

Initial Simulations and Machine Learning for the EPIC ZDC

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Zero-Degree Calorimeter

- Responsible for reconstructing photons and neutrons in the far-forward region
- Located 30 m from the interaction point



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Current ZDC Design

- Stacked EM and hadronic calorimeters
 - Based on the ALICE FoCal design
- 67 layers:
 - Si tracker (3 layers)
 - PbWO4 crystals
 - 22 W/Si
 - 12 Pb/Si
 - 30 Pb/scint



10cm x 10cm



Initial ZDC Simulations Using DD4hep

- Initial studies have focused on high-energy neutrons as test particles
 - 10 / 50 / 100 / 200 GeV neutrons, single particle trajectories along the detector z-axis
- All simulations performed utilizing the EIC EPIC framework

Goals

- Identify and correct issues in the current dd4hep implementation
- Straightforward validation of physics reactions
- First pass at detector response
- Initial investigations of machine learning for detector response improvements
- These results are preliminary
 - Focus is on debugging the simulation code and starting to build ML frameworks, not evaluate detector response (yet)

Validation of Basic Physics Processes



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Max transverse spread should roughly scale with log(E)

Some potential issues were seen between the pad and pixel layers of the W/Si calorimeter – worked on this with Shima Shimizu (RIKEN) and the DD4hep team, now understood

Also committed fixes for some alignment issues: https://github.com/eic/ip6/search?g=author%3Ademisra&type=commits

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Calibrating Detector Response: Linear Regression

• Standard calorimeter energy resolution function:

$$\frac{\sigma_E}{E} = \frac{a}{\sqrt{E}} + \frac{b}{E} + c$$

where a = stochastic term, b = noise, c = systematics and other energy-independent contributions

For these initial simulations we will only evaluate a

 A straightforward linear regression uses the total energy deposited in each type of layer as input

 $E_{\text{rec.}} = c_1 E_{\text{SiPix}} + c_2 E_{\text{PbWO4}} + c_3 E_{\text{WSi}} + c_4 E_{\text{PbSi}} + c_5 E_{\text{PbScint}} + \text{const.}$ Utilized a single layer in PyTorch to perform the regression:

> $c_1 = 2.1829$ $c_2 = 1.1574$ $c_3 = 100.5793$ $c_4 = 401.0872$ $c_5 = 60.2897$ const. = 2.8002



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Calibrating Detector Response: Multilayer Perceptron (MLP)

- Taking advantage of some of the segmentation of the system – 20x20 array of PbWO4 crystals plus separate layers instead of total energy per section of the calorimeter
- we can use a simple machine learning model with a single hidden layer

Input energy from crystals (usually just 1) + 64 layers



Source: deeplearning.stanford.edu





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Predicted Energy Distribution

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Next Steps in Calibration Detector Response: Graph Convolutional Network

- Further improvement should be possible when the segmentation of all layers is included in the ML model – but ZDC layers have different pixel/pad sizes
 - Standard ML toolboxes are targeted for data sequences and/or grids
 - \rightarrow Graph convolutional networks generically store relationships between nodes



Source: cs224w.stanford.edu



Conclusions

 Initial work is underway to evaluate the ZDC implementation in DD4hep



- PNNL is also starting to investigate machine learning to improve detector response and event ID
 - Initial effort to develop ML models of increasing complexity: energy per detector type \rightarrow energy per layer \rightarrow energy per cell
- Thank you to Michael Murray, Charles Hyde, and Shima Shimizu for the crash-course in the ZDC and the EIC environment!

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3.7

7.94

Thank you

