A Way to Better Hadronic Energy Resolution in the ATLAS Combined Calorimeter

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Abstract. The computational experiments performed with MC events for the ATLAS CTB04 setup showed that application of the artificial neural networks (ANN) technique for reconstruction of energy losses in the dead materials between the barrel LAr and Tile calorimeters allows to reach 40 % reduction of the energy reconstruction error compared to the conventional procedure used in the ATLAS collaboration. Contrary to initial expectations it was found that the use of information on the longitudinal profile of a hadronic shower brings greater improvement in the DM energy reconstruction accuracy than the use of cell energies information in the LAr_3 and $Tile_1$ samplings. Application of the ANN technique for evaluation of energy losses in the dead materials between the barrel LAr and Tile calorimeters leads to essential improvement of the pion energy resolution and allows to fulfill the requirements of the ATLAS calorimeter technical project.

1. Objectives of the present investigation

Procedures for reconstruction of hadronic shower energy usually include an additive term which gives an estimate of energy losses in the dead materials between the barrel LAr and Tile calorimeters (E_{dm}) [1, 2, 3]. The error of the energy loss reconstruction directly affects the overall precision of hadronic energy reconstruction procedures. The present investigation was intended to get answers to the following questions: 1) How good is the conventional procedure for estimating the energy lost in the dead materials between the barrel LAr and Tile calorimeters? The conventional procedure is $E_{dm}^{conv} = C_{dm}^{conv} \cdot \sqrt{E_{Lar_3} \cdot E_{Tile_1}}$, where C_{dm}^{conv} is normalization constant which adjusts experimental data to Monte-Carlo data. 2) Is it possible to construct a procedure of appreciably higher precision? 3) How to realize such a procedure? 4) What gain in precision of such a procedure may be reached by exploiting information content of different sets of the additional variables (parameters) which describe particular features of a calorimeter response?

2. Application of Artificial Neural Networks

In the context of neural networks (NN) application the complexity of the dead matter (DM) energy reconstruction problem was practically tested [4] in the course of computational experiments with the use of a series of feed-forward neural networks [5, 6, 7] of various topologies and numbers of nodes (neurons). The number of hidden layers in NNs ranged from 1 to 4, and the number of nodes in a layer – from 2 to 40. The total number of the tested networks is around 100.

The developed ANN procedures exploit as their input vectors the information content of different sets of variables (parameters) which describe particular features of the hadronic shower of a particular event in the ATLAS calorimeter. The trained NN performs non-linear mapping from multidimensional input space of the function arguments onto one-dimensional space of the function value. Correctly trained NN demonstrates good generalization performance, i.e. ability to model correct mapping of data it has "never seen" before.

We found that the NNs with 2 hidden layers worked satisfactorily, and the use of greater number of hidden layers did not bring better performance. On the other hand, single hidden layer networks with increased number of nodes in a layer showed that during NN training they were more likely to stuck at higher minima of NN cost function than networks with 2 or more hidden layers do.

3. Data of the computational experiment

The investigation was performed on the basis of the MC events generated for 9 energies of the incident pions: 10, 20, 50, 100, 150, 180, 250, 320 and 350 GeV. For events generation the ATHENA release 12.0.6 was used with the QGSP_GN physics list. Events were generated for the ATLAS Combined test beam 2004 (CTB04) data setup with the beam direction: $\eta = 0.25$, $\phi = 0.0$. From 11000 to 25000 events were generated at each beam energy. As the first step we performed thorough investigations for 2 energies: 250 and 10 GeV. The obtained results for these 2 energies clarify well the main aspects of the problem to be solved. In what follows we present distributions of the differences between true values of the E_{dm} (supplied by MC generator) and the E_{dm} values reconstructed by the procedures under consideration. The form of these distributions is not Gaussian, and as a measure of widths of these distributions we used RMS values.

4. Exploration Strategy

To reach higher precision of the E_{dm}^{true} reconstruction in comparison with the conventional method, it is necessary to utilize additional information on hadron showers of events. In the computational experiments we applied neural nets of various structures with ever growing dimension of NN input vector. The input vectors were constructed as subsets of items from the "Pool of variables" which contains derivatives of source raw data of the hadronic showers. Our strategy was like this:

◇ First we performed the detailed exploration of the problem at one fixed value of the beam energy (250 GeV).

◇ Performing the first group of experiments we restricted ourselves to using only data on 2 samplings — LAr_3 and $Tile_1$.

◇ From one experiment to another we step by step added information on the energy distribution among cells of these 2 samplings.

◇ Performing the second group of subsequent experiments we step by step increased the dimension of the NN input vector by adding information on the energies of other samplings.

◇ In the third group of experiments we explored the NNs which use only the sampling energies which represent the longitudinal profile of a shower.

◇ Finally the best NN versions were applied to events of other beam energies.

In total about 100 versions of the NN procedures were tested in the present exploration.

5. Summary of the results

At 250 GeV the obtained results of the E_{dm} reconstruction may be summarized as follows [4]:

1) In a general class of the procedures that use the LAr_3 and $Tile_1$ sampling energies as their arguments the conventional method of the E_{dm} reconstruction proved good precision. Its RMS value in the $(E_{dm}^{true} - E_{dm}^{conv})$ distribution is only slightly (≈ 4 %) greater than the corresponding RMS of the neural network procedure with the 2 inputs.

2) It was shown that application of the neural network procedures for the E_{dm} reconstruction may substantially reduce the RMS value of the $(E_{dm}^{true} - E_{dm}^{rec})$ distribution.

3) Among the E_{dm} reconstruction procedures which use as their arguments 2 central sampling energies (LAr_3,$Tile_1$) together with data on cell energies distributions in the LAr_3 and $Tile_1$ the lowest attained RMS value is 5.95 GeV. Compared to the conventional procedure the attained reduction of RMS amounts to 21 %.

4) A level of 4.25 GeV in RMS may be reached by the neural network procedure which uses the full longitudinal profile of a hadronic shower in the LAr and Tile calorimeters together with data on the cell energies distributions in the LAr_3 and $Tile_1$. Compared to the conventional procedure the RMS of the neural network procedure is 43 % less (see NN-24 net results in Fig. 1).

5) The use of only a central fragment (4 samplings)

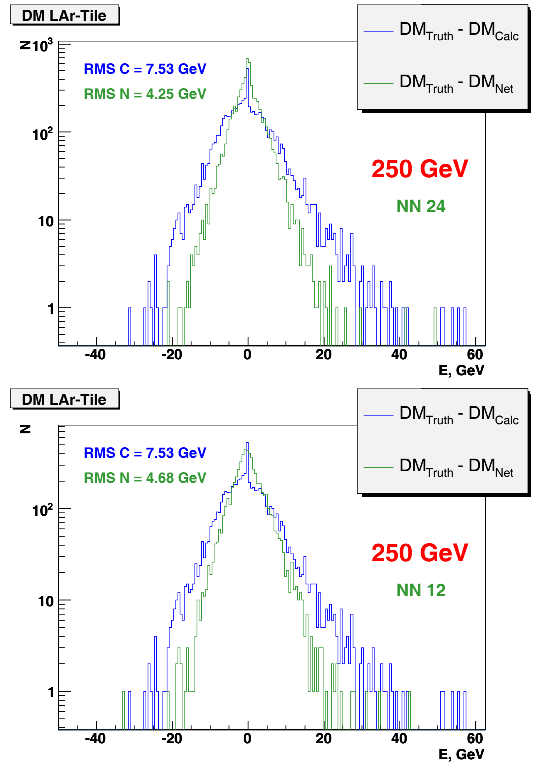

Figure 1: The distributions of the E_{dm} reconstruction error for NN-24 (top) and NN-12 (bottom) approximators at 250 GeV and for the conventional method. The achieved reductions of RMS are 43.6 % and 38.2 %

of the longitudinal profile data of a hadronic shower in the LAr and Tile calorimeters (sampling energies in LAr_2, LAr_3, $Tile_1$, $Tile_2$) allows to reach the RMS at a level of 4.95 GeV. Compared to the conventional procedure the attained reduction of RMS amounts to 34 %.

6) Procedures that use only the full longitudinal profile of a hadronic shower in the LAr and Tile calorimeters (6 sampling energies without cells information) may reach the RMS at a level of 4.65 GeV. Compared to the conventional procedure the attained reduction of RMS amounts to 38 % (see Fig. 1, NN-12 net results).

The results for other beam energies summarized as follows:

7) For the conventional procedure of the E_{dm} reconstruction at 10 GeV the RMS value of the $(E_{dm}^{true} - E_{dm}^{conv})$ distribution amounts to 1.12 GeV (11.2 % of the pion energy). As an example, Fig. 2 illustrates substantial reduction of this RMS attained by the NN procedures for 10 GeV pions.

8) In a wide range of the beam energies (10 – 350 GeV) the neural network procedures which use only the full longitudinal profile of a hadronic shower as their inputs reveal 35 – 41 % reduction in the E_{dm} reconstruction error in comparison with the conventional procedure.

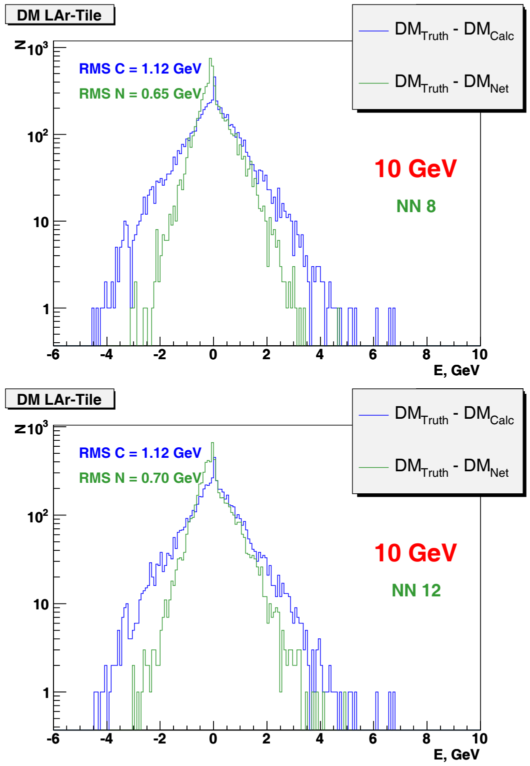

Figure 2: The distributions of the E_{dm} reconstruction error for NN 8 (top) and NN-12 (bottom) approximators at 10 GeV and for the conventional method. The achieved reductions of RMS are 42 % and 37.5 %

6. Application of the developed NN procedures

A hybrid method of the pion energy reconstruction in the ATLAS calorimeter was developed and investigated. The method uses the modified Local Hadronic Calibration scheme (developed in DLNP JINR) and the Artificial Neural Net procedure (developed in LIT JINR) for reconstruction of the energy losses in the dead material of the ATLAS calorimeter. The hybrid method was tested on the ATLAS CTB04 in the range 10 − 350 GeV, $\eta = 0.25$. The test results show that essential improvement of the pion energy resolution is obtained. The results for the MC data at 250 GeV are shown in Fig. 3. The pion energy reconstruction error is reduced by 28.3 %. The results for the CTB04 data at 250 and 350 GeV are shown in Fig. 4 and Fig. 5. The pion energy reconstruction error is reduced by 19.7 ± 0.05 % and 18.8 ± 0.5 % correspondingly.

The energy resolution as a function of energy is shown in Fig. 6. The dashed line is the projected resolution with $\frac{\sigma}{E} = \frac{50}{\sqrt{E}} \oplus 3$ [%]. The full line is the Monte Carlo simulation with the true dead material energy deposition (black circles), $\frac{\sigma}{E} = \frac{(38\pm2)}{\sqrt{E}} \oplus (3.7 \pm 0.1) \oplus \frac{(96\pm11)}{E}$ [%]. Squares are the experimental values with the dead material energy deposition defined by the neural networks,

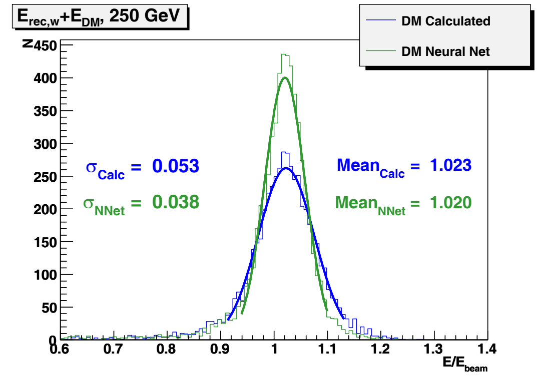

Figure 3: The relative reconstructed pion energy distributions $\frac{E}{E_{beam}}$ at 250 GeV with evaluation of the energy losses in the dead material between the LAr and Tile calorimeters by the conventional method, $\frac{\sigma}{\langle E\rangle} = 5.30 \pm 0.06$ %, and by the Neural Networks method, $\frac{\sigma}{\langle E\rangle} = 3.81 \pm 0.04$ %, on the MC data. The energy reconstruction error is reduced by 28.1 ± 0.5 %

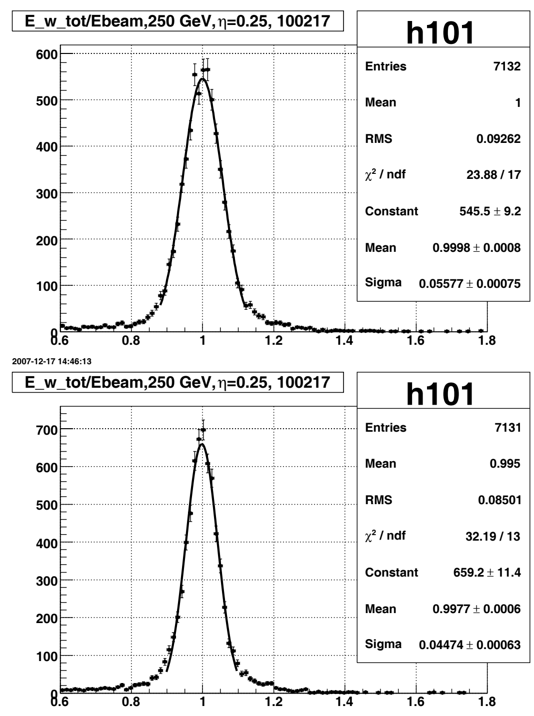

Figure 4: The Combined test beam 2004 data. The relative reconstructed pion energy distributions E/E_{beam} at 250 GeV with the determination of energy deposition in the dead material between the LAr and Tile calorimeters by the conventional method (top) and the Neural Networks method (bottom). The curves are the Gaussian fits within the range of $\pm 2\sigma$. The obtained mean values are equal to: $\frac{\sigma}{\langle E\rangle} = 5.58 \pm 0.08$ % (top) and $\frac{\sigma}{\langle E\rangle} = 4.48 \pm 0.06$ % (bottom). The energy reconstruction error is reduced by 19.7 ± 0.5 %.

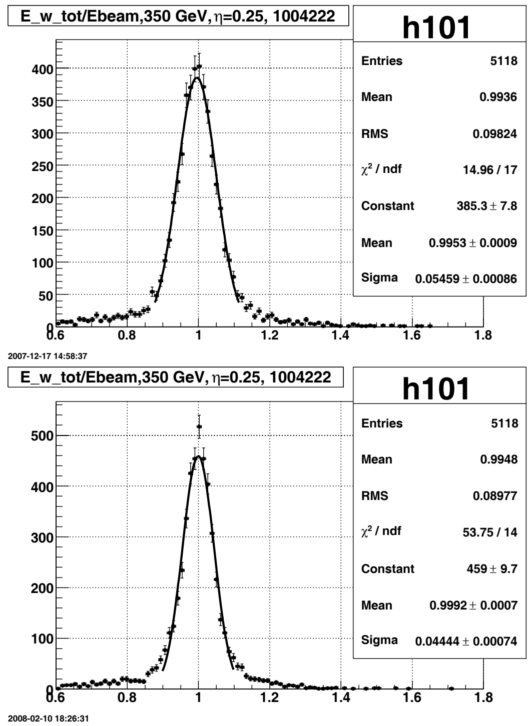

Figure 5: The combined test beam 2004 data. The relative reconstructed pion energy distributions E/E_{beam} at 350 GeV with the determination of the energy deposition in the dead material between the LAr and Tile calorimeters by the conventional method (top) and the Neural Networks method (bottom). The curves are the Gaussian fits within the range of $\pm 2\sigma$. The obtained mean values are equal to: $\frac{\sigma}{\langle E \rangle} = 5.48 \pm 0.08$ % (top) and $\frac{\sigma}{\langle E \rangle} = 4.45 \pm 0.06$ % (bottom). So, the energy reconstruction error is reduced by 18.8 ± 0.5 %.

$\frac{\sigma}{E} = \frac{(42 \pm 3)}{\sqrt{E}} \oplus (2.6 \pm 0.2) \oplus \frac{(36 \pm 22)}{E}$ [%].

In the upshot we have reached the projected energy resolution for hadrons in the ATLAS detector. The resolution for ATLAS combined calorimeter achieved by the new method is the best one compared to the results of other methods (more than 2 times better than in the Hadronic Calibration method used by the Oxford-Stockholm group [8] and about 1.5 times better than the H1 method results for the CTB04 obtained by the Pisa group [9]). The results of the development and investigation were presented at the ATLAS hadronic calibration meeting (CERN, February 2008) and published [10].

7. Conclusion

The computational experiments performed with the MC events for the ATLAS CTB04 setup showed that application of the ANN technique for reconstruction of energy losses in the dead materials between the barrel LAr and Tile calorimeters allows to reach 40 % reduction of the energy reconstruction error compared to the conventional procedure used in the ATLAS collaboration. Contrary to initial expectations it was found that the use of information on the longitudinal profile of a hadronic shower brings greater improvement in the DM energy reconstruction accuracy than the use of cell energies information in the LAr_3 and $Tile_1$ samplings. Application of the ANN technique for evaluation of energy losses in the dead materials between the barrel LAr and Tile calorimeters leads to essential improvement of the pion energy resolution and allows to fulfill the requirements of the ATLAS calorimeter technical project.

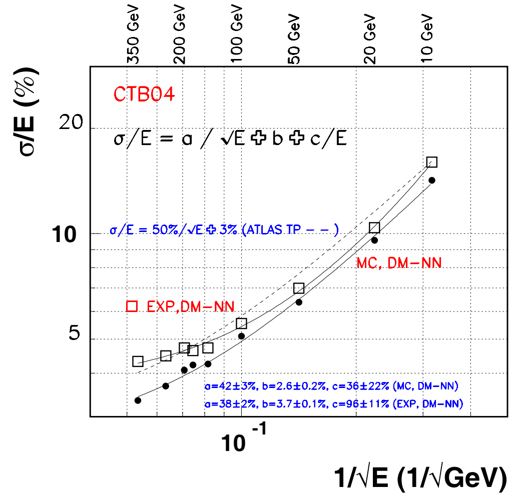

Figure 6: Pion energy resolution as a function of energy. The dashed line is the projected resolution, full circles are the Monte Carlo results with the true dead material energy deposition, squares are the experimental values with the neural networks dead material energy reconstruction.

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