k
Co-PI	Justin Stevens	William & Mary	$153k	$161k	$313k
Co-PI	Sean Dobbs	Florida State University	$75k	$77k	$152k
Grad Student	TBD	TBD	$87k	$91k	$177k
		TOTAL	**$1,731k**	**$1,745k**	**$3,476k**

Table 1: Summary budget by institution