EPJ Web of Conferences **295**, 03009 (2024) https://doi.org/10.1051/epjconf/202429503009
CHEP 2023

Development of particle flow algorithms based on Neural Network techniques for the IDEA calorimeter at future colliders

Adelina D'Onofrio[1,*], *Biagio* Di Micco[2], and *Michela* Biglietti[1]

[1]I.N.F.N., sez. Roma Tre
[2]Universitá & I.N.F.N., sez. Roma Tre

Abstract. IDEA (Innovative Detector for an Electron-positron Accelerator) is an innovative general-purpose detector concept, designed to study electron-positron collisions at future e^+e^- circular colliders. The detector will be equipped with a dual read-out calorimeter able to measure separately the hadronic component and the electromagnetic component of the showers initiated by the impinging hadrons.
Particle flow algorithms (PFAs) have become the paradigm of detector design for the high energy frontier and this work focuses on a project to build a particle flow algorithm for the IDEA detector using Machine Learning (ML) techniques. ML is used for particle reconstruction and identification profiting of the high granularity of the fiber-based dual-readout calorimeter. Neural Networks (NN) are built for electron reconstruction inside the calorimeter. The performance of several NN architectures is shown, with particular attention to the layer setup and the activation function choices. The performance is evaluated on the energy resolution function of the reconstructed particles. The algorithm is trained using both parallel CPUs and GPU, and the time performance and the memory usage of the two approaches are systematically compared.

1 Introduction

IDEA [1] is one of the most promising detector concepts proposed for installation at future e^+e^- circular colliders, such as FCC-ee [2] and CEPC [3]. In order to perform its challenging physics programme, spanning from Standard Model precision measurements to new physics searches, IDEA will rely on breakthrough technologies and efficient algorithms for particle identification and reconstruction. IDEA is currently under design and optimization with dedicated full-simulation investigations. The detector will be equipped with a dual read-out calorimeter, which will guarantee an electromagnetic energy resolution up to $\sim$ 3-4%/$\sqrt{E}$, measuring separately the hadronic component and the electromagnetic component of the showers initiated by the impinging hadrons.

Precision measurements of Z, W, and Higgs boson decays at the next generation of circular lepton colliders will require excellent energy resolution for both electromagnetic and hadronic showers. The resolution is limited by event-to-event fluctuations in the shower

*e-mail: adonofri@cern.ch

development, especially in the hadronic system. Compensating for this effect can greatly improve the achievable energy resolution.

Particle flow algorithms (PFAs) aim at identifying and reconstructing each particle arising from the interaction point, by combining the information from all the sub-detectors and they have become the paradigm of detector design for the high energy frontier. Since PFAs are designed to reconstruct every final state particle in the most suited sub-detectors, they require highly-granular calorimeters.

The approach of dual-readout calorimetry has emerged as a candidate to fullfill both of these requirements by allowing to reconstruct the fluctuations in the shower development event-by-event and offering a high transverse granularity.

The final goal of the project outlined in this proceeding is to construct an algorithm for particle identification, particle-jet assignment, and jet energy regression, based on ML techniques on GPUs. The aim is to maximise the energy resolution of the dual read-out calorimeter exploiting NN.

This work shows preliminary results about ML-based electron energy regression studies in the dual-readout calorimeter of the IDEA detector.

This proceeding is organised as follows: Section 2 briefly describes the experimental apparatus focussing on the dual readout calorimeter, Section 3 highlights the particle flow paradigm, providing an overview of the software project and the I.N.F.N. Roma Tre infrastructure, Section 4 shows a comparison among the neural network (NN) approaches tested and preliminary results about electron energy regression, and finally Section 5 provides conclusions.

2 The IDEA detector concept at FCCee

The Future Circular Collider (FCC) [4] at CERN is a project that integrates a circular leptonic collider FCC-ee, in a first stage, followed by a proton-proton collider FCC-hh [5], in a second stage. The data taking program of the FCC-ee collider foresees to deliver 5 ab^{-1} of integrated luminosity in 3 years of operation at $\sqrt{s} = 240\,\mathrm{GeV}$ and it will run at the Z mass peak and at the W^+W^- production threshold. Finally, the FCC-ee will be operated at the $t\bar{t}$ production threshold with an expected integrated luminosity of $1.5\,\mathrm{ab}^{-1}$ delivered in 5 years. The data collected at these various center-of-mass energies make this machine the only one able to provide extremely high precision measurements of all the Standard Model features of interest and eventually provide hints of new physics.

IDEA is a detector concept based on innovative technologies, developed in recent years. It features a silicon inner tracker, surrounded by a ultra-light drift chamber and a silicon wrapper. The Inner detector is immersed in a 2 T B-field, generated by a very thin superconducting solenoid. A dual readout calorimeter is placed outside the magnet, and within the return joke of the magnet. In the outer part, a muon tracker, based on μ-Rwell technology, is interleaved with the return joke material. This same technology also provides a layer of preshower in front of the calorimeter.

A sketch and a transversal view of IDEA are shown in Fig. 1.

2.1 Dual readout calorimeter

The IDEA calorimeter is based on the dual readout technique [2]. This concept allows to obtain a superior hadronic energy resolution, thanks to the capability to measure the electromagnetic fraction on an event-by-event basis and remove the relative fluctuations in the hadronic shower. This can be achieved by measuring the same shower with two different

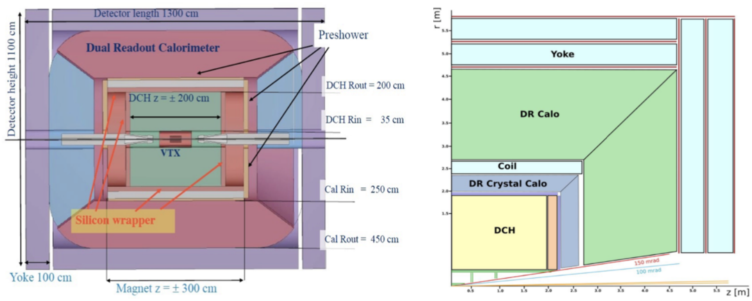

Figure 1. Left: a sketch of the IDEA detector concept. Right: a transversal view of the IDEA detector concept, including a crystal section with dual readout technology, in front of the hadronic calorimeter.

technologies, one sensitive to the deposited energy (scintillation light) and one sensitive only to the electromagnetic component of the hadronic shower, namely electrons and positrons, which produce Cherenkov light. The dual readout calorimeter for the IDEA detector is composed of an unsegmented fiber calorimeter which acts as both electromagnetic and hadronic calorimeter. The achievable energy resolution is compatible with the 3% resolution required to distinguish jets coming from W, Z and Higgs boson decays, and with a 10-20%/ $\sqrt{E}$ resolution for the measurement of the Higgs $\rightarrow \gamma\gamma$ decay channel. The design of the calorimeter is based on a very fine granularity, with a fiber-to-fiber pitch of the order of 2 mm. This also brings an excellent position and angular resolution, A better resolution for the electromagnetic performance may be needed for the heavy flavour physics. This should require an electromagnetic energy resolution around 3-4%/ $\sqrt{E}$, which may be achieved by a crystal section [3], again based on dual readout technique, in addition to the fiber calorimeter (see Fig. 1 right).

3 The particle-flow paradigm

The most promising strategy for achieving the desired IDEA jet energy resolution is the Particle Flow approach, using a highly granular detector. This approach requires the reconstruction of the four-vectors of all visible particles in an event: the reconstructed jet energy is the sum of the energies of the individual particles. Charged particles momenta are measured in the tracking detectors, while the measurement of the energy of photons and neutral hadrons are obtained from the calorimeters.

In practice, the sum of calorimeter energies of a reconstructed particle is obtained by a pattern recognition algorithm, namely the Particle Flow reconstruction Algorithm (PFA).

Only calorimetric information are used in this study, neglecting the tracking simulation at a first stage. The algorithm performance is tested on a full simulation of simple events of single electrons.

3.1 Workflow and software implementation

The workflow of the project is the following: starting from the full simulation of the particles in the IDEA detector, it is possible to extract both the truth particle information (position, momentum, particle type) and calorimeter information (fibre position, fibre type, collected light by the fibre) at the impinging layer, and exploit a NN based algorithm for particle identification and energy regression. A Geant-based [7] description is currently used and the code is developed on the EDM4hep [8] output format. Focusing on the details of the software implementation, this project aims at interfacing Pandora [9] with KEY4HEP [10] using the EDM4HEP data format. Several progresses have been achieved in this context: algorithms have been implemented in KEY4HEP-Pandora and NNs have been trained against the energy resolution of the candite electron, exploiting mono-energetic electrons or electrons with a uniform distribution in energy (in the range [0, 125] GeV) and θ and ϕ coordinates.

3.2 Infrastructure

NN algorithms have been trained on both CPUs and GPU, installed on I.N.F.N. Roma Tre cluster. Technical details about the site are provided below.

- The site is equipped with about 50 servers (mainly based on Blade technology) with a total amount of cores available (or VCPU) of about 1500 interconnected with Infiniband (DDR 20Gbps e QDR 40Gbps).
- The site has also 2 Graphical Processor Units (GPU) K 80 (4 in total: 2 x K40), where jobs can be parallelised if needed. In this work, a single GPU per job was exploited.
- There is a storage system present in the cluster for a total amount of about 700TB.

4 Neural network approaches

NN models are built using the Keras library (https://keras.io) and TensorFlow [11] as a back-end. TensorFlow is an open source platform for ML developed by Google and Keras is its interface used to solve ML problems with high iteration velocity.

The tested approaches are: deep neural networks (DNN) and convolutional neural networks (CNN).

4.1 Deep neural network approach

A DNN is an artificial neural network with multiple layers between the input and output layers.

In this study, the DNN input nodes are the energy and position of each hit in the electromagnetic shower generated by the impinging electron and recorded in both scintillating and Cherenkov fibres. 6 kinematic variables (E, x, y, z, t, fibre-type) are considered, multiplied by the average hit multiplicity per electron per event, resulting in around 60k information per event. A zero padding approach is adopted, meaning that if the number of hits in the event is less than the average hit multiplicity, the remaining positions in the array are set to zero to reduce the complexity of the problem. However, it is needed to further reduce the number of input nodes due to CPU memory issues and an upper cut on the electron truth energy is imposed at 45 GeV. Fig. 2 shows the 10 hidden layers architecture, where the number of nodes is halved at each layer.

The model loss adopted is *MeanSquaredError()* [1], optimised with respect to the simulated energy of the incoming electrons. A stochastic optimiser, Adam [12], is used to minimise the loss. Fig. 3 (left) shows the model loss for the training and the validation samples versus the epochs; Fig. 3 (middle) shows the cumulative electron energy resolution (evaluated as the difference between the truth and the electron energy predicted by the DNN) integrated over all the events considered; finally Fig. 3 (right) shows the truth energy versus the electron energy predicted by the DNN.

[1] $\frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{true}} - y_{\text{pred}}\right)^2$

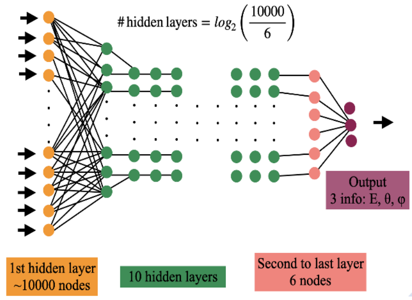

Figure 2. Sketch of the DNN architecture adopted, in the case of 10 hidden layers.

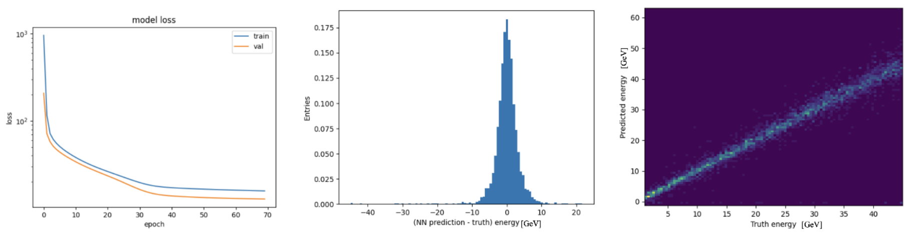

Figure 3. Left: DNN model loss versus epochs for the validation and the training samples. Middle: energy resolution over all the events. Right: truth energy versus the electron energy predicted by the DNN.

A Gaussian fit is performed to the residuals between the truth simulated electron energy and the energy estimated by the DNN outcome (see Fig. 4 left), split into 10 truth electron energy slices. The resolution of each Gaussian fit and its uncertainty, divided by the truth electron energy, is plotted as a function of the truth energy slice, as shown in Fig. 4 right. The red line shows the fit typically used to evaluate the energy resolution of the form: $\frac{\sigma}{E} = \frac{a}{\sqrt{E}} \oplus \frac{b}{E} \oplus c$, where the parameter of interest for this study is the noise term a ($p0$ in the fit panel). The noise term extracted from this fit is higher than expected (it is $\sim 21\%$) and the NN configurations might be under-performing because a too easy architecture is used as first attempt.

The speed of the algorithm: is ~10 minutes on GPU and ~2 hours on a CPU thread.

As a second step, the number of hidden layers increased to 20. As shown in Fig. 5, the energy resolution improves if the NN layers doubles (solid black line) and gets better if only energy information are provided as input to the NN (dashed red line). As a sanity check, the solid red line shows the electron energy resolution calculated as the plain sum of energy over the calorimeter cells.

4.2 Convolutional neural network approach

CNN tests are motivated by memory issues faced with DNN. A VGG-like architecture was adopted, using the following scheme:

- 5 convolutional 2D layers;
- Flatten and 3 dense layers, with one output each;

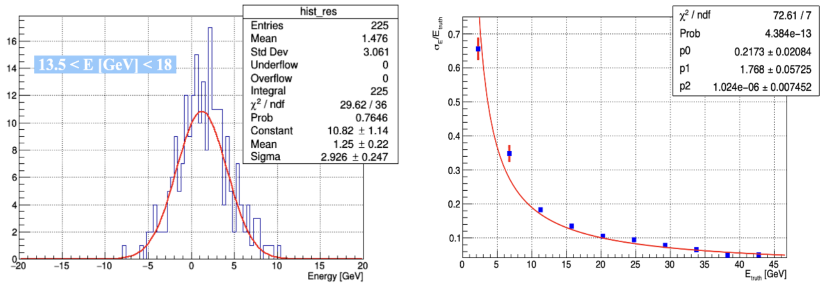

Figure 4. Left: Gaussian fit to the residuals between the truth simulated electron energy and the energy estimated by the DNN outcome, in the energy slice $13.5\,\text{GeV} < E_{\text{truth}} < 18\,\text{GeV}$. Right: energy resolution as a function of 10 truth electron energy slices. The red line shows the fit typically used to evaluate the energy resolution of the form: $\frac{\sigma}{E} = \frac{a}{\sqrt{E}} \oplus \frac{b}{E} \oplus c$.

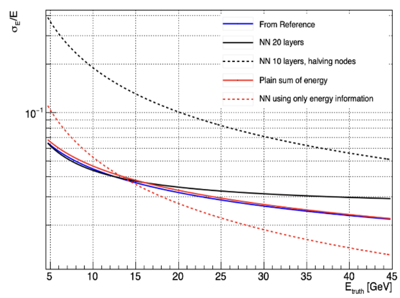

Figure 5. Electron energy resolution as a function of 10 truth electron energy slices. The dashed black line reproduces the results shown in Fig. 3 right. The solid red line shows the plain sum of energy over the calorimeter cells, the solid black line shows the electron energy resolution evaluated using a DNN with 20 hidden layers and all the kinematic information as inputs, the dashed red line shows the electron energy resolution evaluated using a DNN with 10 hidden layers and only energy information as input to the algorithm. Finally, the blue line shows the results previously obtained in Ref. [13].

- No batch normalisation adopted;
- Maxpooling approach and zero padding approach.

With this method it is possible to overcome memory issues, and to use the full electrons energy range. Numpy arrays are generated with shape (N, N, d) where $N \times N$ is a matrix for the $\phi - \theta$ calorimeter coordinates of the simulated electron energy deposits with granularity (100x100 bins). d represents the features associated to each pixel: energy, and z coordinate in the calorimeter. These matrices, used as input images for the CNN, discriminate between scintillating or Cherenkov fibres. A sketch of the CNN configuration is reported in Fig. 6, together with examples of input images.

The electron energy resolution is used as figure of merit for batch size and learning rate optimisation of the CNN, as shown in Fig. 7.

In order to improve the CNN performance, a proto-clustering was implemented considering, as inputs for the CNN, the calorimeter hits and distance with respect to the simulated

https://doi.org/10.1051/epjconf/202429503009

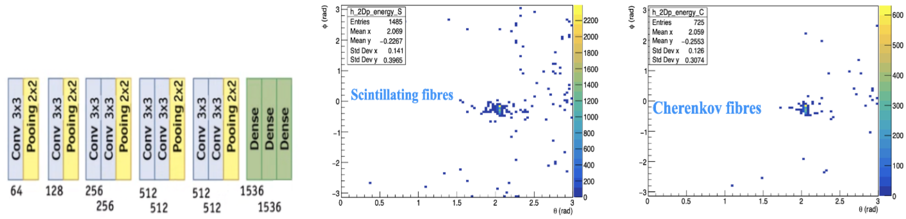

Figure 6. Left: layout of the CNN layers configuration. Middle and right: 2D histograms with $\phi - \theta$ calorimeter coordinates of the simulated electron energy deposits with granularity (100x100 bins), filled with the electron energy recorded in the Cherenkov or scintillating fibres.

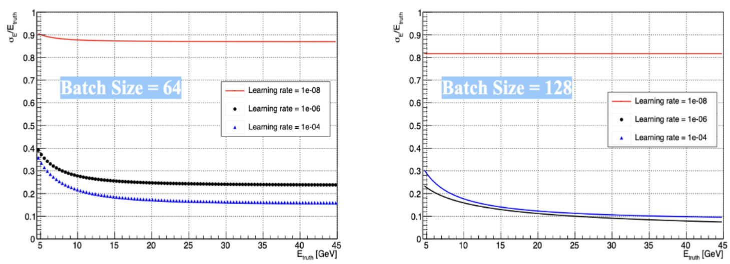

Figure 7. Electron energy resolution obtained with different batch size and learning rate optimisation of the CNN.

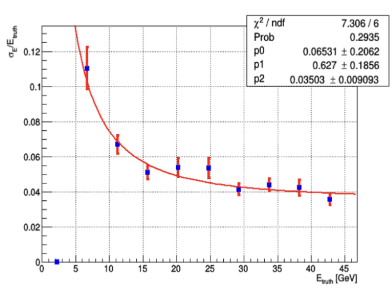

Figure 8. Electron energy resolution obtained with the CNN and a proto-clustering approach.

electron energy centroid. Finally, Fig. 8 shows the optimised electron energy resolution obtained with the CNN and a proto-clustering approach.

5 Conclusions

Future colliders are foreseen in the European (and Chinese) strategy for particle physics and IDEA is a feasible detector concept at future colliders. R&D studies for detector and software solutions are ongoing, in particular the IDEA dual readout calorimeter simulation is solid and can be used for PFA. A preliminary machinery for the PFA is in place and the first

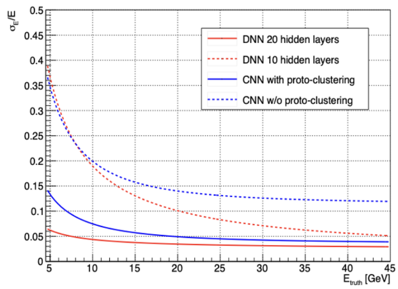

Figure 9. Electron energy resolution obtained with several NNs tested.

distributions are reasonable using electrons as input. As summarised in Fig. 9, the CNN approach seems promising and overcomes the memory issues faced with the DNN approach. The long term goal is to test a GNN approach, move to Pytorch for better optimisation with Pandora and fully develop NN-based particle identification and jets reconstruction.

References

[1] M. Antonello, *IDEA: A detector concept for future leptonic colliders*, IL NUOVO CIMENTO **43C** (2020), DOI10.1393/ncc/i2020-20027-2

[2] Alain Blondel and Patrick Janot, *FCC-ee overview: new opportunities create new challenges*, arXiv:2106.13885

[3] The CEPC Study Group, CEPC Conceptual Design Report, Volume 1 - Accelerator, arXiv:1809.00285 .

[4] https://fcc.web.cern.ch/Pages/default.aspx

[5] https://fcc.web.cern.ch/Pages/fcc-hh.aspx

[6] M. Lucchini at al, *New perspectives on segmented crystal calorimeters for future colliders* IOP Publishing **15** (2020)

[7] Agostinelli, S. and others, GEANT4–a simulation toolkit, Nucl. Instrum. Meth. A (506) 2003 .

[8] C. Helsens, V. Volkl, C. Neubuser, G. Ganis, and J. C. Villanueva, A software framework for FCC studies: status and plans, Nov., 2019. https://doi.org/10.5281/zenodo.3599139. 2

[9] J. Marshall and M. Thomson, The Pandora Software Development Kit for Pattern Recognition, Eur. Phys. J. C75 (2015) no. 9, 439 .

[10] Declara, Gaede et al., Key4hep Letter of Interest - Snowmass 2021 .

[11] M. Abadi et al., Tensorflow[..] A system for large-scale machine learning, 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), pp.265-283, 2016

[12] Diederik P. Kingma, Jimmy Lei Ba *ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION*, https://arxiv.org/pdf/1412.6980.pdf

[13] L. Pezzotti, *Particle detectors R&D: Dual-readout calorimetry for future colliders and micromegas chambers for the ATLAS new small wheel upgrade*, Ph.D. thesis, Pavia U. (2021)