SDHCAL Energy Resolution Studies Using the Neural Network Method

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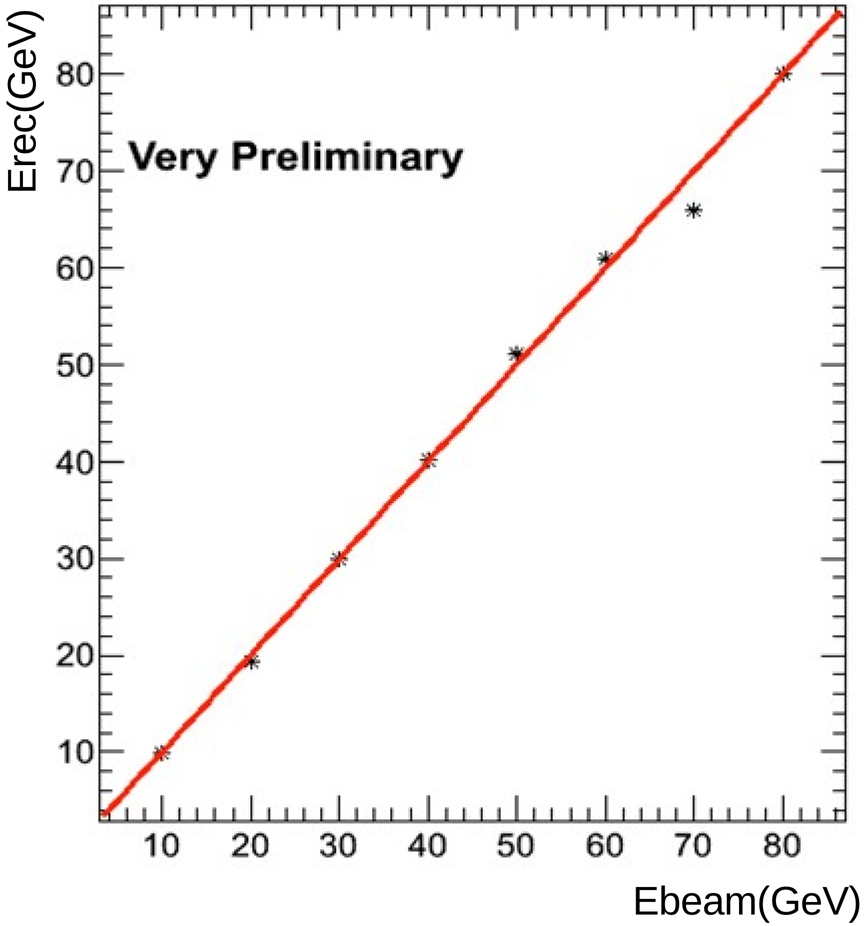
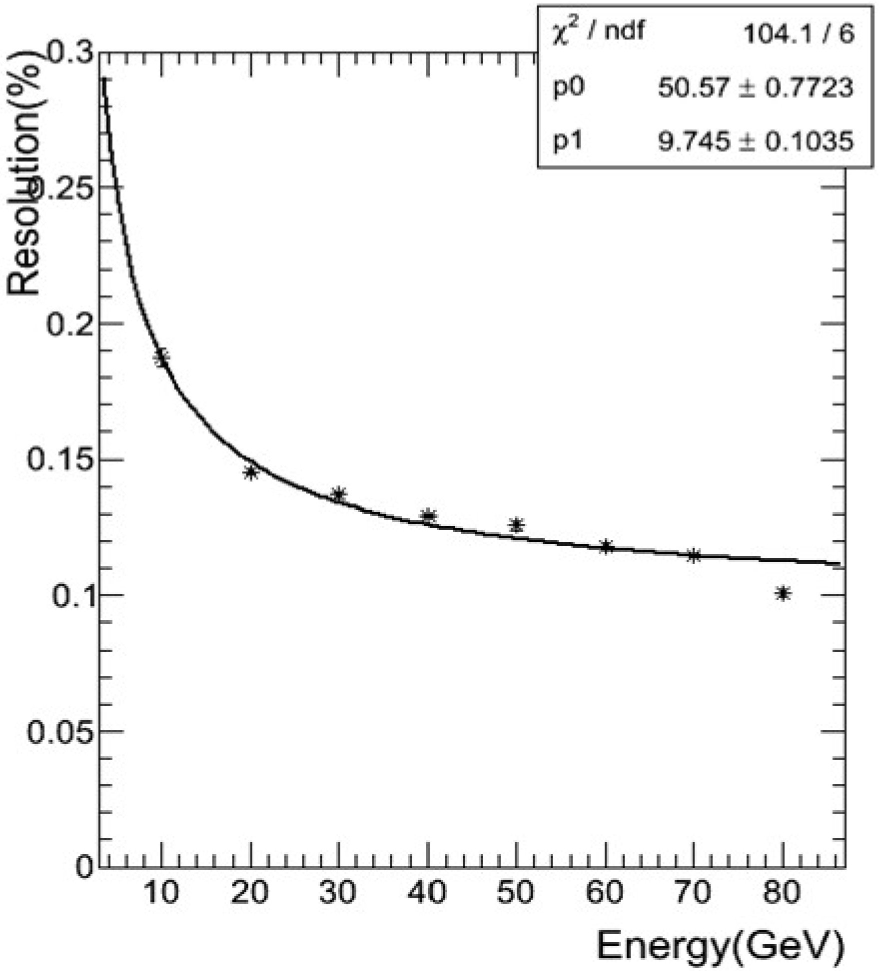
September 2013, Annecy

Counting Method





SPS test beam data from November (plot from March)

Neural Net for Test Beam Data

Motivation: To improve the energy resolution reconstructed from the test beam data.
The Neural Network allows to exploit the topological and structural (EM vs Hadronic part) aspects that were not account for in the counting method.
Also it will allow to exploit the correlation among the different variables to better estimate the energy of the hadronic showers

Use: MLP Neural Network implemented to ROOT (Toolkit for Multivariate Data Analysis TMVA 4.0.3)

Input: Aug-September SPS test beam data for training (5-80 GeV), step=5-10 GeV, 4000 events for each energy point

Output: November data to check a final energy resolution

Details: 3000 training cycles, 1 hidden layer, 10 input variables, 15 nodes, target = beam energy

Input Variables:

- Number of hits for 3 thresholds and hough transform hits
- Maximum radius of hadronic shower
- Shower starting layer
- Reconstructed energy with parameters from the counting method:

Erec=N1(a1+a2Ntot+a3NtotNtot)+N2(b1+b2Ntot+b3NtotNtot)+N3(c1+c2Ntot+c3NtotNtot)

Data Samples

Data collected during August-September (H6) and November (H2) pion test beam runs

E= 80 GeV: 715756, 716282, 716319, 716280

E= 70 GeV: 715493, 715754, 716290

E= 60 GeV: 715511, 715531, 715753, 716296, 716297, 716298

E= 50 GeV: 715751, 715551, 716299, 716303, 716305

E= 40 GeV: 715651, 715748, 716307

E= 30 GeV: 715671, 715747, 716264, 716308

E= 25 GeV: 715700, 715703

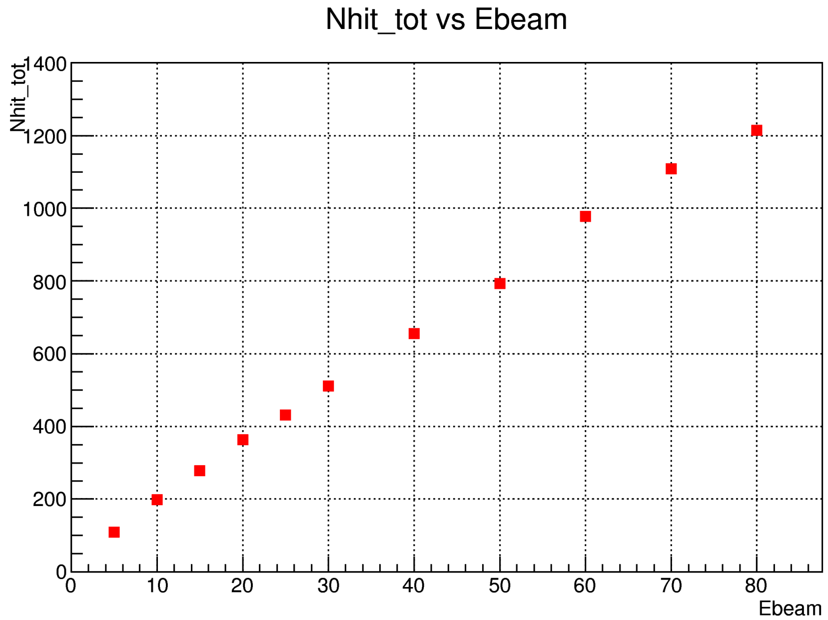
E= 20 GeV: 715675, 716310, 716312, 716313, 716315

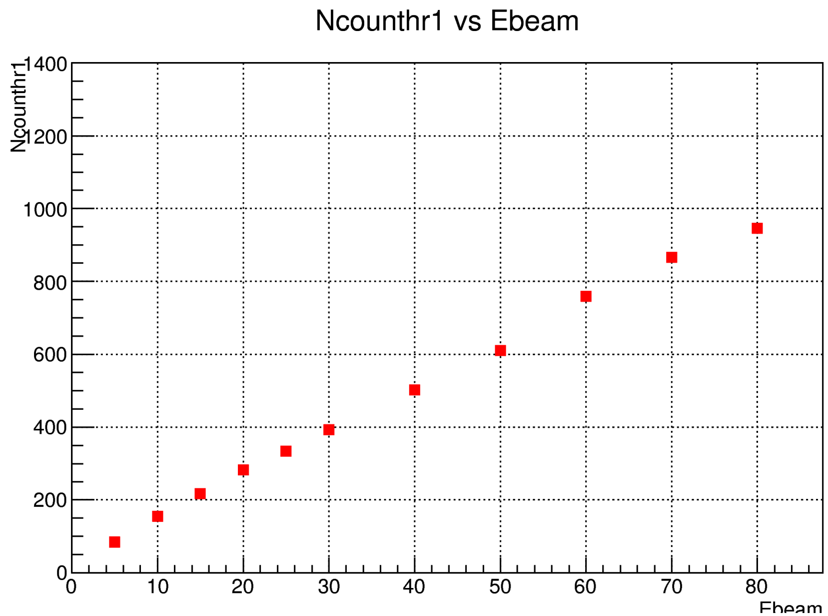
E= 15 GeV: 715699

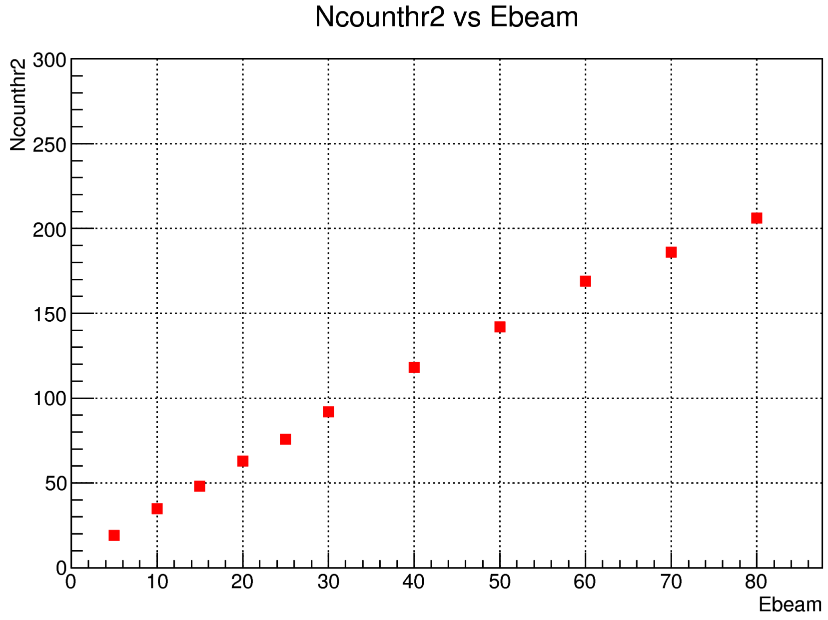
E= 10 GeV: 715692, 715693, 716321

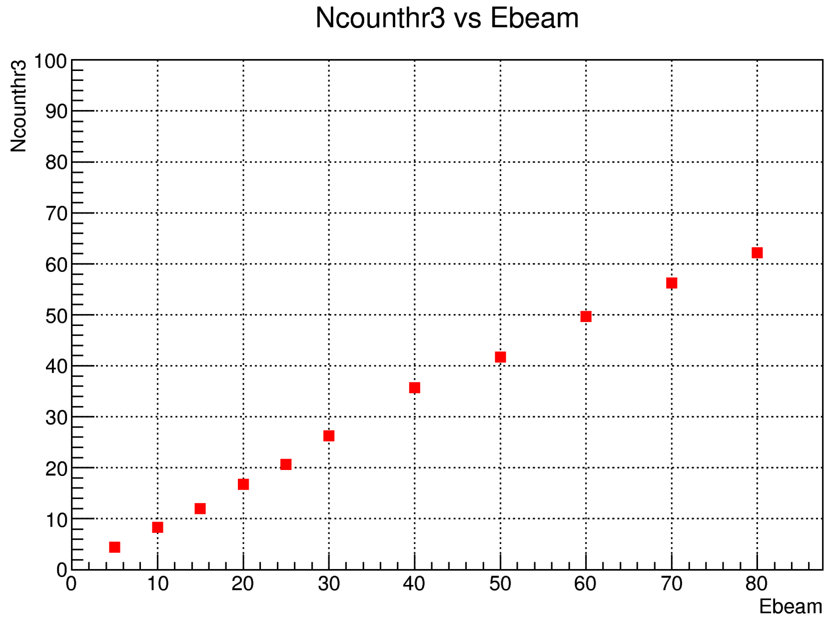
E= 5 GeV: 715694, 715698

Input Variables Nhits

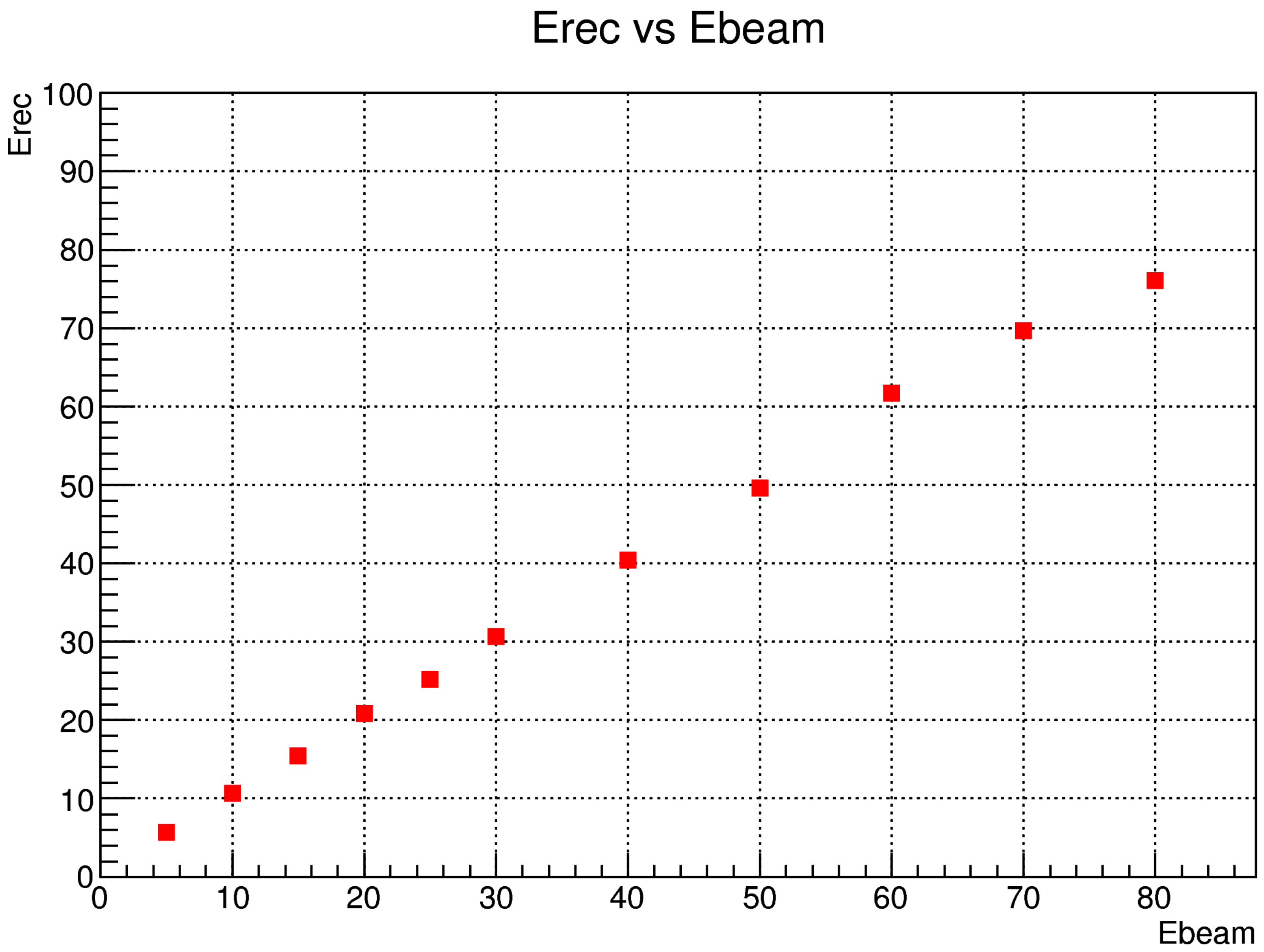






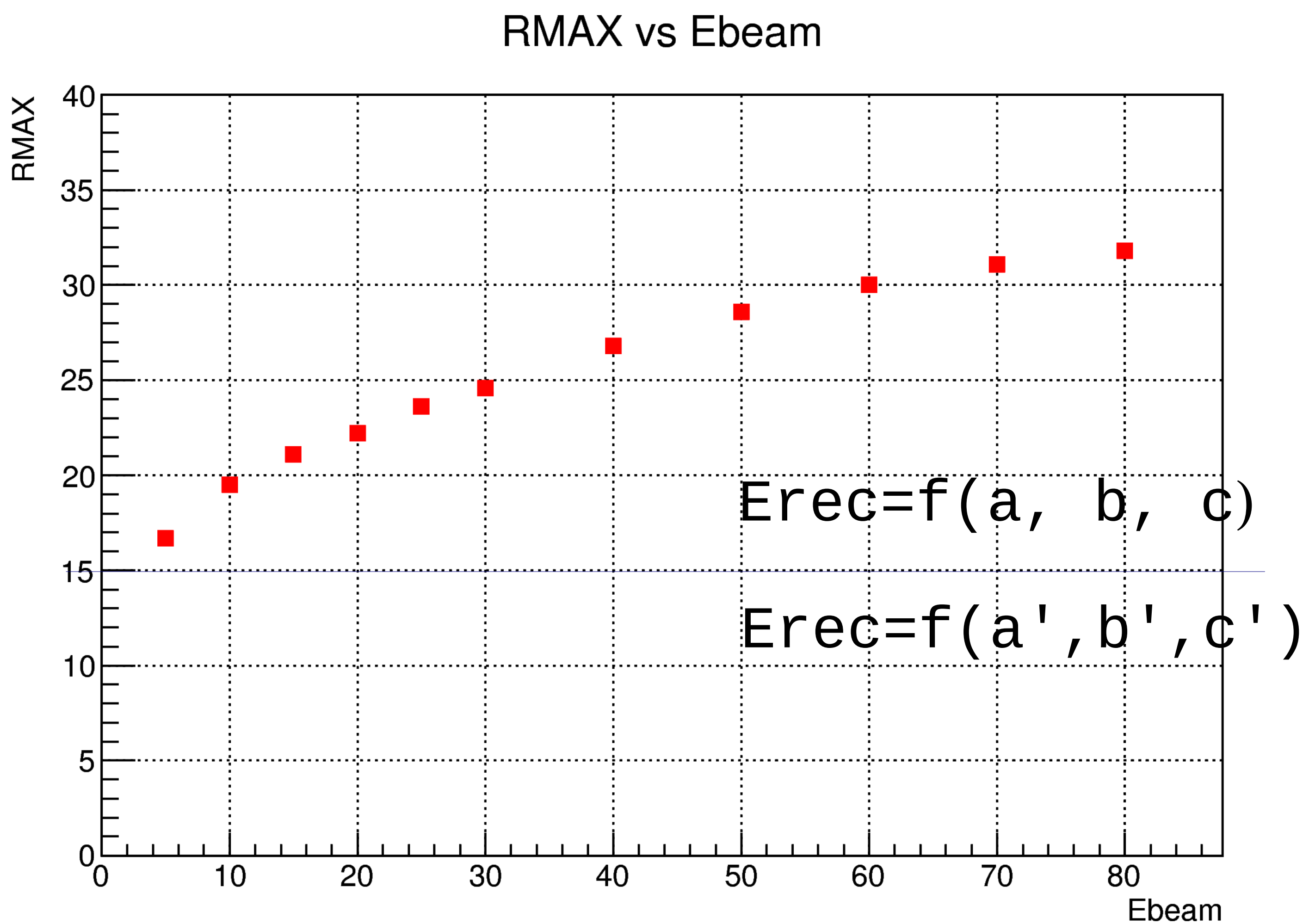


Input Variable Erec



Erec=N1(a1+a2Ntot+a3NtotNtot)+N2(b1+b2Ntot+b3NtotNtot)+N3(c1+c2Ntot+c3NtotNtot)

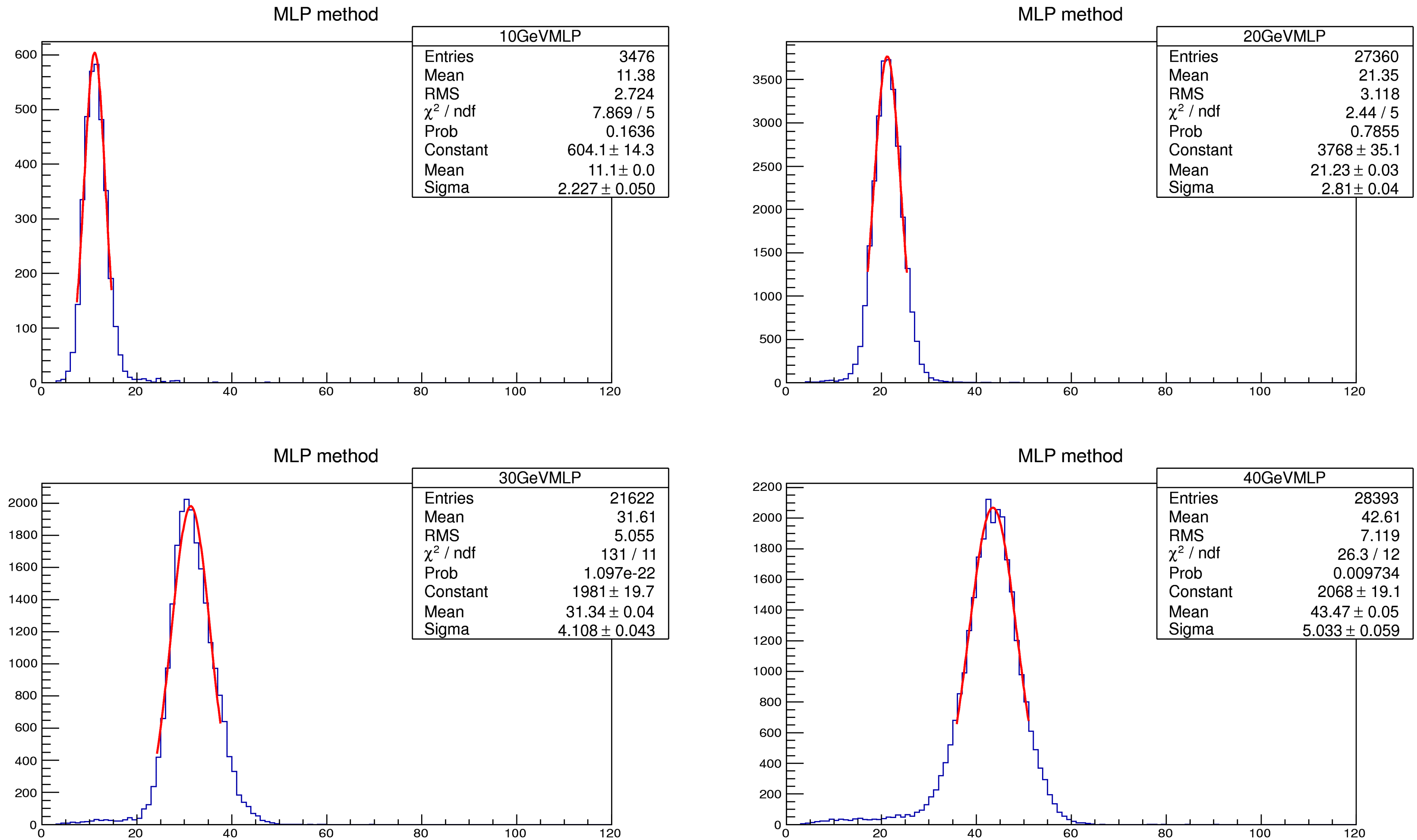
Input Variable Rmax



Rmax – maximum radius of the hadronic shower

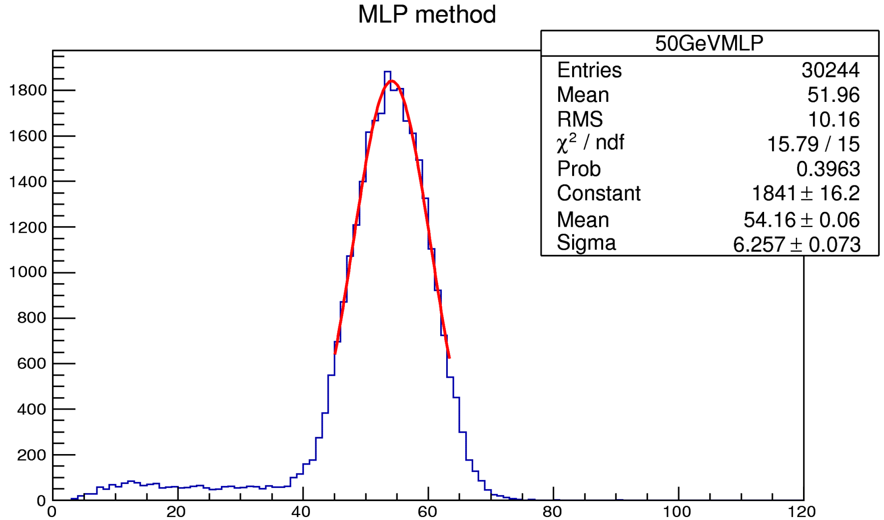
Erec=N1(a1+a2Ntot+a3NtotNtot)+N2(b1+b2Ntot+b3NtotNtot)+N3(c1+c2Ntot+c3NtotNtot)

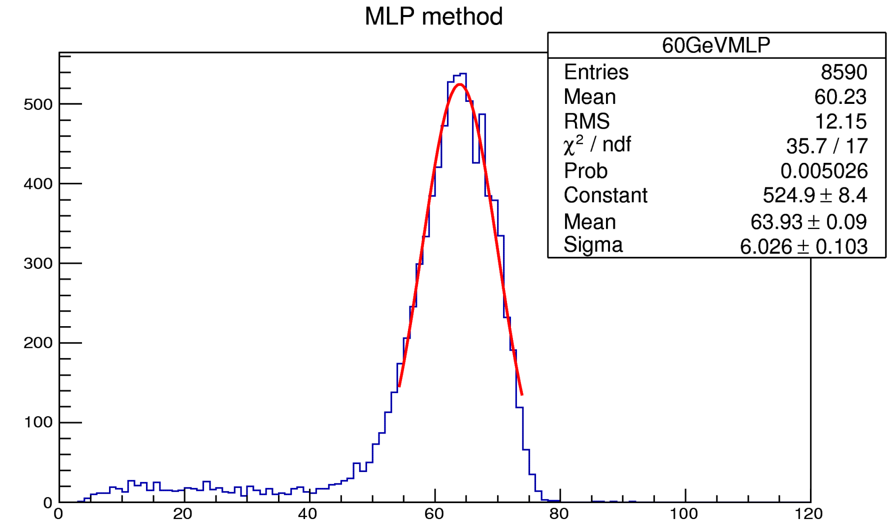
Control Plots, 10-40 GeV

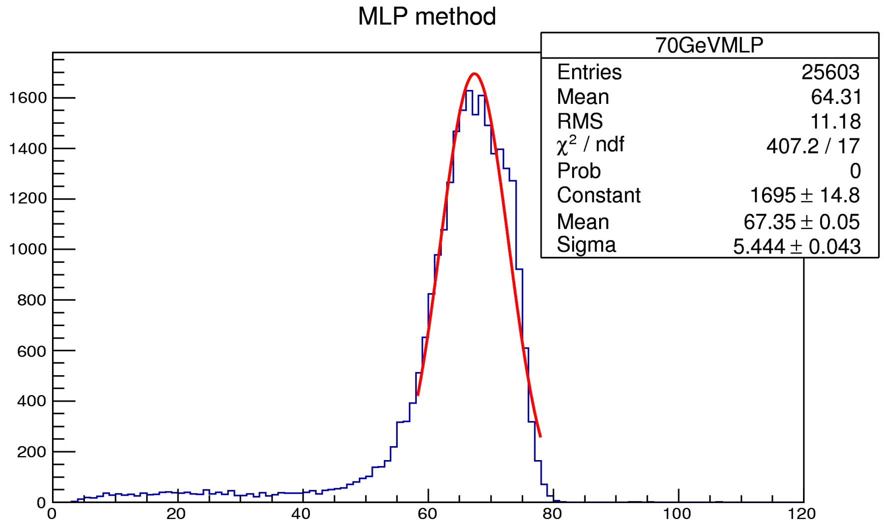


1.5 sigma fit

Control Plots, 50-70 GeV







Reasonable shapes of the reconstructed energy compare to the counting method

Results, 10-70 GeV

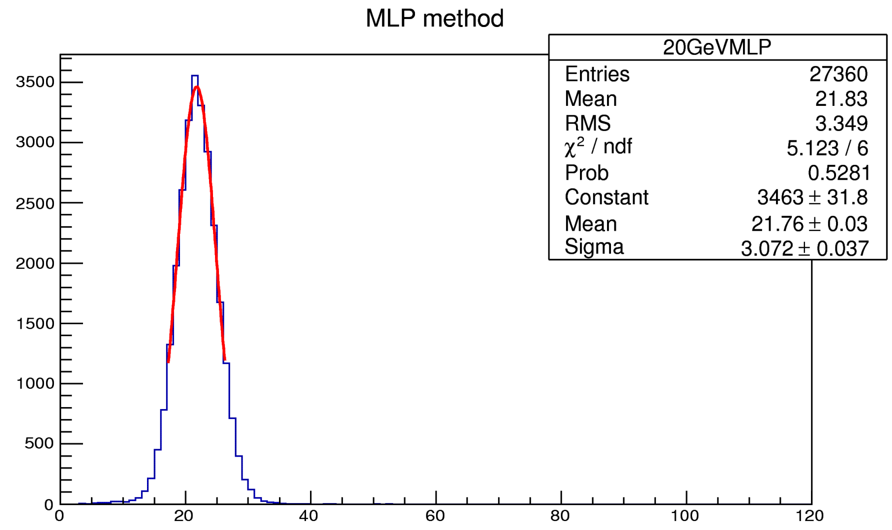
Counting		Neural Net	
Energy, GeV	Resolution %	Energy, GeV	Resolution %
10.3	18.9	11.1	20.0
19.6	14.4	21.2	13.2
30.0	13.4	31.3	13.1
40.1	12.6	43.4	11.6
50.8	12.2	54.1	11.5
60.6	11.2	63.9	9.4
65.3	10.8	67.3	8.1

Test beam data from November

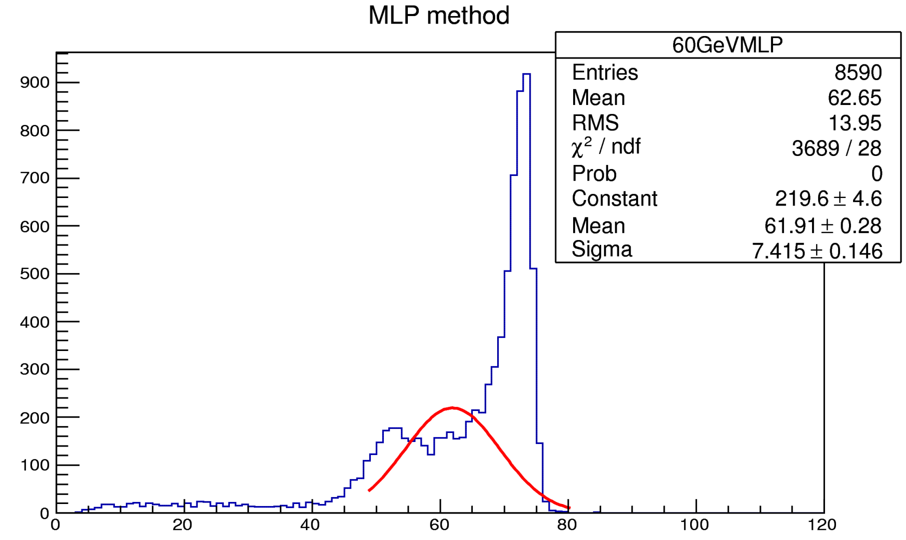
Exclusion Test

Idea: exclude some energy points for training. Apply this energy points for final check of the resolution

E = 20 GeV is excluded, E = 15 and 25 GeV are used, step=10 GeV



E = 60 GeV is excluded, E = 50 and 70 GeV are used, step=20 GeV



Step of E=20 GeV is too big for the current procedure

Neural Net for MC

Simulation:

- Geant4 version 9.6.p01
- FTFP_BERT_HP physic list
- TMVA 4.0.3, 1-90 GeV with 1 GeV step, 5000 events per energy point
- Only Nhits for training

Digitizer:

- Geant4 gives info on the deposited energy => need a Polya function to simulate the induced charge in RPC
- Charge spreading:
    - integration of f_3 over the pads area

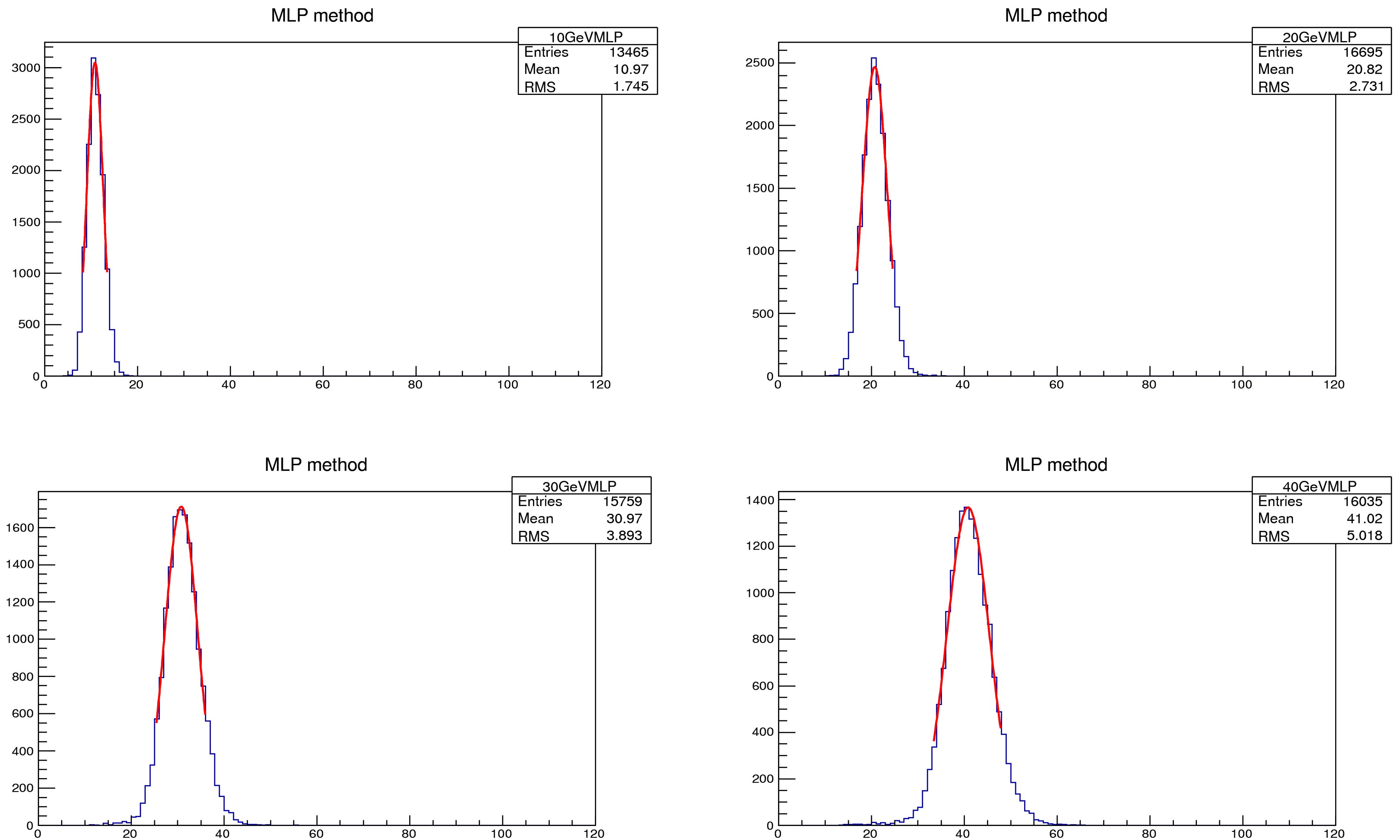
$$f_3(x,y)=\sum_{i=1}^{3}\alpha_i e^{\frac{(x_0-x)^2+(y_0-y)^2}{\sigma_i^2}}$$

$\alpha_1=1$, $\alpha_2=0.00065$, $\alpha_3=0.000057$
$\sigma_1=1$, $\sigma_2=9.5$, $\sigma_3=100$

- Thresholds: 0.114, 5.0, 10.0 *pC*

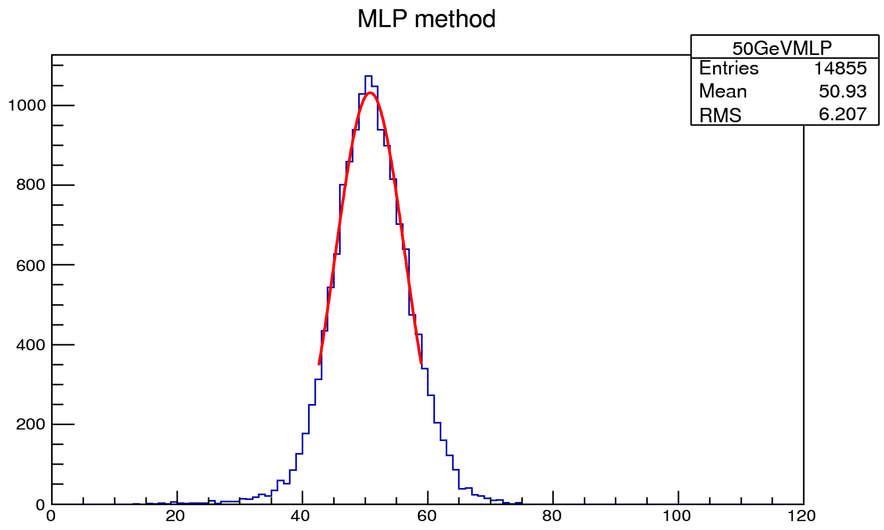
Details in the talk of Arnaud Steen

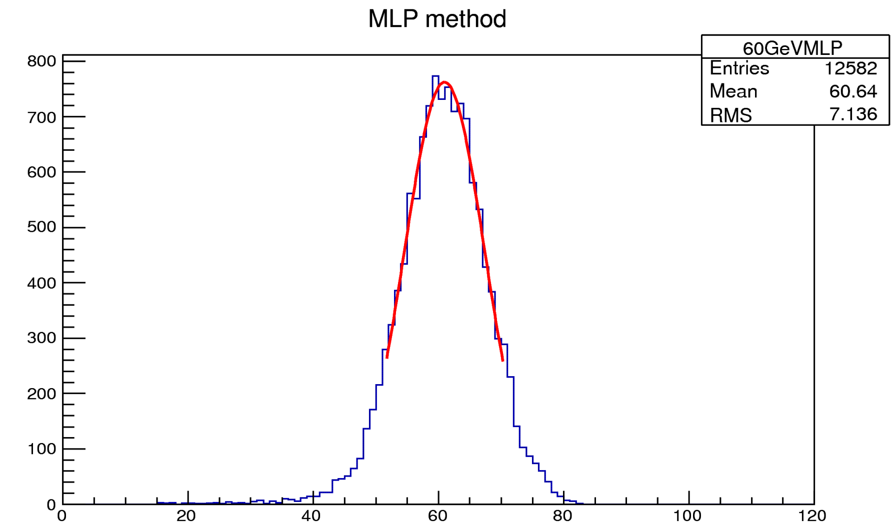
Control Plots, 10-40 GeV, MC

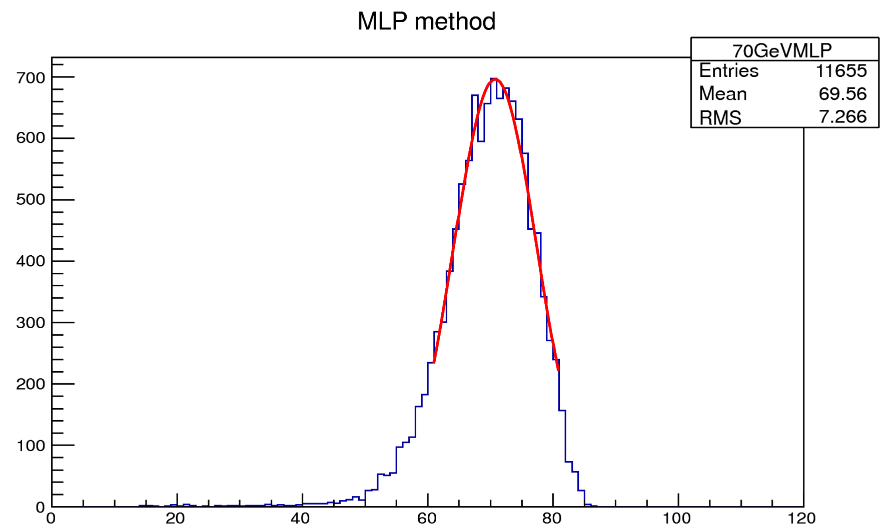


1.5 sigma fit

Control Plots, 50-70 GeV, MC





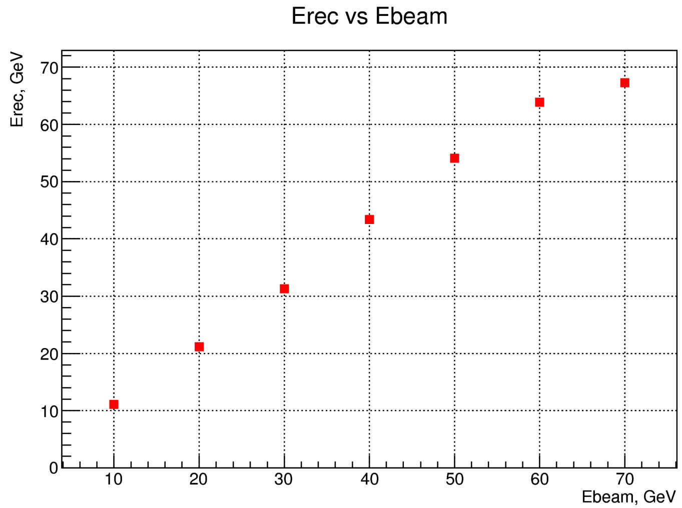


Energy shapes in MC are comparable to the data

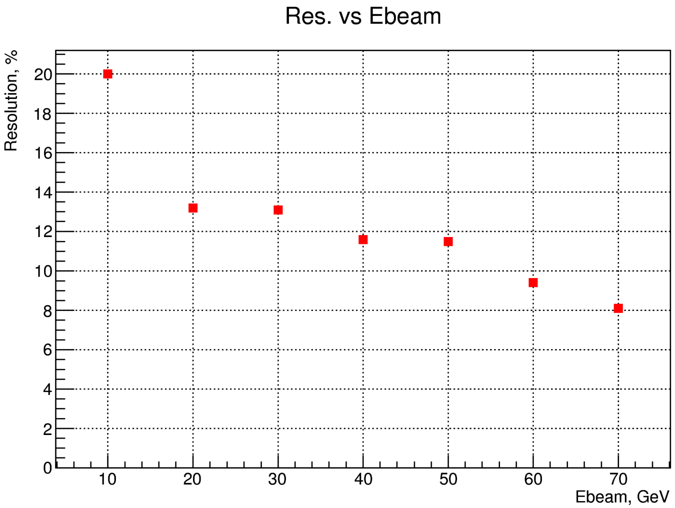
Results, 10-70 GeV

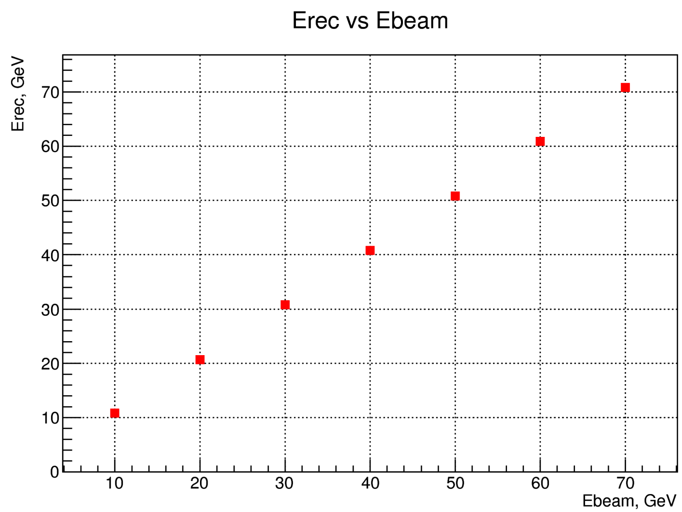
TB data		MC	
Energy, GeV	Resolution %	Energy, GeV	Resolution %
11.1	20.0	10.8	17.5
21.2	13.2	20.7	13.3
31.3	13.1	30.8	11.8
43.4	11.6	40.8	11.4
54.1	11.5	50.8	11.1
63.9	9.4	60.9	10.5
67.3	8.1	70.8	9.5

November data and MC

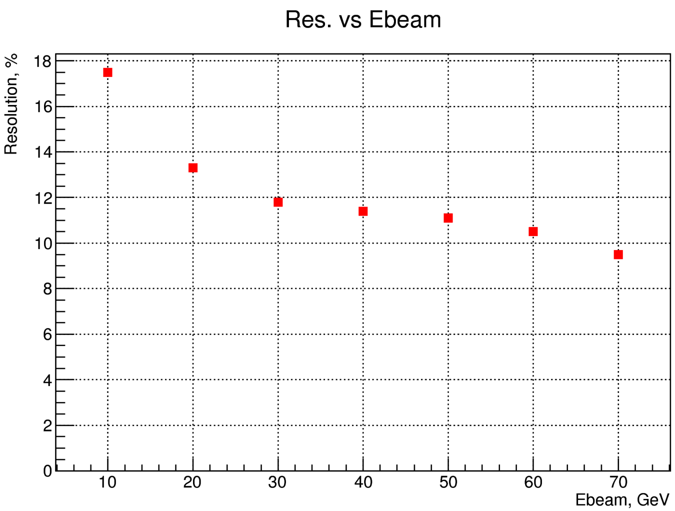


data





MC



- Admissible linearity until 70 GeV in data, good in MC
- Some plateau in resolution is observed at medium energies (leakage is possible)

Conclusions

- Applying the Neural Network method to data allows us to improve the SDHCAL energy resolution by ~10% in the studied energy range
- We should use the energy step smaller than 10 GeV for training of the Neural Network
- Two independent analysis for data and MC show a reasonable shape of energy distributions and comparable in resolution
- This is not a final result, it is a work in progress ...

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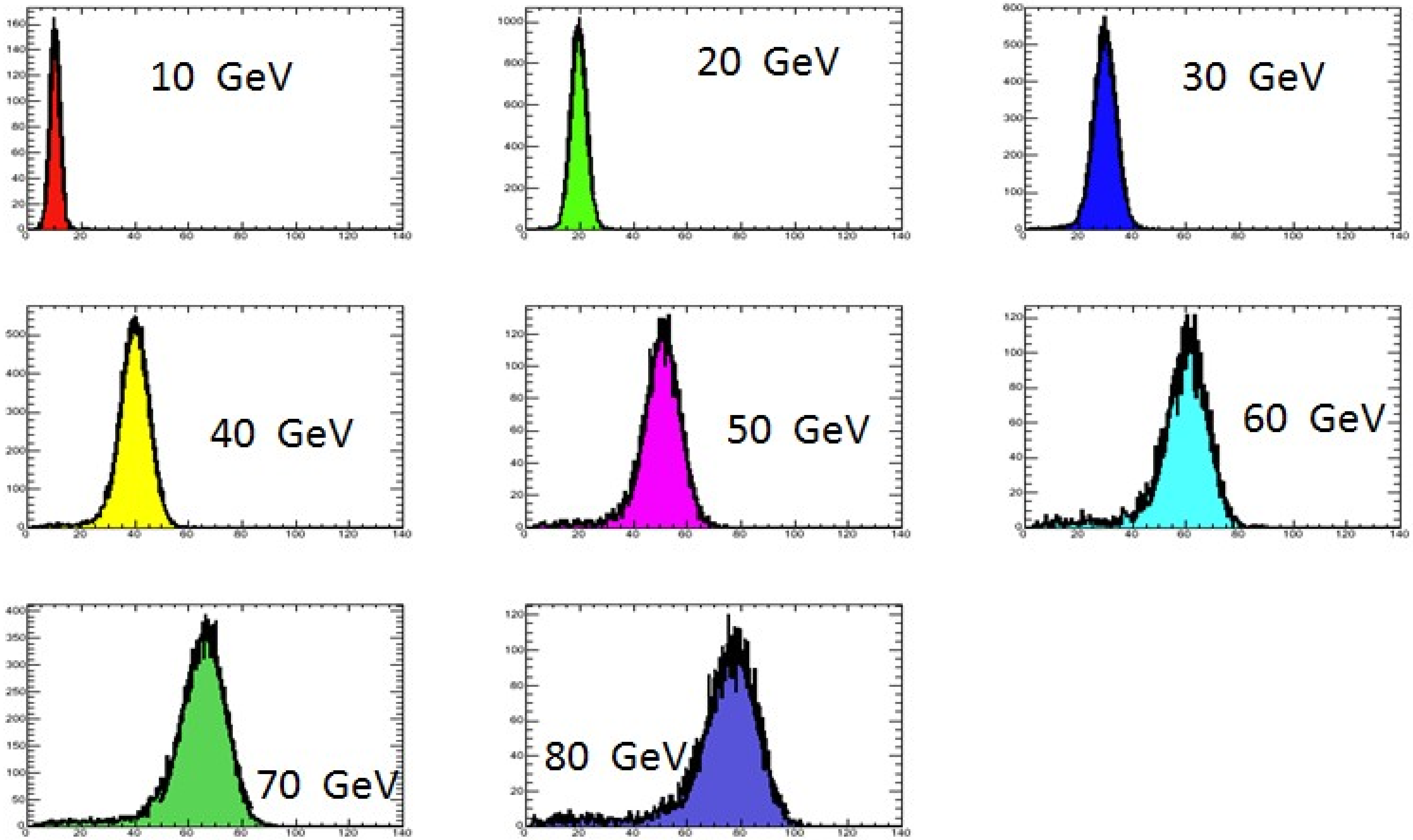
Counting Method



November data, plot from March