R&D of the EM Calorimeter Energy Calibration with Machine Learning based on the low-level features of the Cluster

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Abstract. We have developed an energy calibration method using machine learning for the ILC electromagnetic (EM) calorimeter (ECAL), a sampling calorimeter consisting of Silicon-Tungsten layers. In this method, we use a deep neural network (DNN) for a regression to determine the energy of incident EM particles, improving the energy calibration resolution of the ECAL. The DNN architecture takes cluster hit data as low-level features of the cluster. In this paper, we report the status of our R&D and present results on energy calibration accuracy.

1 Introduction

In the high energy colliding experiments, the precise energy measurement of the particle clusters detected with the electromagnetic (EM) and hadron calorimeters are crucial for the physics analyses. We have developed an energy calibration method using machine learning for the ILC EM calorimeter (ECAL), which is a sampling calorimeter that measures the energy of the particle cluster produced by the incident EM particle (electron or photon), for the precise energy determination. In our energy calibration method, we treat the energy calibration as a regression problem and use a deep neural network (DNN) architecture. Cluster hit data are used as low-level features in the DNN model. This paper reports the current status of the research and development (R&D) efforts.

Both ILD and SiD detector designs employ the sampling type calorimeter for ECAL to measure the energies of incident electrons and photons for ILC experiments. In this study we use the ECAL detector simulation data for SiD. The SiD ECAL is the Silicon-Tungsten sampling type calorimeter, where absorbing Tungsten layers alternate with sensitive Silicon layers with 20 thin (2.5mm) Tungsten layers followed by 10 thick (5.0mm) layers for a total of $26X_0$. The design value of the energy resolution is $\Delta E/E = 0.17/\sqrt{E} \oplus 0.01$. The SiD ECAL design is described in the ILC Technical Design Report (TDR)[1].

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In this study, we use the MC data for SiD ECAL, here single EM particle is injected to the detector, and ECAL hits originating from the same incident particle are gathered as a cluster. Figure 1 shows the diagram of the ECAL which consists of twelve trapezoidal modules, with coordinate (left) and the schematic drawing of the hit production from an incident EM particle(right).

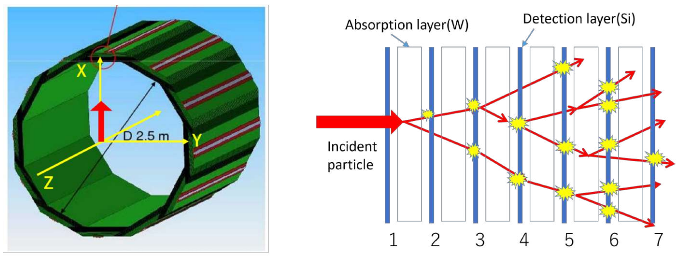


Figure 1. Diagram of the ECAL with coordinate (left) and the schematic drawing of the hit production from an incident EM particle(right), used in the study.

In the conventional energy calibration, the energy of a cluster, which is regarded as an incident particle energy, is obtained by summing all hits in a cluster, and multiply by a single coefficient. We call the method the simple reconstruction. In the simple reconstruction, there exist several problems of :

1. Non-linearity between the true incident energy and the determined cluster energy due to the shower energy leakage in the high energy region;

2. Particle-species dependence, due to the different shower development between electrons and photons; and

3. Angular dependence due to the detector geometry.

The third problem is from the ECAL detector design, where twelve trapezoidal modules are designed to overlap[1] in order to provide mechanical stability and cover projective gaps, as shown in the Figure 2.

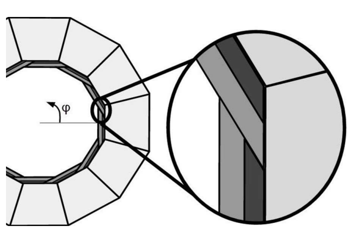


Figure 2. Technical drawing of the SiD ECAL, where trapezoidal modules are designed to overlap.

To improve the energy calibration performance, we have developed an energy calibration method using regression neural networks (NN) and evaluate the energy calibration performance.

2 Energy Calibration Using Machine Learning

In the regression NN based energy calibration, we input cluster data to NN and obtain the cluster energy as an output, as shown in Figure 3.

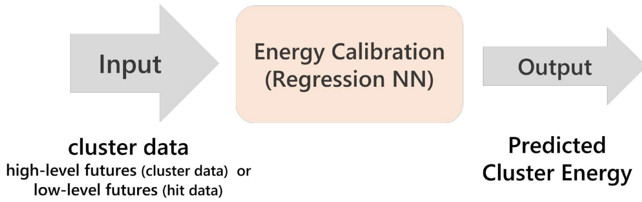
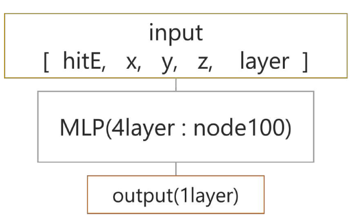


Figure 3. Energy calibration using a regression NN. we input cluster data to NN and obtain the cluster energy as an output.

For the cluster data, in our previous study, we firstly try the cluster data (based on the cluster CM position, sum of the hit energy, and kinematical variables for the cluster) as high-level feature data[2]. In that study, we get the better energy calibration performance than the simple reconstruction, but there remain the ϕ-dependence. To obtain the better performance, we directly input the all hit data in a cluster, as the low-level feature data input to NN.

2.1 Architecture of the Neural Network

We construct the regression NN for low-level feature data input based on the 4-layer multi-layer perceptron neural network (MLP), as shown in Figure 4 left. Each hit has 5 parameters: hit energy, hit position (x, y, z), and the layer number of the hit, and all hits in a cluster are combined into one input vector. The size of the input data is fixed to be 5×1900, and we apply 0-padding for the input without hit information. The number of nodes in one hidden layer is fixed to 100. The hyper parameters for the architecture is summarized in Figure 4 right. A PyTorch[3] framework is used to implement the NN design.



NN module	Pytorch
loss function	MSELoss
active function	Adam
batch size	128
epoch	100

Figure 4. Schematic design of the regression NN model (left) and its hyperparameters (right).

3 Results

We apply the regression NN with low-level feature data (hit data), and evaluate the energy calibration performance. Here we evaluate 1. NN training is performed for photon or electrons separately, and 2. NN training is performed with a data including both photon and electrons (electron and photon mixed data).

3.1 Energy Resolution for Photons or Electrons

We show the energy resolution results using hit data 1) for incident electrons (Figure 5) and, 2) for incident photons (Figure 7), in the energy range of 2-40 GeV. The figures (a) to (d) in Figures 5 and 7 show the learning curve, the 2-D graph for the true energy and predicted energy (by NN regression) , the energy resolution with respect to the incident energy, and the energy resolution with respect to phi, respectively.

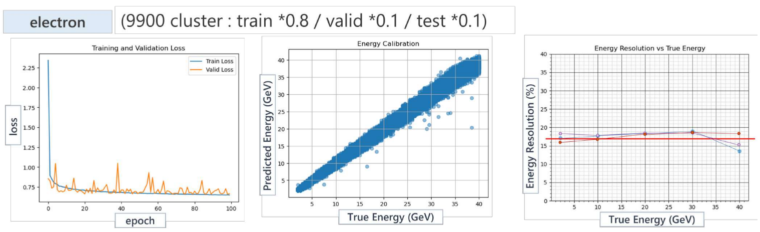


Figure 5. Results for electrons: (a) learning curve, (b) the 2-D graph for the true energy and predicted energy (by NN regression), and (c) the energy resolution with respect to the incident energy.

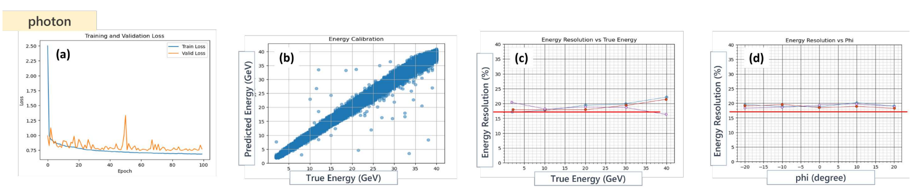


Figure 6. Results for photons: (a) learning curve, (b) the 2-D graph for the true energy and predicted energy (by NN regression), (c) the energy resolution with respect to the incident energy, and (d) energy Resolution with respect to phi.

Looking at the learning curve of the neural network (NN), the loss value is around 0.7-0.8, indicating successful training (a). As a result, a linear relationship between the true energy (horizontal axis) and the calibrated energy (vertical axis) is obtained (b), leading to the energy calibration accuracy shown in Figures (c) and (d). The energy resolution achieved is 16-18% for electrons and 16-22% for photons, which is close to the design value across all energy ranges. Furthermore, the phi distribution shows no angular dependence. Therefore, better results are obtained compared to the values (22-25%) from previous studies using high-level feature data.

3.2 Energy Resolution Based on the NN Trained with Electron-Photon Mixed Data

In the previous section3.1, the regression NN is trained only based on the electrons or photons. In this section, we show the energy resolution results with a NN which is training with a data including both photon and electrons (electron and photon mixed data).

The results of (a) learning curve, (b) the 2-D graph for the true energy and predicted energy (by NN regression) , (c) the energy resolution with respect to the incident energy, and (d) the energy resolution with respect to phi are shown in Figure7. The results of training with mixed data show a deterioration compared to the results of training with separate electron/photon samples, but an energy calibration accuracy of approximately 18-21% is achieved.

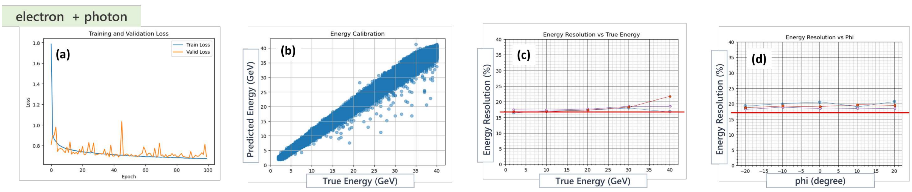


Figure 7. Results for electron and photon mixed training data: (a) learning curve, (b) the 2-D graph for the true energy and predicted energy (by NN regression), (c) the energy resolution with respect to the incident energy, and (d) energy Resolution with respect to phi.

As results shown in the sections 3.1 and 3.2, the energy resolution improves across all energy ranges (2-40 GeV) by directly input the low-level feature (hit data) to the NN :

- Achieved to an ideal energy resolution of 17(+1)% across the entire energy range;
- Disappeared the angle ϕ dependence; and
- Good energy accuracy even for the NN, which is trained with electron and photon mixed data.

4 Conclusion

We have developed an energy calibration method using a regression neural network with low-level hit data for the EM calorimeter in the ILC experiment. The NN-based energy calibration method provides better performance than conventional reconstruction methods by accounting for non-linear detector responses. The use of low-level feature enables the network to learn spatial information from hits, leading to stable energy resolution with respect to the ϕ angle.

As future works, we will applying this method to the ILD detector design and exploring alternative NN architectures, such as graph neural networks (GNN), to further improve energy calibration performance.

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