Machine Learning for Detection of Low-Energy Photons in the EIC ZDC

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Abstract

The baseline Zero Degree Calorimeter (ZDC) for the EIC Detector-1 is a highly segmented calorimeter that will measure both energy and position for both neutrons and photons. The ZDC is critical for distinguishing between coherent diffractive scattering in which the nucleus remains intact, incoherent scattering in which the nucleus breaks apart, and incoherent excitations of the nucleus. While spectator high-energy photons and neutrons can help identify incoherent breakup of the nucleus, the ZDC needs to have high efficiency for detecting lower-energy photons emitted from excited nuclei and Lorentz-boosted up to a few hundred MeV.

The performance requirements for the ZDC require detection efficiency > 90% for soft photons with energies O(100) MeV. Neutrons from beam background and detector noise are expected to confuse the soft photon energy signal in the calorimeter when traditional layer weighting methods are used. However, the surplus of information in the segmented, multi-layer calorimeter design should provide machine learning (ML) algorithms with potentially significant capability to identify patterns even in the presence of noise. PNNL proposes to build upon machine learning techniques developed previously for the Belle II experiment and the ILC to improve soft photon ID in the ZDC. Once proven, this capability may also enable on-detector real-time particle identification, which would significantly reduce the amount of data received by the global streaming-readout DAQ system.

Motivation

The EIC Detector-1 Zero Degree Calorimeter (ZDC) [1] is designed to detect photons and neutrons and is located 38m from the interaction point (see Figure 1). It will be critical for EIC physics needs such as vetoing incoherent events by tagging photons and/or neutrons from nucleus breakup, reducing uncertainties in e+d data for proton PDF determination by tagging neutrons, and contributing to direct measurements of meson structure via identification of neutrons and lambdas in far-forward regions.

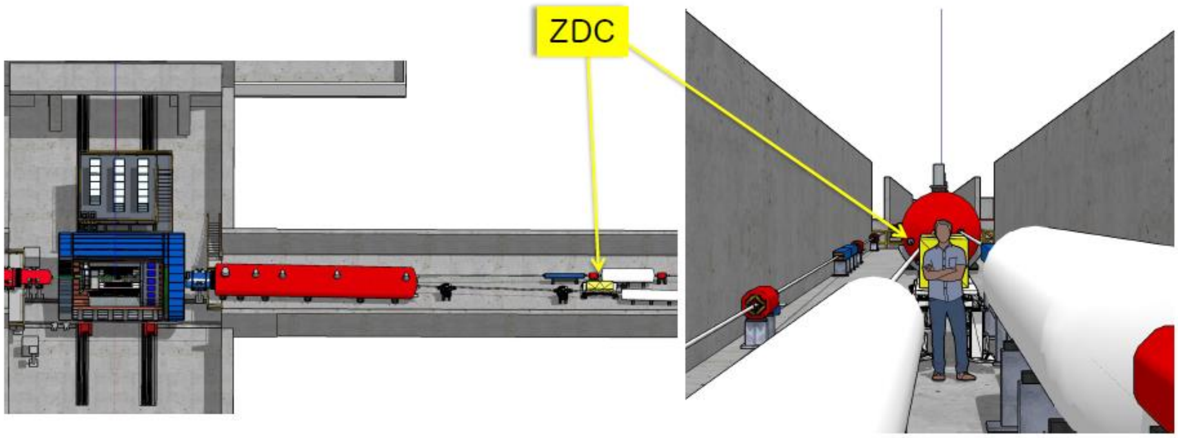

Figure 1. ZDC location and size for scale.

The current ZDC design consists of 64 layers of calorimeter materials optimized for both EM and hadron interactions (see Figure 2). The pixelated crystal calorimeter and first W/Si layers of silicon calorimeter will be used to measure lower-energy photons, while the deeper W/Si, Pb/Si, and Pb/scint layers will measure GeV photons and hadrons, providing both energy and position information with varying granularity on different layers. The resulting amount of information available for analysis in this calorimeter design is significant, but not currently being used by the standard analysis methods.

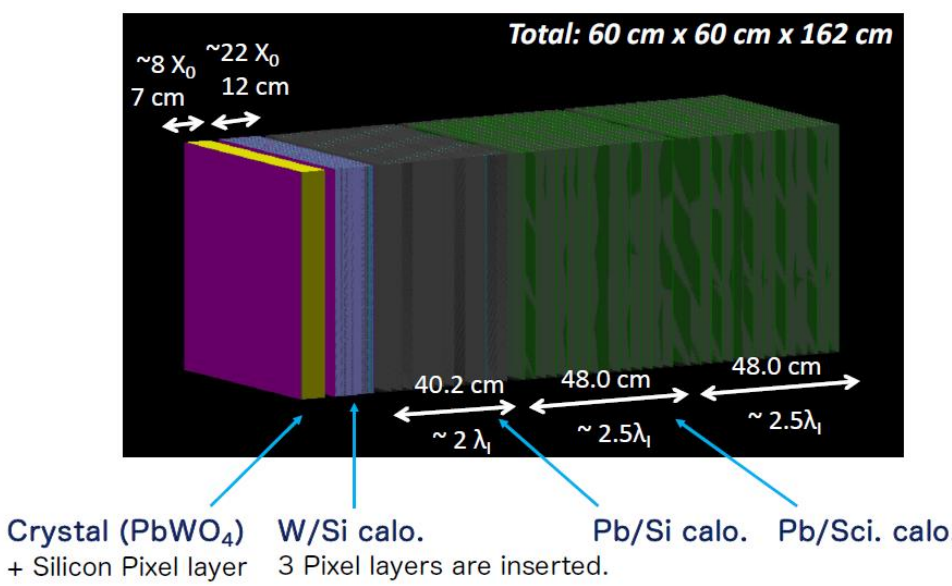

Figure 2. Primary design of the Det-1 Zero-Degree Calorimeter.

The diffraction pattern found in the differential cross-section of interactions such as J/ψ (see Figure 3) provide valuable information on phenomena such as gluon saturation and are currently the only way of understanding the gluon spatial distribution in nuclei [2]. However, the incoherent cross section is 2-3 orders of magnitude greater than the coherent cross section for higher values of photon momentum transfer and can easily wash out the minima in the diffraction pattern. While detection of spectator neutrons can help identify interactions where the nucleus breaks up, even incoherent excitation of bound states can have this effect on the cross section and another method of detecting incoherent excitation events is necessary.

For a doubly-magic nucleus such as ^{208}Pb, every possible bound-state decay nucleus has at least one photon of energy at least 2.6 MeV. These photons will be Lorentz-boosted up to ~500 MeV, and about 20% of those will appear in the acceptance of the ZDC in its current design. Detection of these "soft" photons would allow tagging of incoherent excited states and provide a much cleaner sample of coherent interactions.

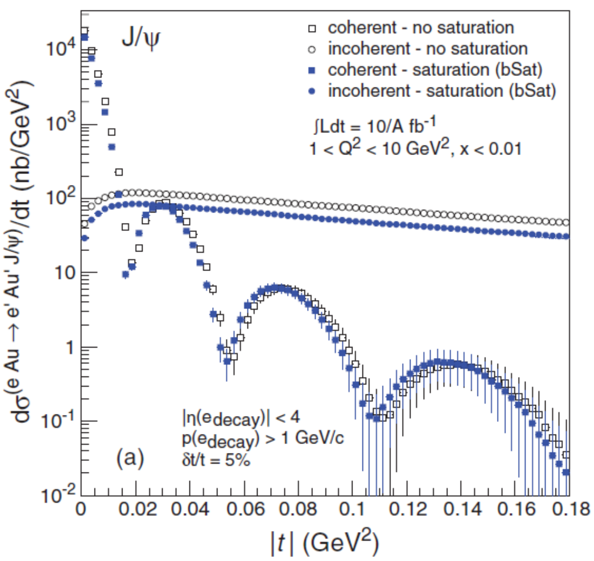

Figure 3. (left) dσ/dt for coherent and incoherent J/ψ photoproduction with and without saturation; (right) same analysis for phi mesons [2].

While initial simulations show that expected energy and position resolution performance will meet the baseline Yellow Report requirements, these simulations have not modeled realistic beam backgrounds or other noise signals. Figure 4 and Figure 5 show recent calculations of the neutron fluence in the far-forward region and in the ZDC specifically. There is significant concern that the neutron background will present a challenge to the efficiency of detecting the soft photon signal. The currently proposed method of photon identification in the ZDC relies on the traditional calorimetry approach of applying weighting factors to different layers in the detector, but with the segmented nature of the layers in the ZDC a significant amount of geometric information is not being utilized and the soft photon identification efficiency would benefit from analysis that includes that additional information.

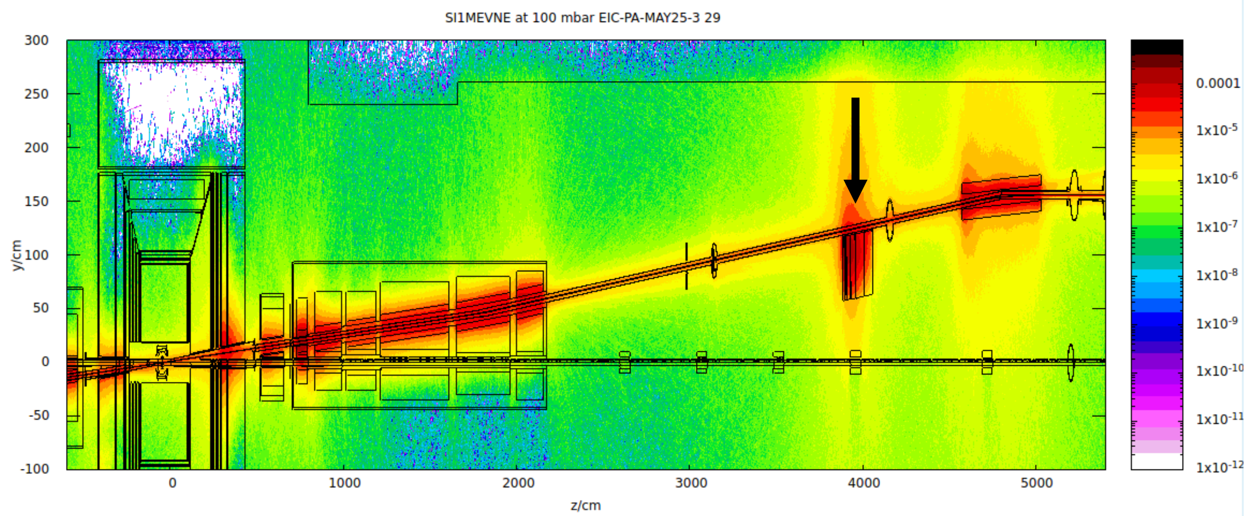

Figure 4. Neutron (1MeV equivalent) fluence at B=3~T field in the Central Solenoid and corresponding fields in two bending magnets. The ZDC is indicated by the black arrow. Color scale is relative *fluence; maximal fluence with 1A proton beam and 10^{-9} mbar residual gas pressure is $2x10^4$ n/cm^2/s.*

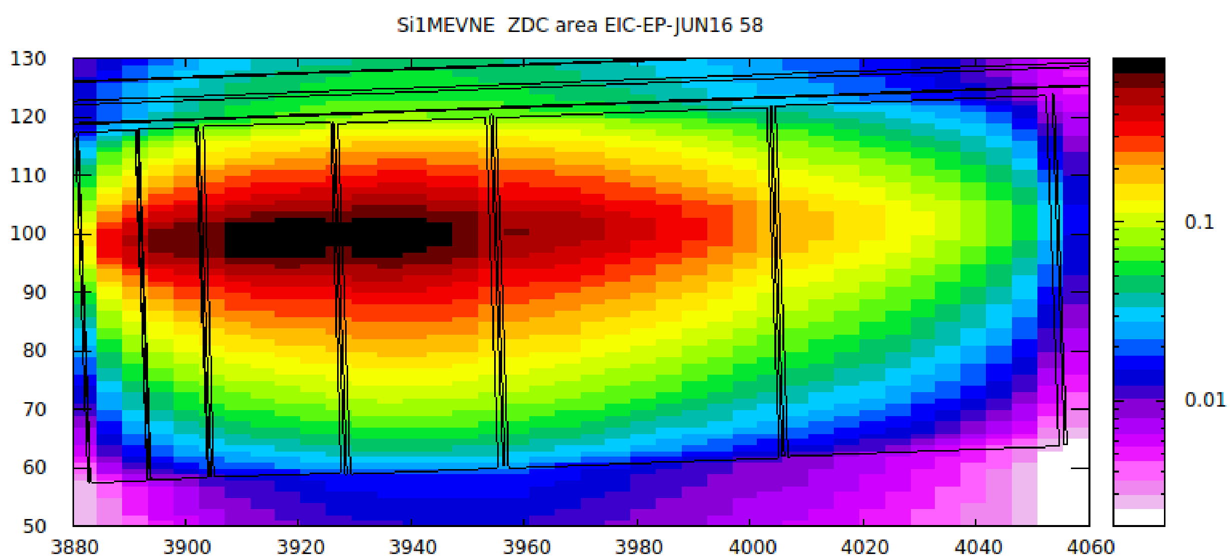

Figure 5. Neutron (1MeV equivalent) fluence in regions of the nominal ZDC from e (10 GeV) + p (275 GeV) collisions. Color scale is relative *fluence; at maximal luminosity of 10^{34}/cm^2/s, maximal fluence in the ZDC is $4x10^5$ n/cm^2/s.*

Machine learning algorithms have always shown strength at pattern recognition, and with the rapid growth in the past decade enabled by the combination of computational power, deep neutral networks (DNN), and big data, ML has been finding applications in highly disparate fields, include nuclear and particle physics. We propose to develop machine learning methods for the efficient separation of photons and neutrons at lower energies than currently possible. Various approaches will be pursued to achieve this goal.

a) Software calibration techniques have been used to improve the energy resolution of clusters in highly segmented calorimeters [3]. Implementing this scheme will improve the background reduction and improve the overall energy reconstruction by weighting clusters in dense parts of showers with the EM calibration and in sparse parts with the hadronic calibration of non-compensating calorimeters.

b) Two-dimensional “jet image” methods apply convolutional image recognition networks to the reconstruction of LHC events [4]. We will extend this method to the 3-dimensional structure of the ZDC, a method we are familiar with from the reconstruction of computer tomography images [5]. This kind of reconstruction is also structurally similar to the identification of particles in a liquid Argon TPC, which can be viewed as a calorimeter with extreme segmentation. We have successfully developed particle ID algorithms for such a detector and run it on HPC hardware [6]. Additionally, we will investigate the use of shower timing, which may be challenging for the reconstruction, particularly for low-energy showers, but it might come with low overhead on the hardware, since scintillation light in SiPMs arrives fast, and existing CALICE calorimeters achieve sub-ns time resolution on individual hits. Dedicated timing chips could achieve even better time resolution (see, e.g. [7] for an overview).

c) The combination of the spatial and temporal structure of neutron vs. photon clusters could be accommodated by graph neural networks, which have been used with some success to reconstruct high-energy clusters in the CMS HGCAL [8]. The extension to lower energies and the incorporation of time information will require significant developments, with relevant expertise at PNNL.

d) The optimization of the structure of the ZDC will require large computational resources. With a large number of possible parameters to optimize (granularity, time resolution, number and placement of high-granularity vs. low-granularity layers, and so on) we will use Gaussian processes to optimize these for the identification of low-energy clusters. Our goal for this project is not a global optimization of the ZDC, but rather a better understanding of the limitations of detector hardware, reconstruction software, and their interplay for this important physics channel.

While our optimization will initially be limited to low-energy physics, it is quite likely that findings translate to the general case, particularly since we intend to include background in our simulation.

Required Resources

This proposal is requesting funding for labor; the funds will be utilized at PNNL, Old Dominion University, and University of Kansas. The tasking is broken down as follows:

PNNL – project management, machine learning model development and optimization

- Lynn Wood – 0.10 FTE for project management and model development
- Jan Strube – 0.25 FTE for model development, evaluation and optimization, and supervision of student(s) while at PNNL

RIKEN – ZDC geometry and simulations

- No funding is requested

University of Kansas – simulation, machine learning model development and optimization

- Grad student – 0.5 FTE for machine learning development and evaluation; expected to spend part of the year at PNNL under the supervision of Jan Strube

Old Dominion University – far-forward backgrounds

- Vitali Baturin (postdoc) – 0.25 FTE for background generation

University of Bergen – calorimeter simulations

- No funding is requested

Chicago State U. – input from FoCal development and simulations

- No funding is requested

PNNL will also propose supporting students from collaborating universities via the DOE Office of Science Graduate Student Research program (SCGSR); it has been used successfully in the past to bring students to PNNL for Belle II research. Consideration will also be given to the many summer internship opportunities provided by PNNL.

Research Program

The proposed one-year program is targeted at exploring how machine learning can augment the current soft photon ID capabilities in the ZDC. PNNL will work with the eRD27 group and others involved with the EIC far-forward detectors to leverage expertise and prior work.

This program will be accomplished as four subtasks, listed here:

- Generation of simulated data and backgrounds as a training set [RIKEN, Bergen]
- Development of an initial ML model for identifying low-energy photons [PNNL, Kansas]
- Optimization and evaluation of the model [PNNL, Kansas]
- Investigation and identification of further possible work [all]:
    - Scaling the ML model to support real-time analysis on the detector, enabling a reduction in the DAQ throughput/bandwidth requirements for the ZDC
    - Applying similar ML techniques to the B0 detector and improving the far-forward particle ID capabilities

The simulations will be supported by RIKEN and the University of Bergen, which have prior experience with far-forward detector simulations. The beam backgrounds in the far-forward region have been previously investigated by Old Dominion University, who will provide relevant data sets for training. The PNNL team has extensive machine learning experience and has implemented ML models on high-energy physics detectors at the Belle II experiment at KEK. Chicago State University has been closely involved with the ALICE FoCal upgrade, which portions the current EIC ZDC design is based upon, and will provide valuable expertise and observations from their work with that detector.

The final investigative phase can be used to prioritize further ML work for the far-forward detectors. Potential improvements include reducing the ZDC load on the DAQ by processing events on the detector in real time, applying similar ML analysis techniques in the B0 detector, or applying ML methods to the other particle identification methods in the ZDC.

Cost effectiveness

This proposal is predominantly a computational effort, and will utilize modern supercomputing systems designed for energy efficiency:

- PNNL's Constance supercomputer is housed in the LEED Gold-certified Computational Sciences Facility
- RIKEN Fugaku supercomputer was #1 on the "Green 500" most energy-efficient supercomputer list in 2019

Diversity, Equity, and Inclusion

PNNL is committed to fostering a work environment that fully embraces and values diversity and inclusion. By doing so, we benefit from a breadth of perspectives, insights, and experiences that enables the innovation and creativity one expects from a DOE national laboratory.

PNNL supports multiple summer internship programs, such as the Young Women in Science summer program and the Minority Serving Institution Partnership Program with NNSA. These opportunities will be leveraged whenever possible to bring students to PNNL for an immersive research experience.

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Budget

The material presented is submitted for informational purposes and is not binding on behalf of the PNNL or the US DOE. Binding commitments can only be made after submission of a formal proposal which sets forth a specific SOW, estimated costs, and which has been approved the Department of Energy, Pacific Northwest Site Office.

Table 1 displays the standard money matrix for the proposed nominal budget, while Table 2 breaks the funding requests down in further detail for each institution and budget scenario. Amounts shown are fully burdened by the respective institutions.

Table 1. Money Matrix, Nominal Budget

	ML Detection in ZDC	Total
Pacific Northwest National Laboratory	$181k	$181k
University of Kansas	$16k	$16k
RIKEN	-	-
Old Dominion University	$29k	$29k
University of Bergen	-	-
Chicago State University	-	-
Total	$226k	

The nominal, -20%, and -40% budget scenarios are described below and summarized in Table 2.

Nominal budget: $226k

Milestones:

- Generation of data set for ML training and evaluation
- Development of initial model for soft photon detection
- Optimization and evaluation of ML model
- Investigation of further applications

80% budget: $180k

The 20% budget cut would remove the investigation of further applications task (evaluation of on-detector ML analysis to reduce DAQ load, application of similar techniques on other far-forward detectors).

Milestones:

- Generation of data set for ML training and evaluation
- Development of initial model for soft photon detection
- Optimization and evaluation of ML model

<u>60% budget: $135k</u>

The 40% budget cut would remove the ML model optimization phase; the project will provide an evaluation of the proof-of-concept model with documented performance, but without optimal performance improvements.

Milestones:

- Generation of data set for ML training and evaluation
- Development of initial model for soft photon detection
- Evaluation of ML model (no optimization)

Table 2. Proposed Budget by Institution and Budget Scenario

	Nominal	**-20%**	**-40%**
PNNL			
Scientist labor	$181k	$144k	$108k
University of Kansas			
Graduate student labor	$29k	$23k	$17k
RIKEN			
No funding requested	-	-	-
Old Dominion University			
Postdoctoral labor	$16k	$13k	$10k
University of Bergen			
No funding requested	-	-	-
Chicago State University			
No funding requested	-	-	-
Total	**$226k**	**$180k**	**$135k**