Energy Reconstruction for a Hadronic Calorimeter Using Neural Networks

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Outline

- Introduction
- Experimental Setup
- Energy Reconstruction
- Results
- Conclusions

Introduction

- Reconstruct the energy scale for hadrons
  - calorimeters often are non-compensating ($e/h \neq 1$)
    - degradation of response to hadrons - non-linearities arise
  - minimization of the energy resolution
  - recover linearity
- Use of experimental data from beam tests with the hadronic calorimeter of ATLAS - Tilecal

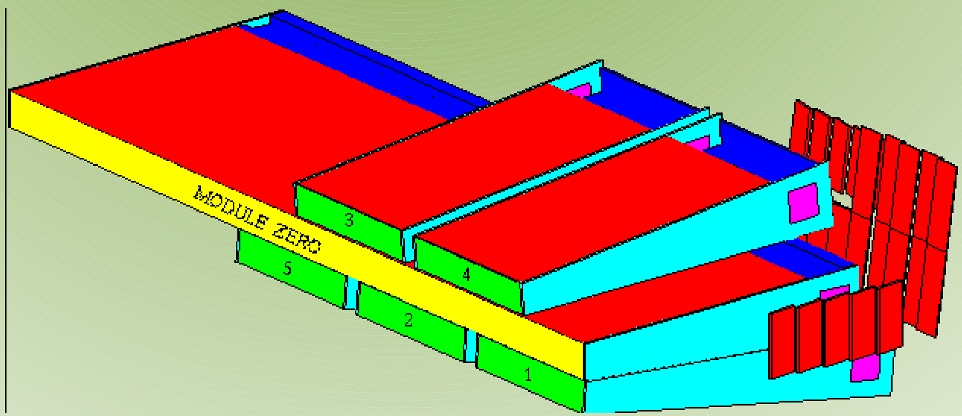
Introduction (cont.)

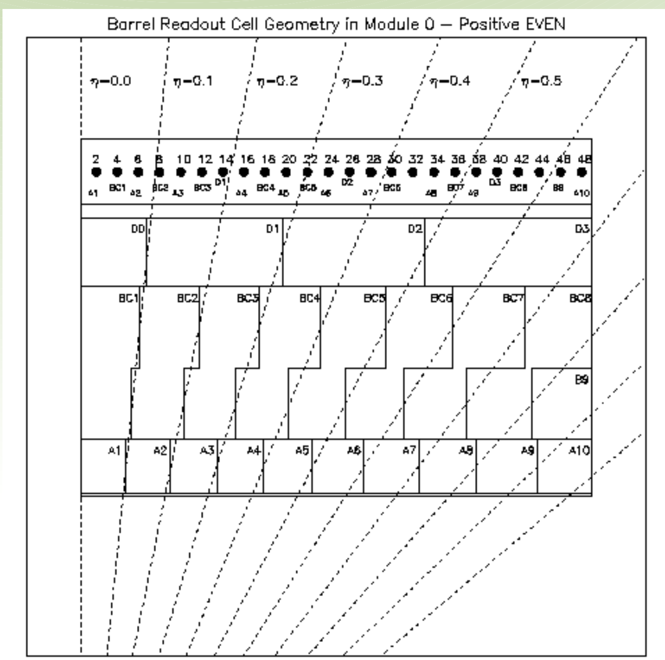
- A neural network was chosen for energy reconstruction
  - can perform complex input/output mappings
  - good generalization capabilities
- Comparison to the classical weighting techniques (H1 inspired)

Experimental Setup

- Prototype module of Tilecal was tested
  - 5 old Tilecal modules were placed around it
- Eight different pion beam energies were acquired
  - 20, 50, 80, 100, 150, 180, 300, 400 GeV
- One η point was used (-0.35)

Experimental Setup (Cont.)





Cell—PMT configuration

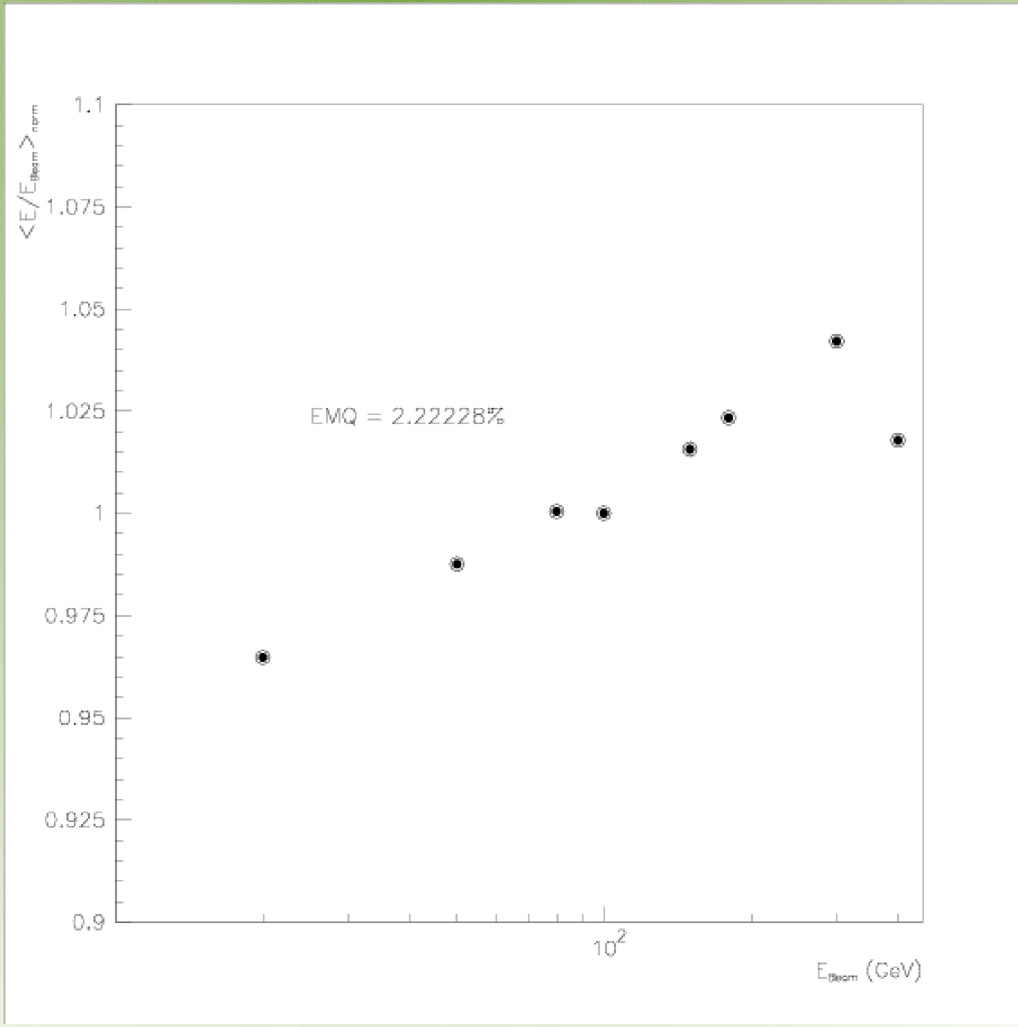
Energy Reconstruction

- Energy deposited in the calorimeter cells was used to perform the reconstruction
  - classical methods divide the energy cell space in several bins
  - the neural network uses the cell information or sum of cells without binning
- The H1 method minimizes the following function: $\varepsilon^2 = \frac{1}{N}\sum_{i=1}^{N}(Erec_i - Ebeam)^2 + \lambda\frac{1}{N}\sum_{i=1}^{N}(Erec_i - Ebeam)$

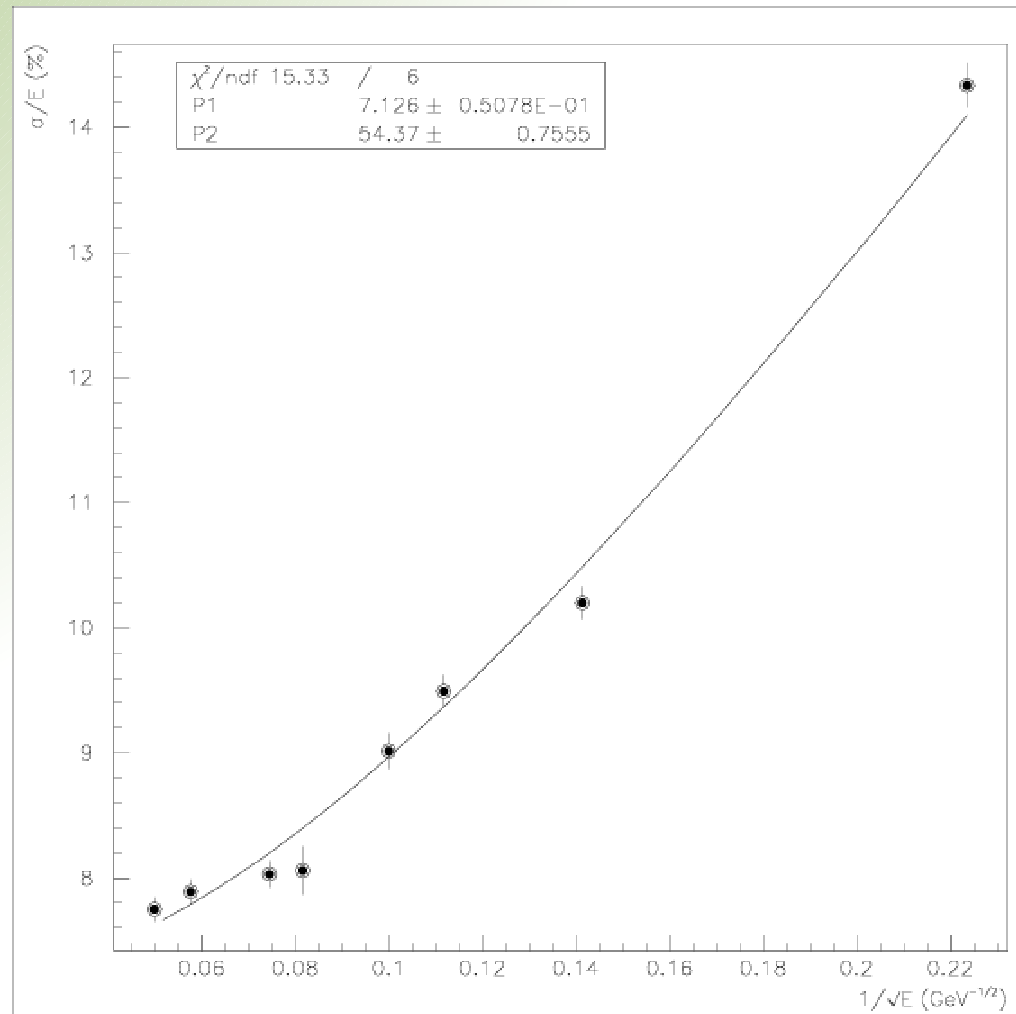
$$Erec_i = \sum_{j=1}^{13} w_j \times Ecell_{ij} + b \times Eold$$

Results

- Two main measurements are used to determine the energy reconstruction quality
  - non-linearity and energy resolution (σ/μ)
- No corrections (raw data)
  - noise cuts are applied to all cells
  - non-linearity -> 2.2 %
  - energy resolution -> $\frac{\sigma}{\mu} = \frac{(54.4 \pm 0.8)\%}{\sqrt{E}} + (7.13 \pm 0.05)\% + \frac{6}{E}$

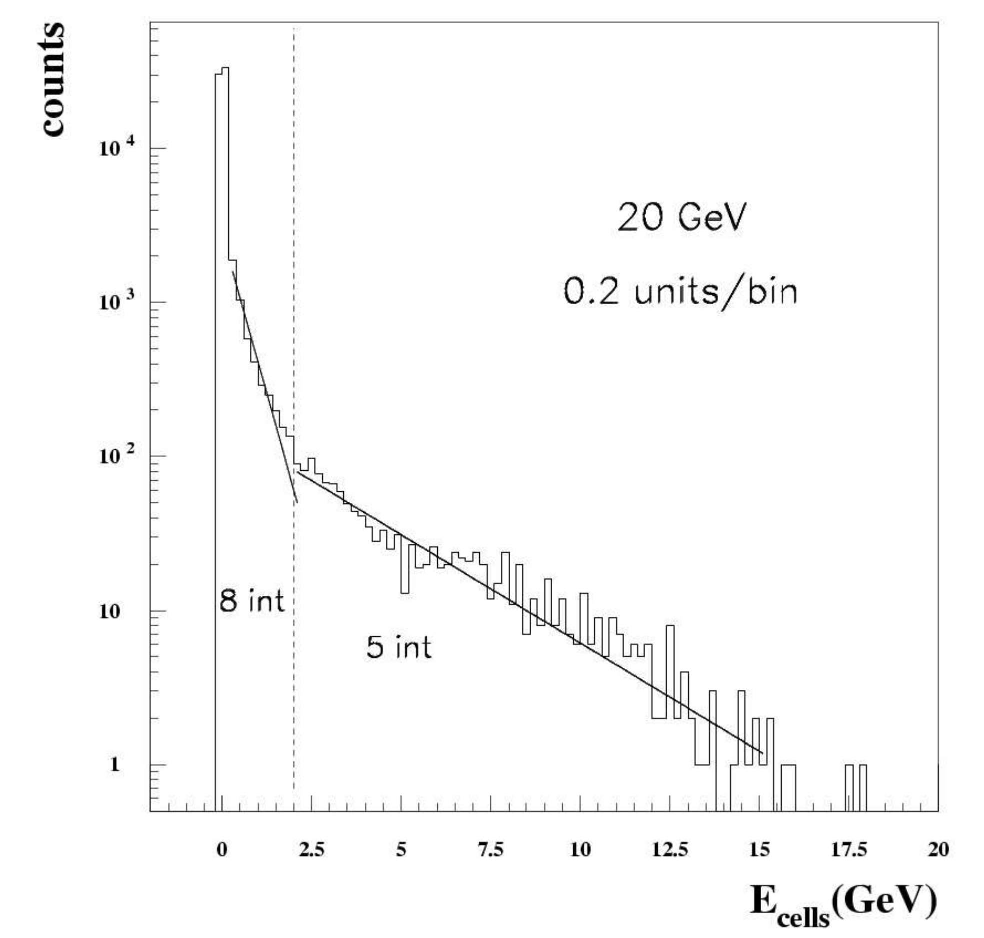

1.1
1.075
1.05
1.025
1
0.975
0.95
0.925
0.9
EMQ = 2.22228%
10^2
E_Beam (GeV)

Raw data


χ²/ndf 15.33 / 6
P1 7.126 ± 0.5078E-01
P2 54.37 ± 0.7555
σ/E (%)
14
13
12
11
10
9
8
0.06
0.08
0.1
0.12
0.14
0.16
0.18
0.2
0.22
1/√E (GeV^-1/2)

Results (H1 method)

- All cell's energies are plotted in one histogram
  - divided into bins -> 13
- Minimization is performed for each energy using the formula shown before

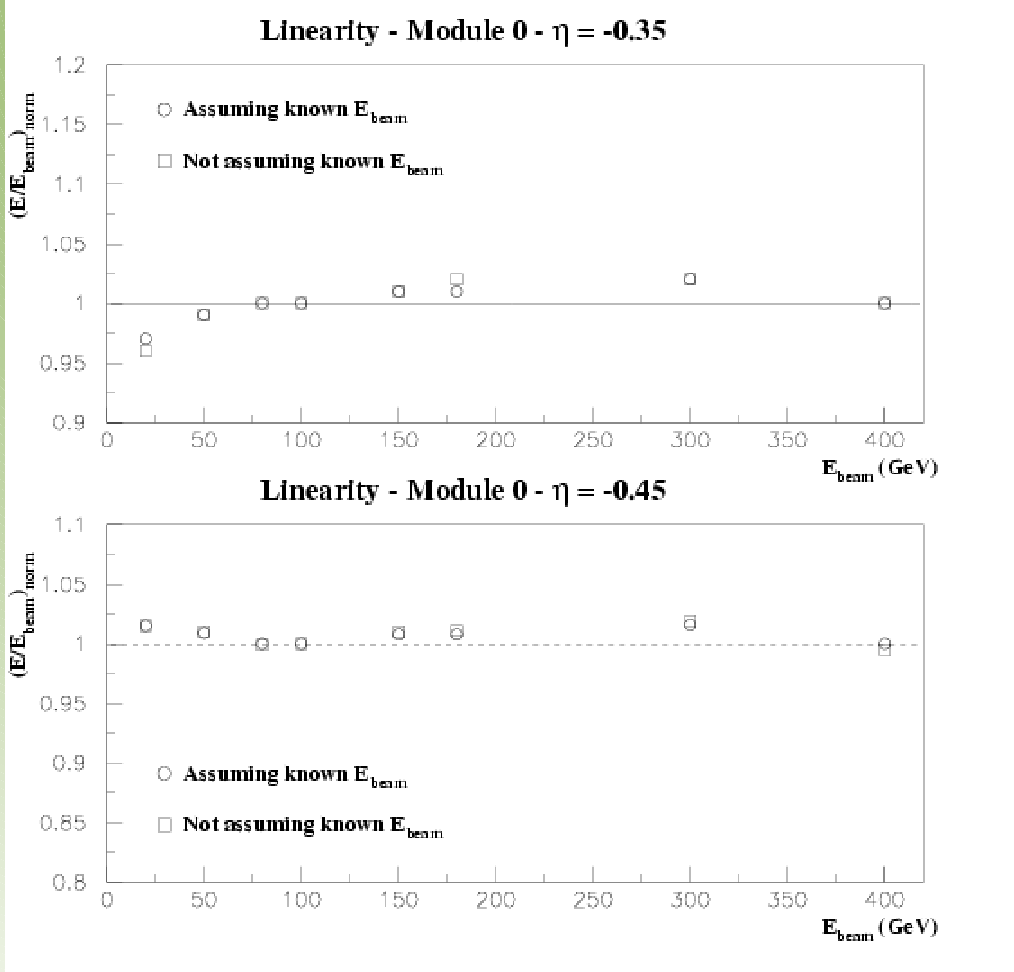


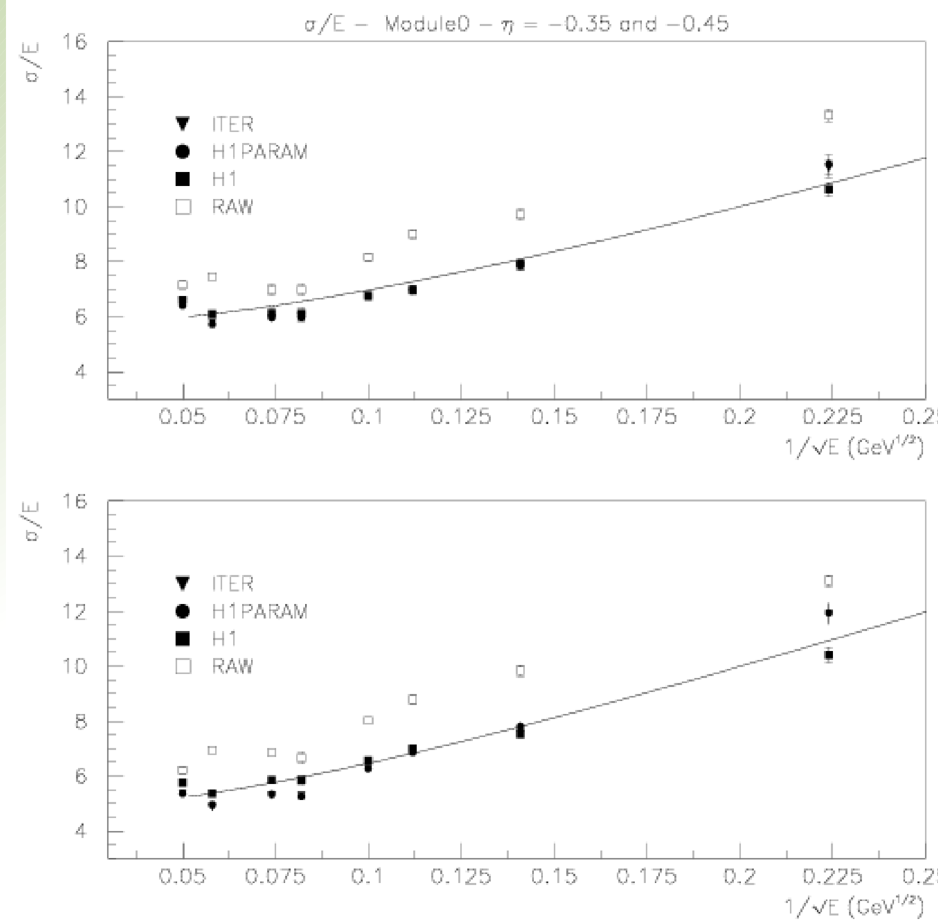
Results (H1 method)

- Weights are parametrized with respect to the cell bins
- The results are parametrized again with respect to the beam energy
- During operation beam energy is not known *a priori* - iterations needed to converge
- Non-linearity -> 1.3 %
- Energy resolution -> $\frac{\sigma}{\mu} = \frac{(40.8 \pm 1.2)\%}{\sqrt{E}} + (5.30 \pm 0.08)\% + \frac{6}{E}$

H1 method

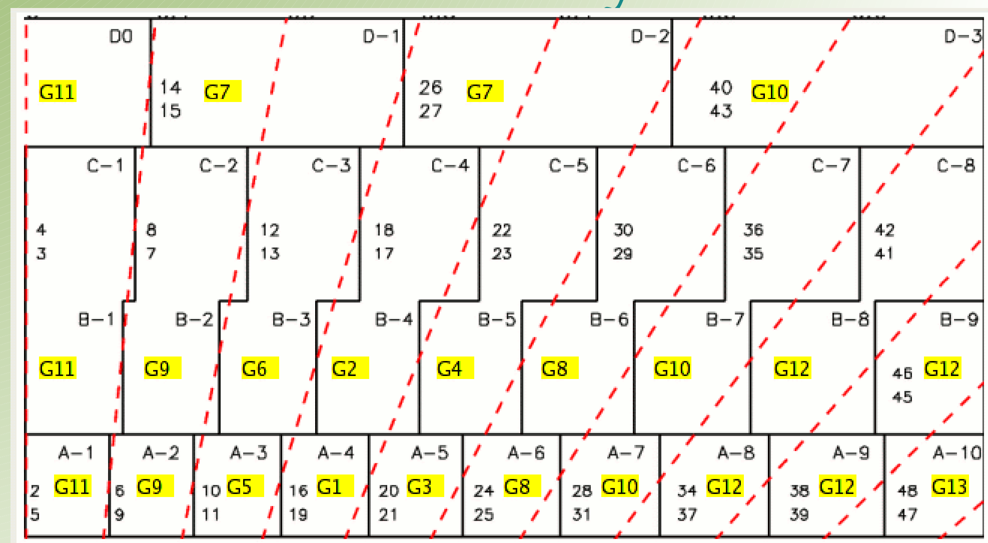
done by Santiago Gonzalez





Results (neural network)

- Input data were normalized by a constant multiplier



- Neural network desired output:

$$d_{nn}(i,n)=\left[\frac{\varepsilon_{sum}(i,n)}{\varepsilon_{mean}(i)}-1\right]\times\alpha(i)\times\varepsilon_{beam}(i)+\varepsilon_{beam}(i)$$

$$\varepsilon_{sum}(i,n)=\sum_{k=1}^{Ninputs}\varepsilon_{input}(i,n,k)$$

$$\varepsilon_{mean}(i)=\frac{1}{Nevents}\sum_{n=1}^{Nevents}\varepsilon_{sum}(i,n)$$

$$\mu_{nn}(i)=\frac{1}{Nevents}\sum_{n=1}^{Nevents}d_{nn}(i,n)=\varepsilon_{beam}(i)$$

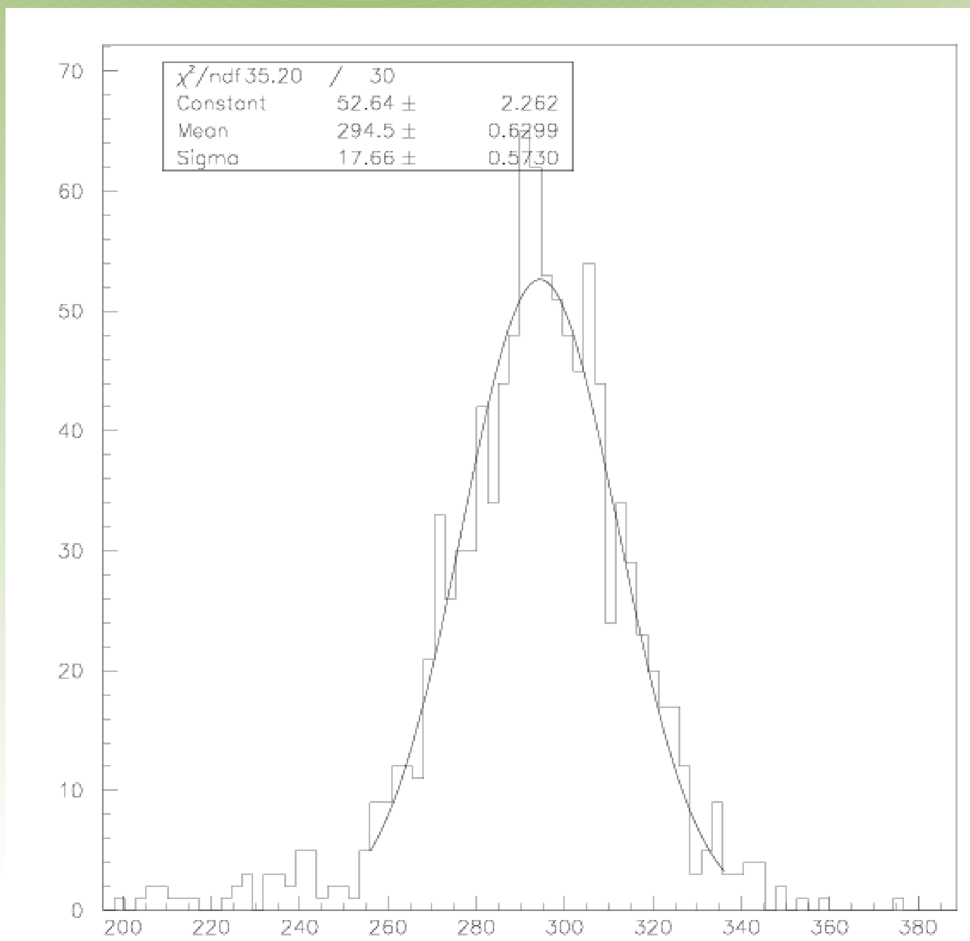
$$\frac{\sigma_{nn}(i)}{\mu_{nn}(i)}=\alpha(i)\times\frac{\sigma_{raw}(i)}{\mu_{raw}(i)}$$

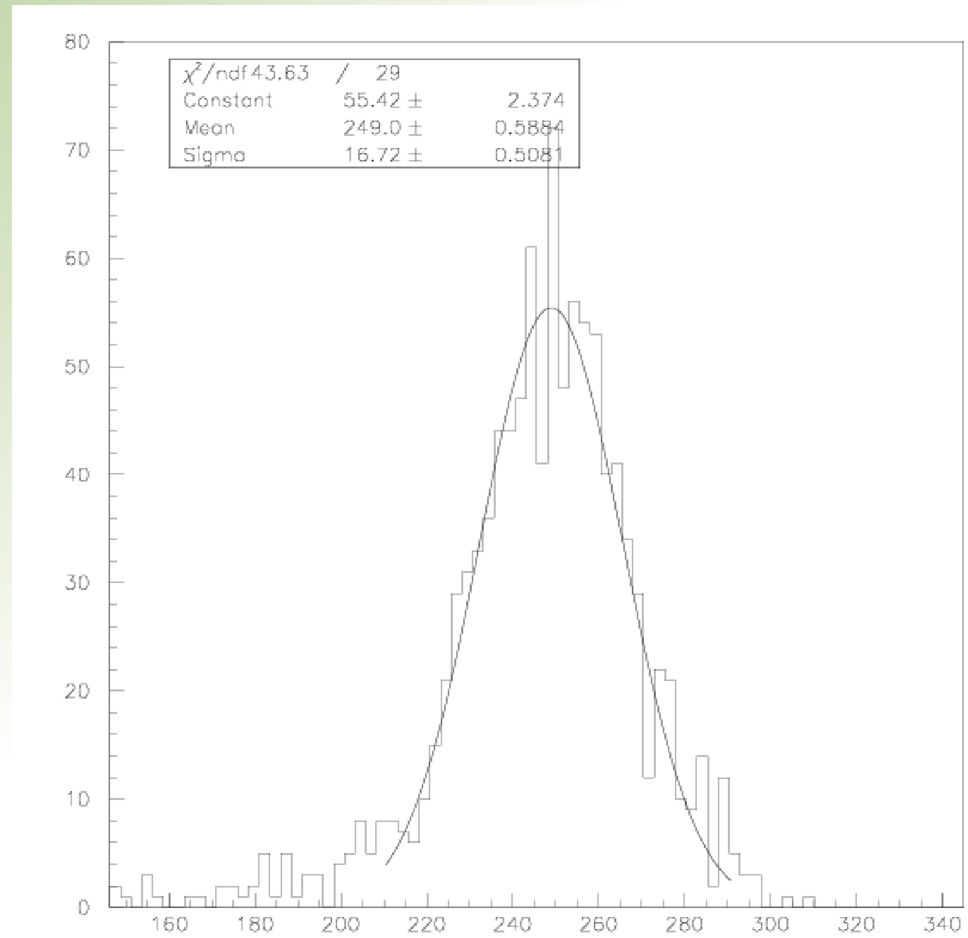
Results (neural network)

- Feedforward network: two hidden layers (14-7)
  - better results for the lower energy range
- Standard backpropagation learning was used
- Non-linearities of 0.42% and 0.75% were achieved for the training and test set, respectively
- Energy resolution for the training set:

$$\frac{\sigma}{\mu} = \frac{(47.7 \pm 1.4)\%}{\sqrt{E}} + (4.74 \pm 0.14)\% + \frac{6}{E}$$

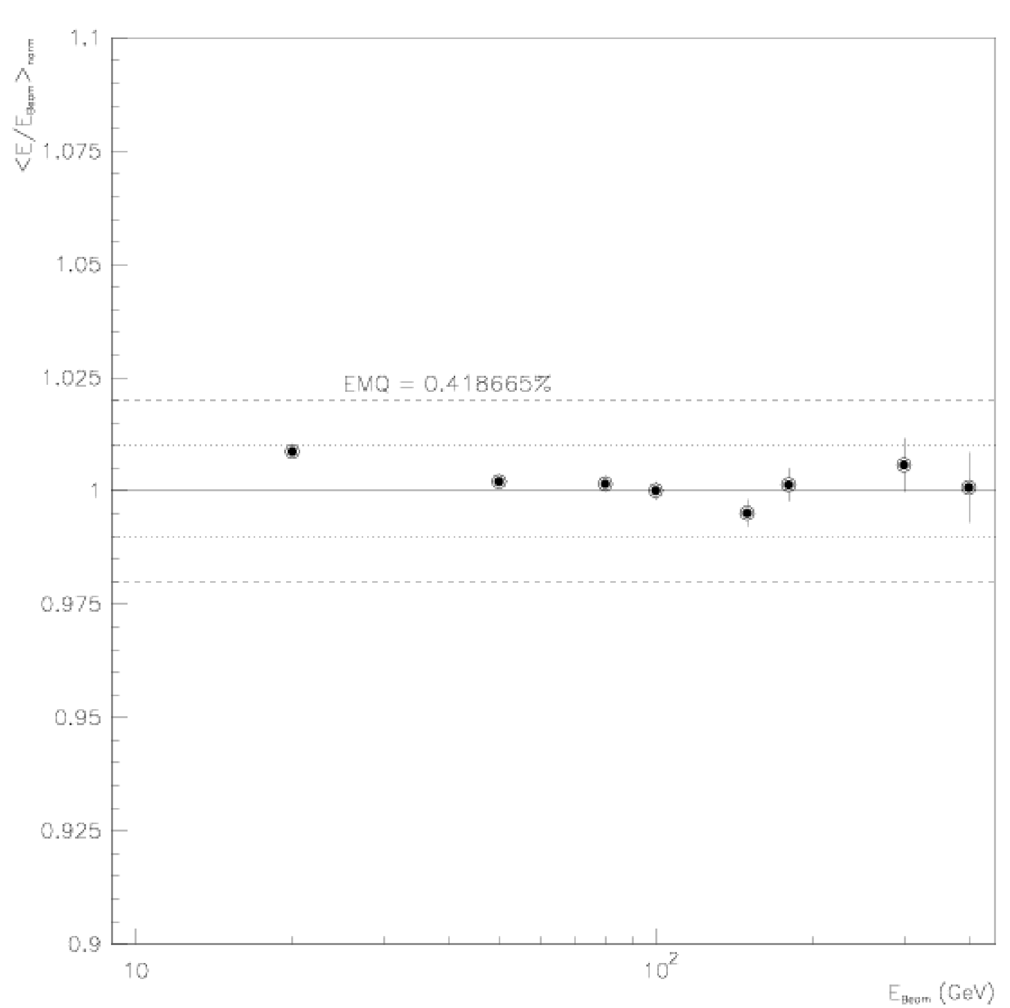
Results (neural network)



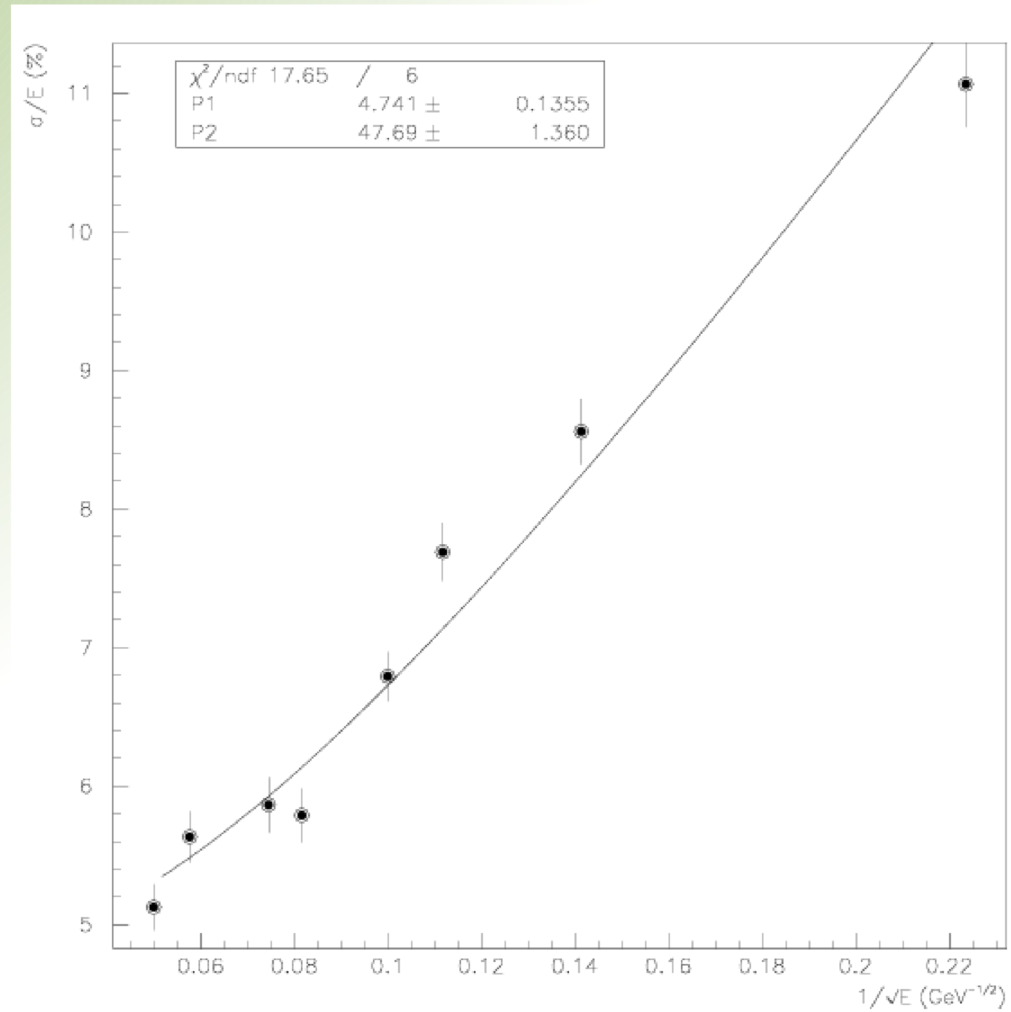


$$NNoutput\,,\quad \frac{\sigma}{\mu} = 6.0\,\%$$

$$Raw\ data\,,\quad \frac{\sigma}{\mu} = 6.7\,\%$$



Neural Network



Conclusions

- A neural network was applied to reconstruct the energy scale of hadrons for the Tilecal calorimeter
  - improve both linearity and energy resolution
- Recovery from non-linearity is considerable

	Non-linearity (%)
Raw	2.2
H1	1.3
Neural Net.	0.42

Conclusions

- Energy resolution :

	a%	*b%*
Raw	54.4 ± 0.08	7.13 ± 0.05
H1	40.8 ± 1.2	5.30 ± 0.08
Neural Net.	47.7 ± 1.4	4.74 ± 0.14

- Neural network - no need for energy estimation or iterations
- Other η points are under investigation