ISBN: 978-3-95450-232-5 ISSN: 2673-7000 doi:10.18429/JACoW-NAPAC2022-TUPA55

PROGRESS TOWARD IMPROVING ACCELERATOR PERFORMANCE AND AUTOMATING OPERATIONS WITH ADVANCED ANALYSIS SOFTWARE*

J. E. Koglin†, J. E. Coleman, M. McKerns, D. Ronquillo, A. Scheinker
Los Alamos National Laboratory, Los Alamos, NM, USA

Abstract

The penetrating radiography provided by the Dual Axis Radiographic Hydrodynamic Test (DARHT) facility is a key capability in executing a core mission of the Los Alamos National Laboratory (LANL). A new suite of software is being developed in the Python programming language to support operations of the of two DARHT linear induction accelerators (LIAs). Historical data, built as hdf5 data structures for over a decade of operations, are being used to develop automated failure and anomaly detection software and train machine learning models to assist in beam tuning. Adaptive machine learning (AML) techniques that incorporate physics-based models are being designed to use non-invasive diagnostic measurements to address the challenge of time variation in accelerator performance and target density evolution. AML methods are also being developed for experiments that use invasive diagnostics to understand the accelerator behavior at key locations, the results of which will be fed back into the accelerator models. The status and future outlook for these developments will be reported, including how Jupyter notebooks are being used to rapidly deploy these advances as highly-interactive web applications.

DATA STRUCTURES AND ANALYSIS TOOLS

A new systematic data representation of calibrated DARHT accelerator diagnostics data has been developed that includes relevant information needed to describe the data as well as model the beam tune (i.e., metadata). Open-source Python libraries are used to load and calibrate DARHT data which include:

- Shot Based Data:
    - Scalar Data
    - Vector Data (e.g., waveforms and spectra)
    - 2D Arrays (e.g., camera images)
- Calibration Data:
    - Waveform attenuation
    - Integrator time constants
    - Time offsets
    - Scale factors
- Processing Information:
    - Waveform filter time scale
    - Waveform processing time windows
    - Configuration information for automated warnings and alerts

* Research presented in this conference paper was supported by the Laboratory Directed Research and Development program of Los Alamos National Laboratory under project numbers XXG2, XX8R and XXB6.
† koglin@lanl.gov

The DARHT data are structured as xarray Dataset objects [1], which map directly onto the HDF5 file format [2].

Highly-interactive applications for DARHT data analysis can be launched locally or hosted on a server and used by multiple users through web browsers. These applications are built using HoloViz [3], a set of high-level Python packages, in a way that allows for rapid deployment of new analysis tools. Figure 1 illustrates how increasingly higher-level packages are used to build interactive plots from named data arrays and high-level parameter objects. The apps are served directly from Jupyter notebooks either locally or from a serve, providing a convenient programming platform for rapid development.

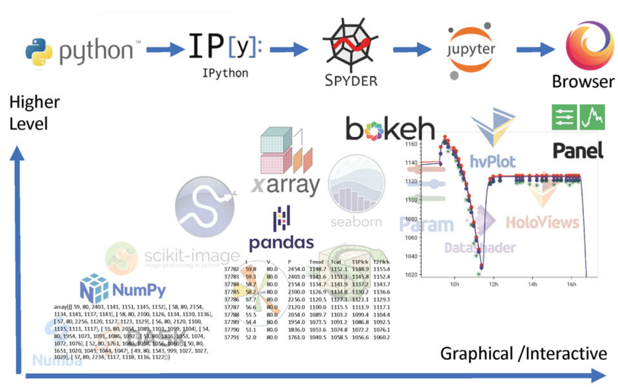

Figure 1: The graphic illustrates how increasingly higher-level packages are used to build interactive plots from named data arrays and high-level parameter objects. The apps are served directly from Jupyter notebooks either locally or from a server, providing a convenient programming platform for rapid development.

In order to promote code robustness and provide reusability, the data input/output and calibration/reduction modules are managed separately from interactive analysis and visualization tools. New analysis methods and data processing pipelines are typically developed using the IPython interactive interpreter [4] or a development environment like Spyder [5]. It is often more convenient to use Jupyter Notebook [6], a web-based application, for visualizing data and developing higher level analysis processes.

Juptyer Notebooks can also be used to create highly interactive analysis tools and dashboards from xarray Dataset objects and HoloViz libraries:

- hvplot [7]: provides high-level plotting directly from xarray data objects using Bokeh and HoloViews.

5th North American Particle Accel. Conf. NAPAC2022, Albuquerque, NM, USA JACoW Publishing
ISBN: 978-3-95450-232-5 ISSN: 2673-7000 doi:10.18429/JACoW-NAPAC2022-TUPA55

- param [8]: turns parameters with defined data types into interactive widgets that can be used to set analysis and visualization parameters.
- panel [9]: used to organize interactive plots, parameters and tables; manage reactive functions and callback methods; and deploy as web-server application.

This framework has enabled the rapid development of DARHT analysis tools, including a general waveform calibration tool show in Figure 2. Other examples of this type of interactive tool are available in the catemis python package [10], which is used to evaluate the operating temperature of the dispenser cathode that supplies electrons for the DARHT Axis-II accelerator. As described in [11], three spot pyrometers are used to measure the temperature of the cathode and a camera is used to spatially monitor the temperature uniformity. In the example shown in Figure 3, dozens of 'param' objects were used to allow the user to set a date and shot number that the analysis tool uses to locate and load a cathode camera image. The spatial temperature distribution is then calculated based on parameters that define the camera alignment and calibration parameters used to convert the image intensity to temperature.

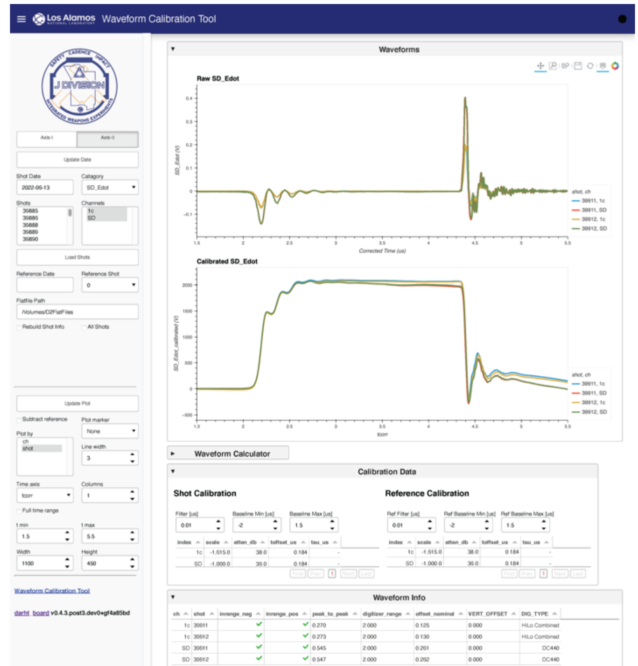

Figure 2: Example of an interactive waveform calibration application showing the raw differential waveforms (top) and numerically integrated waveforms (middle) for two diagnostics in the Axis-II injector region.

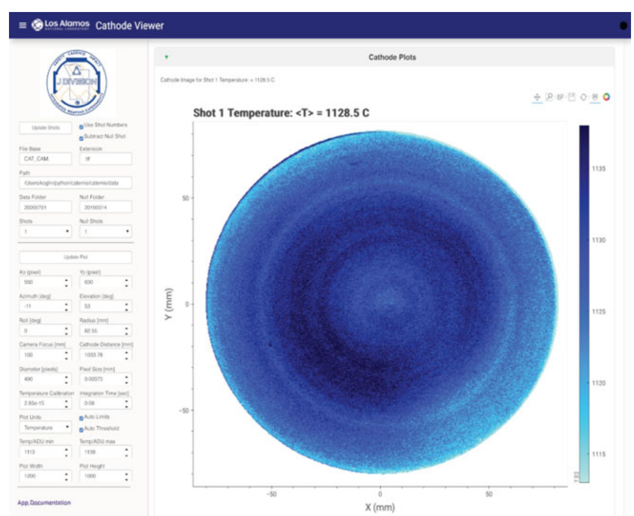

Figure 3: Example of DARHT Axis-II Cathode temperature interactive analysis application from the catemis python package.

MACHINE LEARNING

Machine learning (ML) methods are beginning to be applied to DARHT data analysis. A particularly interesting application is in predicting the radiograph spot size, which must be measured with an invasive diagnostic setup and is thus not always available. Preliminary work has begun utilizing neural networks to predict image spot sizes based on accelerator settings and non-invasive beam diagnostics. The spot size of each of the four DARHT Axis-II pulses are characterized by a scalar metric denoted MTF. The neural network model allows for information from previous pulses to contribute to subsequent pulses as illustrated in Figure 4a). Starting with a relatively limited set of data, the MTF values of the four pulses for three measurements were kept separate for use in model validation and all other data were used as training data for the ML model. The ML model was then applied to the three sets of validation data to predict the spot size metric. The ML model used contains no actual physical model of the accelerator system and allows only enough freedom to provide a good, but not perfect, prediction of the true MTF metric for the training data set as show in Figure 4b). The ML model performs nearly as well on the unseen validation data set. While this initial sample size is relatively limited, the results are promising and we are actively building up larger datasets to further develop this predictive capability for both Axis-I and Axis-II.

We anticipate that noise in accelerator diagnostic measurements and changes over time in how accelerator components respond to configuration settings will contribute to time-variation in the accelerator spot size. To overcome these challenges, we have been developing adaptive machine learning (AML)-based tools by combining ML tools such as convolution neural network (CNN)-based encoder-decoder architectures with model-independent adaptive feedback control algorithms [12, 13]. We also plan to include physics-informed learning using the mystic framework [14–16].

ADAPTIVE ANALYSIS TOOLS

We have also begun developing new techniques for waveform calibration to provide advanced baseline subtraction and numerical integration of differential signal measurements that are directly recorded with high-speed

ISBN: 978-3-95450-232-5 ISSN: 2673-7000 doi:10.18429/JACoW-NAPAC2022-TUPA55

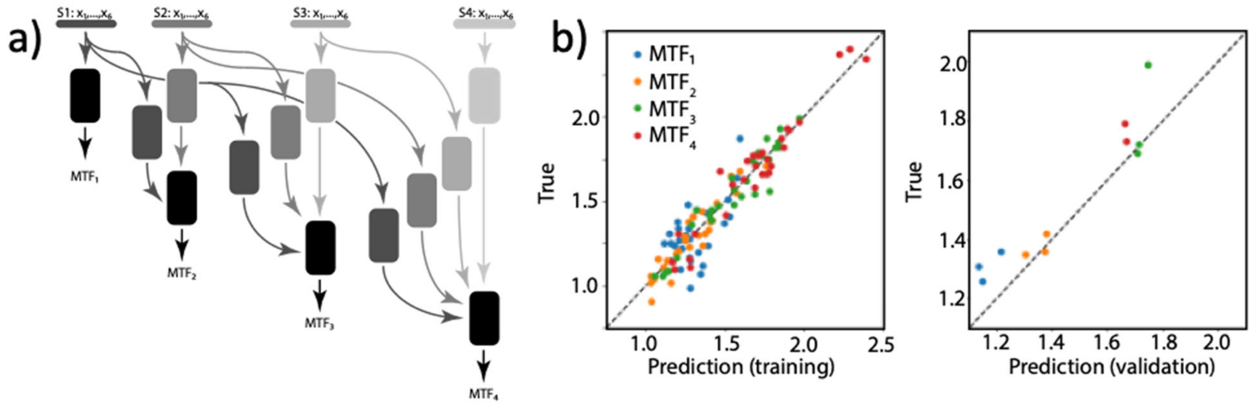

Figure 4: Spot size predictions for training and validation data for four pulses at DARHT based on magnet settings.

digitizers. The challenge in numerical integration is illustrated in Figure 2, where waveforms for two diagnostics in the Axis-II injector region that provide the same basic measurement, but use different digitizers, are shown for two sequential shots. The repeatability for each is relatively good, but the integrated signals for one diagnostic shows noticeable droop. While this channel with the droop is not needed for accelerator operations, it illustrates the type of correction that might be needed as the response of a diagnostic system (including cables, digitizers, etc.) changes with time. A general description of waveform processing methods can be found in the Voss Scientific DAAAC software user's manual [17].

Some of the challenges in processing the accelerator Beam Position Monitor (BPM) data that have been previously described [18, 19] include variability due to noise from pulse power systems and environmental factors as well as systematic affects like aliasing due to the discrete number of B-dot loops in the BPM [20]. The impact of such issues in some cases is mitigated by the diagnostic design. For example, the Axis-II B-dot loops are designed to have two output signals, which are proportional to the positive and negative rate of change of flux through the b-dot loop plus any common signal in the loop. Subtracting the signals provides twice the rate of change of flux with any common mode being subtracted out. In the conventional BPM analysis, other potential background from the pulse power is removed by subtracting the signal from a reference shot where the pulsed power was present but with no electron beam.

The differential signals are too large to be directly input into digitizers, so inline attenuators are used to reduce the signal to between 200 mV to 5 V depending on the signal and digitizer type. At some locations along the beamline, passive integrators are used to avoid some of the issues introduced in numerical integration, particularly in the downstream transport after a kicker has been used to produce four short pulses from the long electron beam pulse. To correct for the effective time constant of the passive integrator signals, a droop correction must be applied that involves numerical integration and scaling by a factor that has been experimentally determined. Because this scale factor, or more generally the underlying frequency response of the system, may change with time in a way that is similar to what was illustrated in Figure 2, we are building adaptive techniques for waveform processing.

Past reports have demonstrated that it is possible to achieve accurate and reliable enough beam position measurements for accelerator operations [18]. This capability has been successfully maintained for more than a decade of continuous operations, over which time numerous repairs and upgrades to accelerator and diagnostic components have been made. Noninvasive beam diagnostics, together with beam simulations, have for example been successfully used to suppress beam-centroid motion [21]. However, the beam tuning process is time consuming and it is challenging to adjust for example for the failure or change in response of an accelerator component. Our diagnostics systems also show signs of aging that are time consuming and often difficult to account for through component repair and/or recalibration.

FUTURE DEVELOPMENT

We are developing advanced techniques that look to capture more complex signal propagation and background contributions by applying AML techniques to entire systems of diagnostic data and training surrogate models using large historical datasets in addition to accelerator simulations. We are also beginning to applying uncertainty quantification (UQ) techniques in order to more robustly assign uncertainties to accelerator measurements including beam position, current and energy. In order to improve operations, we are also building tools to automatically detect anomalies and highlight potential issues to guide troubleshooting. Through these efforts we expect to provide continued improvement to the accelerator performance and operational efficiency.

REFERENCES

[1] https://xarray.pydata.org
[2] http://www.hdfgroup.org
[3] https://holoviz.org
[4] https://ipython.readthedocs.io

ISBN: 978-3-95450-232-5 ISSN: 2673-7000 doi:10.18429/JACoW-NAPAC2022-TUPA55

[5] https://www.spyder-ide.org

[6] https://jupyter.org

[7] https://hvplot.holoviz.org

[8] https://param.holoviz.org

[9] https://panel.holoviz.org

[10] https://github.com/lanl/catemis

[11] J. E. Koglin, "DARHT Axis-II Dispenser-Cathode Emissivity and Temperature", presented at *Weapons Engineering Symposium and Journal*, Los Alamos, NM, USA, Aug. 2021. Rep. LA-UR-21-25647

[12] A. Scheinker, "Adaptive machine learning for time-varying systems: low dimensional latent space tuning", *J. of Instrum*, vol. 16, no. 10, p. P10008, 2021. doi:10.1088/1748-0221/16/10/P10008

[13] A. Scheinker, "Adaptive Machine Learning for Robust Diagnostics and Control of Time-Varying Particle Accelerator Components and Beams", *Information*, vol. 12, no. 4, p. 161, 2021. doi:10.3390/info12040161

[14] M. M. McKerns *et al.,* "Building a framework for predictive science", in *Proc. of the 10th Python in Science Conf.*, Austin, TX, USA, 2011. http://arxiv.org/pdf/1202.1056

[15] M. M. McKerns, P. Hung, and M. Aivazis, "Mystic: highly-constrained non-convex optimization and UQ", Github 2009. https://uqfoundation.github.io/project/mystic

[16] M. M. McKerns, "Mystic: physics-informed learning and automated design/control under uncertainty", presented at Applied Machine Learning Symposium, Los Alamos, NM, United States, July 2021. Rep. LA-UR-21-27369.

[17] https://www.vosssci.com/products/daaac/daaac.html

[18] J. B. Johnson, W. Broste, and C. Ekdahl, "DARHT II Accelerator Beam Position Monitor Performance Analysis", in Proc. PAC'09, Vancouver, Canada, May 2009, paper TH5RFP074, pp. 3615-3617.

[19] J. B. Johnson, C. A. Ekdahl, W. Broste and C. Y. Tom, "B-dot detector signal recording at the DARHT II accelerator", in Proc. 2007 *16th IEEE Intl Pulsed Power Conf.*, 2007, pp. 490-492. doi: 10.1109/PPPS.2007.4651888

[20] C. Ekdahl, "Aliasing errors in measurements of beam position and ellipticity", *Review of Scientific Instruments* vol. 76, p. 095108, 2005. doi:10.1063/1.2038304

[21] C. Ekdahl *et al.*, "Suppressing beam-centroid motion in a long-pulse linear induction accelerator", *Physical Review Special Topics - Accelerators and Beams*, vol. 14, p. 120401, 2011. doi:10.1103/PhysRevSTAB.14.120401