Energy reconstruction in a highly granularity semi-digital hadronic calorimeter

Sameh Mannai[1], **Kais Manai**[2], **Eduardo Cortina**[3] **and Imad Laktineh**[4]

1, 3 Université catholique de Louvain, Belgium
2 Université Tunis El-Manar, Tunisie
4 Université Claude Bernard, Lyon, France

E-mail: sameh.mannai@uclouvain.be

Abstract. The Semi-Digital Hadronic CALorimeter(SDHCAL) using Glass Resistive Plate Chambers (GRPCs) is one of the calorimeters proposed for particle physics experiments at the future electron-positron collider. It is a high granularity calorimeter which is required for the application of the particle flow algorithm in order to improve the jet energy resolution as one of the goals of this experiments. We discuss the energy reconstruction, based on digital and semi-Digital methods, to study the effect on the improvement of the single particle energy resolution and the linearity of the detecor response. This study was performed with the GEANT4 simulation. Results on the energy resolution and linearity, for negative pions over an energy range from 1 to 100 GeV are presented and compared with different energy reconstruction methods including Artificial Neural Networks.

1. Introduction

The CALICE collaboration [1] has developed several calorimeter prototypes to evaluate the most appropriate one to be used in the future Linear Collider. One of them is the semi-digital hadronic calorimeter (SDHCAL) constructed in IPNL with the collaboration of other laboratories.

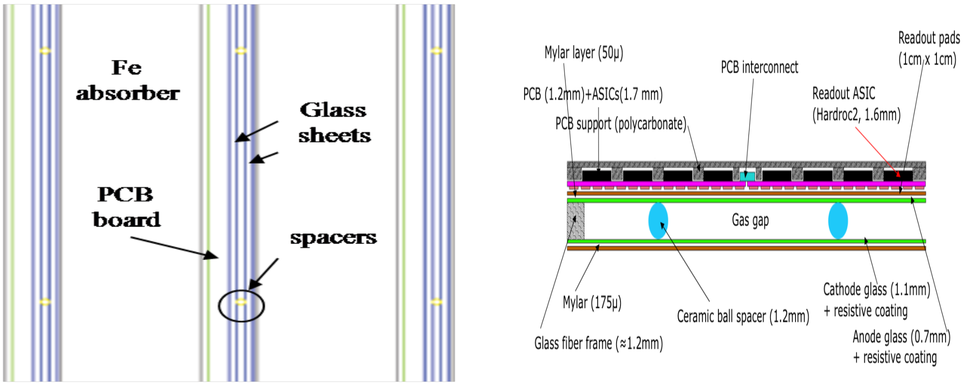
In this paper we first present the geometry of this prototype used in simulation. Then, we present the different techniques of energy reconstruction used in SDHCAL. Finally, the results of the energy resolution and linearity obtained are presented and commented upon.

2. Detector geometry and Monte Carlo simulation

The SDHCAL is a sampling calorimeter with 48 layers of 2 cm stainless steel interleaved with active layers made of Glass RPCs, a gaesous detector of 1 m^2 area(Figure 1). The gas used is a mixture of tetrafluoroethane(TFE, 93%), isobutane (5%) and SF_6 (2%).

The high granularity is insured by finely segmented readout planes which are divided into pads of a size of 1 cm^2 where collected the signal created by the passage of the charged particles through the gas gap [2]. The pad fired is called "hit".

The data samples used in this analysis have been generated using version 4.9.3 of GEANT4 [4], [3]. We simulated 1000 events of negative Pions per energy, betwen 1 and 100GeV considering QGSPBERTINI physics list [5], [6].



(a) Detector view (b) Schematic view of a glass RPC

Figure 1: Geometry of SDHCAL

3. Analytic Energy Reconstruction methods

The energy measured in the digital calorimeter is proportional to the number of the fired pads, called "hits", and counted only when the energy is above a given threshold. This concept has shown a deterioration of the response of the calorimeter observed at high energies [7] Figure 2. Therefore, we provided a semi-digital approach for the energy reconstruction while using three thresholds instead of one [7], [8]. To measure the energy deposited in the calorimeter, we count naively the number of hits over each of the thresholds affected by three weights(A,B,C) to obtain the reconstructed energy as:

$$E_{\text{rec}} = A \times N_1 + B \times N_2 + C \times N_3 \tag{1}$$

N_1,N_2,N_3 represent respectively the number of hits beyond threshold 1(S_1) but below threshold 2(S_2), beyond threshold 2 but below threshold 3(S_3) and beyond threshold 3.
Our strategy of optimisation of the energy resolution in the semi-digital method, consits of two steps. The first one, is the determination of the best thresholds values giving good linearity and energy resolution in the digital case. Thus, the thresholds(S_1) and (S_2) giving a good linearity can be fixed to 5 and 10 Mips [7]. The third threshold(S_3) must be lower, then we use the one giving the best energy resolution which is 0.25 Mip. Once the thresholds are choosen, the second step consists in the determination of the best set of the calibration constants (A,B,C) which give us a reconstructed energy closest to the beam energy and allowing a better energy resolution.
To realise the second task we used a minimisation procedure and our minimisation function is a χ^2-like minimisation defined by R:

$$R = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \frac{((E_{\text{beam}} - (A \cdot N_1 + B \cdot N_2 + C \cdot N_3))^2}{E_{\text{beam}}}} \tag{2}$$

Where 'i' is the event number.
To check the validity of the thresholds mentionned above, we tried in the past several values of thresholds to minimise equation 2. S_1, S_2 and S_3 are choosen to varry respectively from 0.1 to 3 Mips, 4 to 8 Mips and 9 to 15 Mips. The minimisation is studied for each energy and the results obtained are of the same order of the values of the thresholds used above.
To perform this analysis a macro written in C++ and based on the root class "TMinuit" [10],

has been used and allowed the determination of the calibration constants by the minimisation of the equation 2. Once the calibration constants A, B and C are determined, they are used to calculate the reconstructed energy according to equation 1.
Each reconstructed energy distribution is fitted with a gaussian. Then from the fit parameters we can deduce the standard deviation σ and the average reconstructed energy to calculate the energy resolution and the linearity.

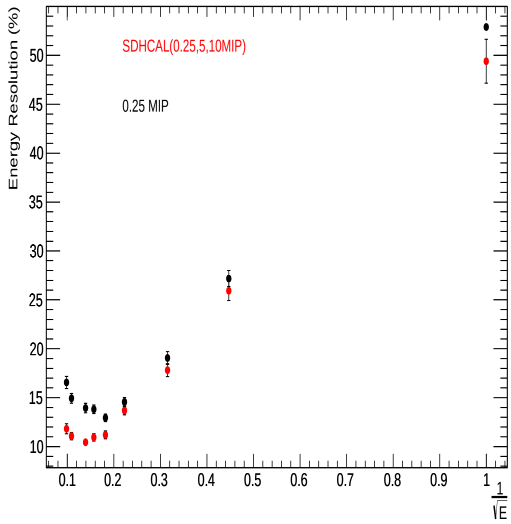


Figure 2: SDHCAL and DHCAL energy resolution comparison

We used different methods of energy reconstruction to find the best optimisation of the calibration constants described above. These methods depends of the nature of the calibration constants, each offer a modelisation depending or not of the energy of the beam. The comparison between the results obtained with each method will be summarised in figures 7 and 8 at the end of this paper.
The first analytic method used is called "Energy Dependent Calibration Constants". In this method, the calibration parameters are supposed to be contants and are optimised independently for each energy. This method shows good results, especially the best linearity compared to the other reconstruction methods but has a drawback which is the dependence of the calibration constants of the beam energy supposed to be unknown.
This lead us to try a second method called "Free Dependent Energy Calibration Constants". In contrast to the first method, in which the minimisation is done energy by energy, this second method consists in minimising equation 2 for all the energies at the same time and thus provide a set of universal calibration parameters.
Nevertheless, inspecting the behaviour of the calibration constants with the first method, we observed that they depend strongly of the energy of the beam and the total number of hits in the detector N_{tot}. Therefore, we tried a third method of reconstruction called "Quadratic Parametrisation" consiting in the correction of the reconstructed energy formula by replacing (A,B,C) with new quadratic parameters with respect to N_{tot}. The new reconstructed energy formula is defined by:
$E_{\text{rec}} = A(N_{\text{tot}}).N_1 + B(N_{\text{tot}}).N_2 + C(N_{\text{tot}}).N_3$
Where:

$A(N_{\rm tot}) = A_1 + A_2.N_{\rm tot} + A_3.N_{\rm tot}^2$
$B(N_{\rm tot}) = B_1 + B_2.N_{\rm tot} + B_3.N_{\rm tot}^2$
$C(N_{\rm tot}) = C_1 + C_2.N_{\rm tot} + C_3.N_{\rm tot}^2$

This last method is adopted as the official method used in the energy reconstruction by SDHCAL. It was used in the publication of the last results of SDHCAL [9]. The three analytic methods described above will be completed by a last method of reconstruction using Artificial Neural Networks.

4. Energy reconstruction using Neural Network

We used the root class TMultiLayerPerceptron to build our neural network [11]. The neural network is created with two hidden layers containing respectively 6 and 2 nodes. The input variables are choosen to be the number of hits beyond the 3 thresholds discussed previously: N_1, N_2 and N_3. A representation of the neural network architecture used in this analysis is depicted in Figure 3. The correlations between the input variables and the real particle energy are automatically learnt during the training of the neural networks. We used the simulated odd particle energies as training samples and the even ones as test samples. As a result, from the test samples, the Neural Network should estimate the energy of the incident particle defined as the output variable $E_{\rm rec}$.

The estimated energies obtained with this method are then directly reconstructed in Figure 4. The neural network technique gives a good prediction of the incident energy resulting in a good energy resolution (Figure 5) and Linearity (Figure 6). The results of this method are promising and achieve an improvement compared to the results obtained from the analytic methods of the energy reconstruction discussed in the previous section. Moreover, with the neural network method of reconstruction we don't use the calibration constants and thus we avoid the difficulties of their parametrisation since, as discussed previously, it's complicated to know the real modelisation of this constants with respect to the energy. Figures 7 and 8 show a comparison between the results obtained with the different methods of energy reconstruction highlighting the goodness of the results obtained with the neural network technique.

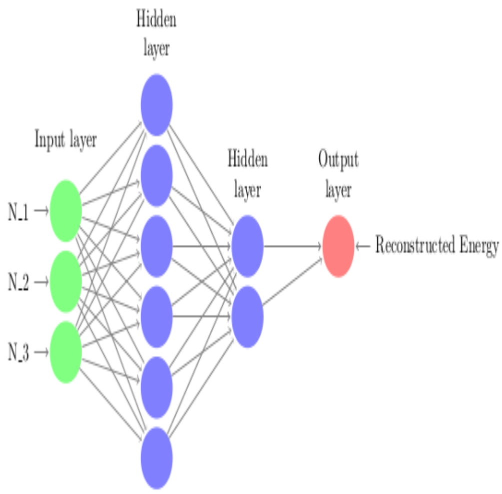


Figure 3: ANN Architecture used in the analysis.

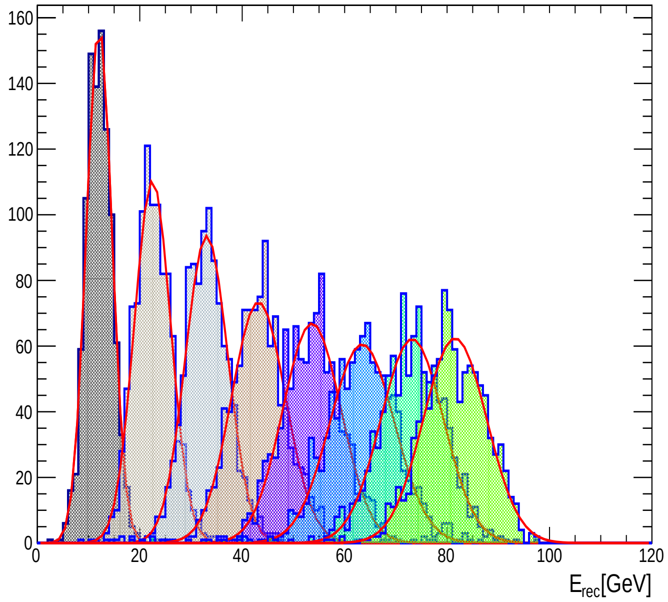


Figure 4: Pion Energy reconstruction with Neural Network (10,20,30,40,50,60,70,80 GeV).

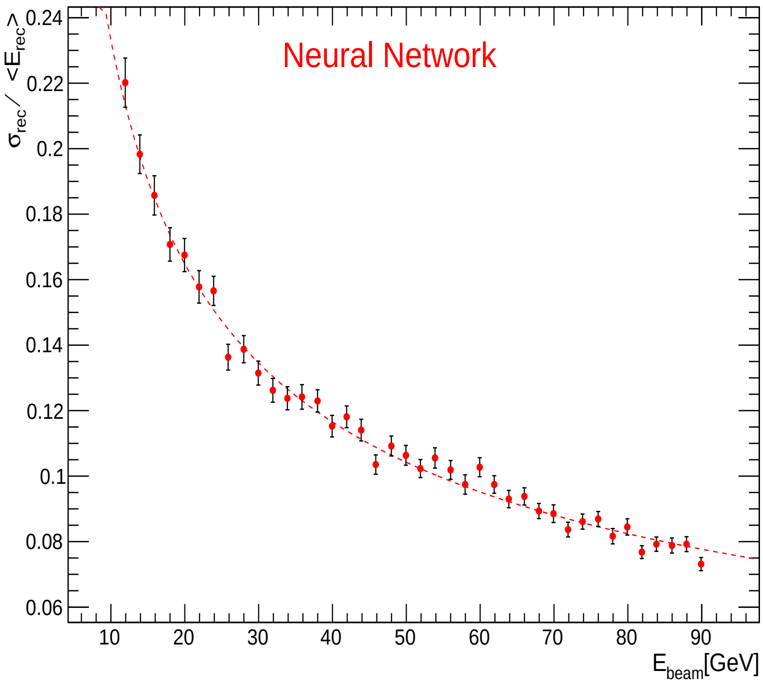


Figure 5: Pion Energy resolution measured with ANN.

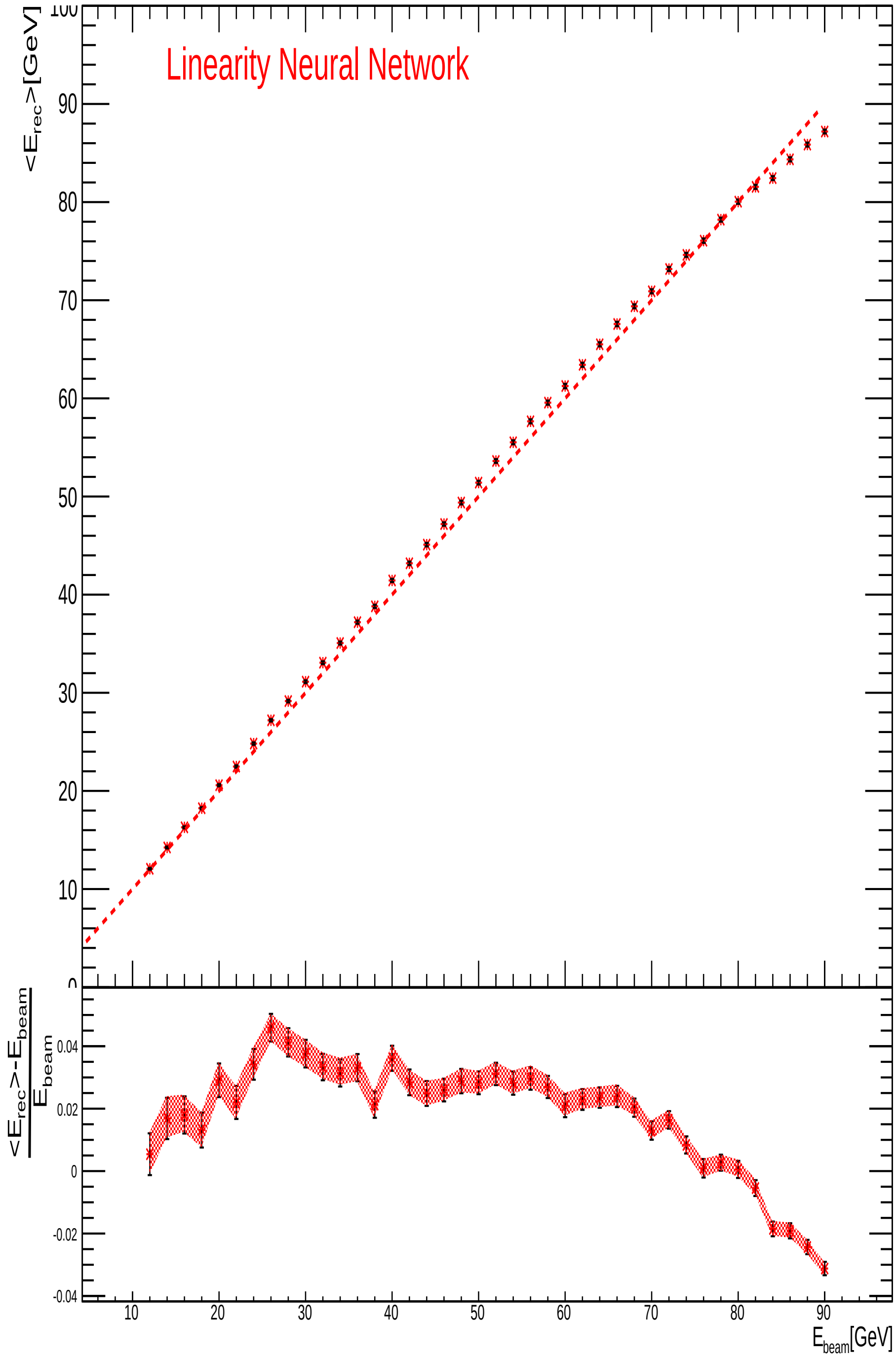


Figure 6: Pion Mean reconstructed energy measured with ANN. The dashed line corresponds to x=y.

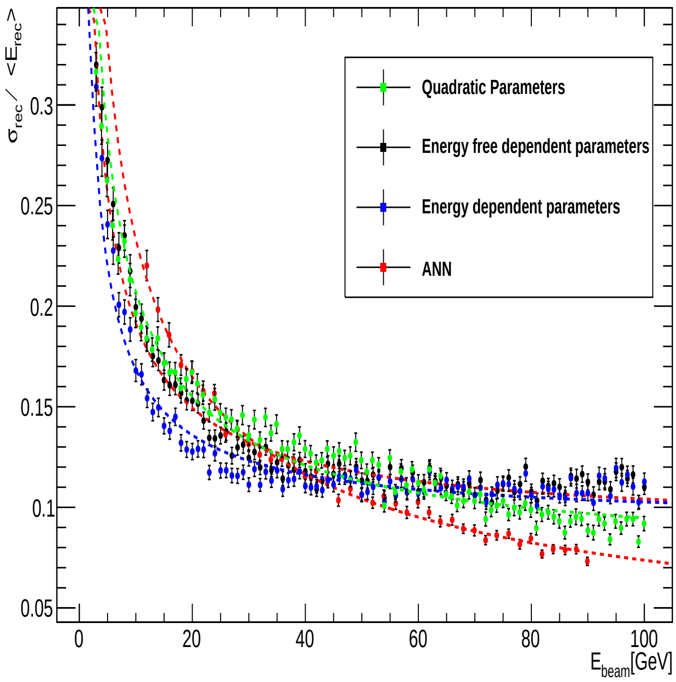


Figure 7: Comparison of the energy resolution between the different methods of energy reconstruction described in the text.

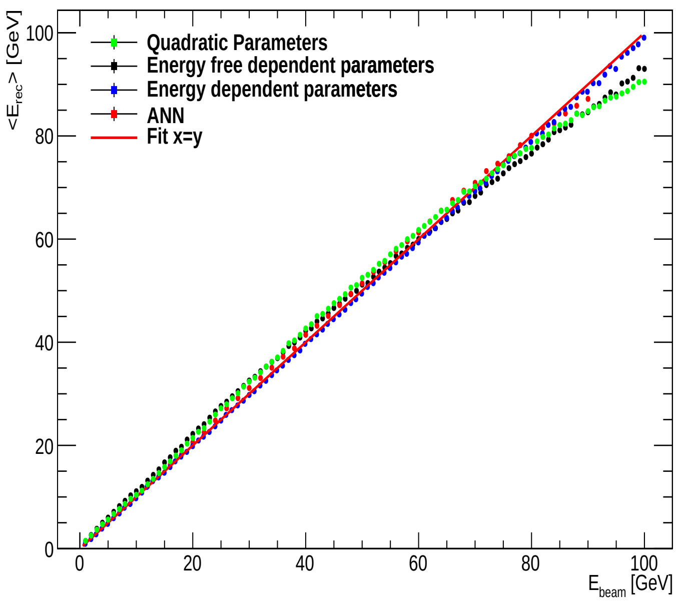


Figure 8: Comparison of the linearity between the different methods of energy reconstruction. The fit line corresponds to x=y.

5. Summary

The semi-digital hadronic calorimeter prototype has been conceived and built for the future Linear collider experiments. We discussed the energy reconstruction with Geant 4 simulation data in SDHCAL. We have developed different methods of energy reconstruction. The best results are given by the neural network method of reconstruction with the lowest energy resolution at high energy (0.07 at 90GeV) and a good linearity with the advantage of removing the calibration constants parametrisation complexity. An ongoing study aims to improve the results obtained with the neural network method by adding more input variables related to the hadronic shower topology and test it on test beam data.

References

[1] CALICE: `http://twiki.cern.ch/CALICE`
[2] Bedjidian M et al 2011 *Journal of Instrumentation.* **6** P02001
[3] Agostinelli et al 2003 *Nuclear Instruments and Methods in Physics Research A.* **506** 250-303
[4] Allison J et al 2006 *Nuclear Science, IEEE Transactions.* **53** 270-278
[5] Geant4 working group, `http://www.geant4.org/geant4/support/proc_mod_catalog/physics_lists/referencePL.shtml` - accessed february 17th 2010.
[6] Apostolakis J et al 2008 *Nuclear Science Symposium Conference Record.*
[7] Mannai S `http://ilcagenda.linearcollider.org/getFile.py/access?contribId=16&sessionId=1&resId=1&materialId=slides&confId=3642`
[8] Mannai S et al 2013 *Nuclear Instruments and Methods in Physics Research A* **718** 91–94
[9] CALICE Collaboration, First results of the CALICE SDHCAL technological prototype, CALICE Analysis Note CAN-037
[10] TMinuit, `http://root.cern.ch/root/html/TMinuit.html`.
[11] TMultiLayerPerceptron: Designing and using Multi-Layer Perceptrons with ROOT, `http://cp3.irmp.ucl.ac.be/~delaere/MLP/`