Neural network technique for energy resolution study in SDHCAL

HGC4ILD - High Granularity Calorimeters for ILD - Paris

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Outline

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   - ANN Results
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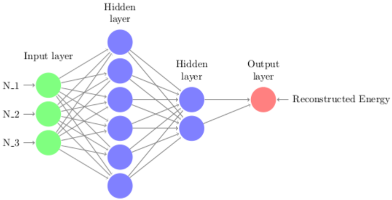
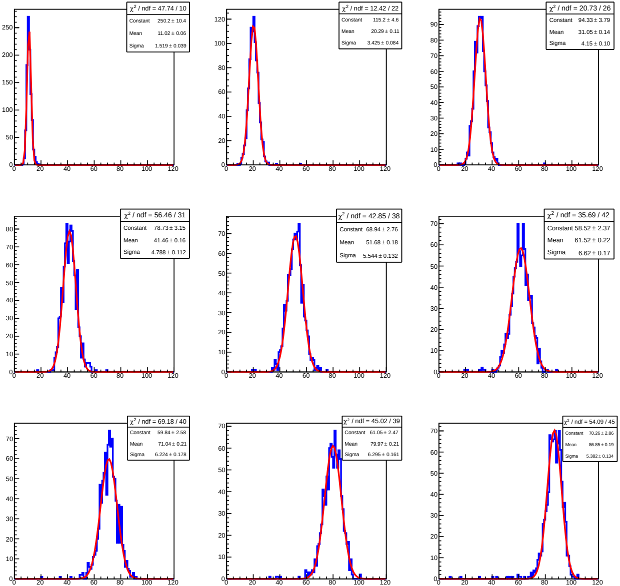
   - ANN results comparison with Quadratic parametrisation
3. Conclusion

ANN Architecture and Energy samples

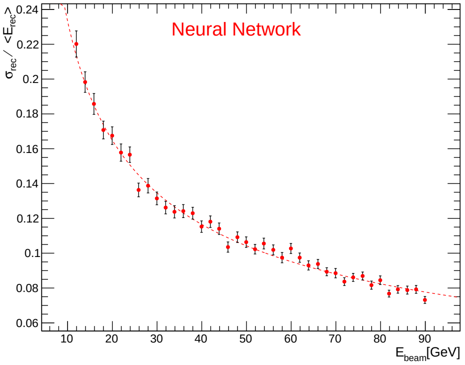
- TMultiLayerPerceptron of root package.
- 2 hidden layers with respictively 6 and 2 neurons.
- The input variables: $\mathrm{N_1}$,$\mathrm{N_2}$,$\mathrm{N_3}$.
- The output variable is the reconstructed energy: $\mathrm{E_{rec}}$.
- Monte Carlo Simulation
    - Training Samples: Odd energies, 1-99 GeV (50 points of energy)
    - Test Samples: Even energies, 10-90 GeV (40 points of energy)

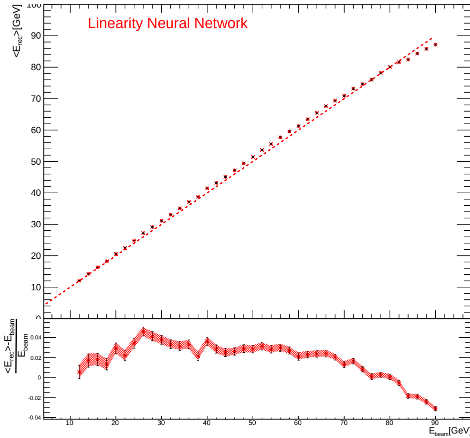


ANN Results: Energy estimation from ANN

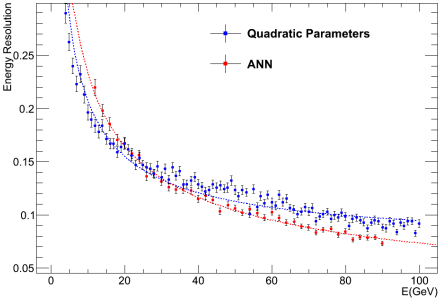


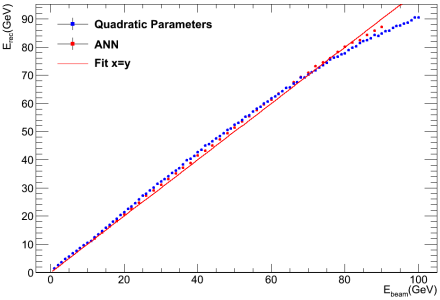
ANN Results: Energy resolution and linearity





ANN results comparison with Quadratic parametrisation





Data Samples and Event selection

- Test Beam data SPS H6 December 2014
- Pions, energies: 10,20,25,30,35,40,45,50,55,60,65,70,75,80GeV
- Pions Data contaminated: Event selection
  - Shower Start:
  - The center of gravity of the shower along X Y and Z axis

$$X_{cog} = \frac{1}{N}\sum_{i}^{N} X_i \qquad Y_{cog} = \frac{1}{N}\sum_{i}^{N} Y_i \qquad Z_{cog} = \frac{1}{N}\sum_{i}^{N} Z_i$$

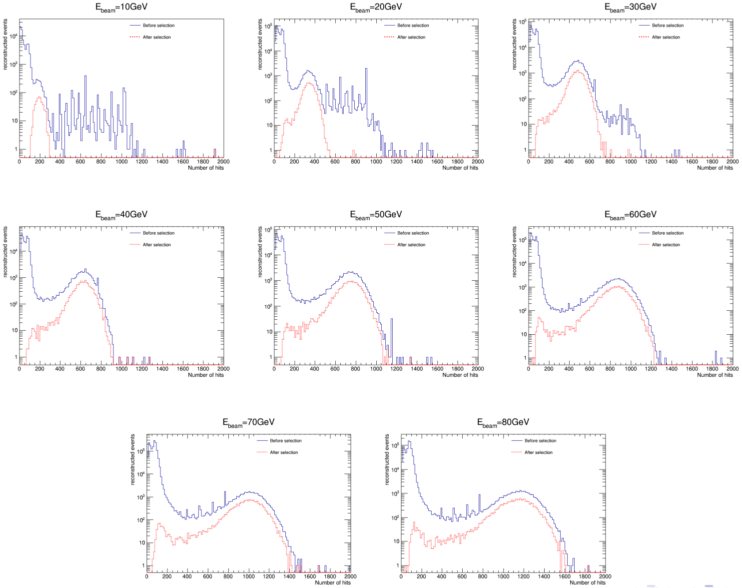
  - Mean shower radius

$$\overline{R} = \frac{1}{N}\sum_{i}^{N} R_i \qquad R_i = \sqrt{(X_i - X_{cog})^2 + (Y_i - Y_{cog})^2}$$

Event Selection

Electrons and Muons Rejection	Shower Start≥ 3, $\overline{R} \geq 4cm$, $Z_{cog} \geq 50cm$
Double incident particles	distance between hits in each of the first 5 layers $\leq 5cm$
Neutral Rejection	N_{Hits} in the first 5 layers ≥ 5
Leakage reduction	Shower Start≤ 30

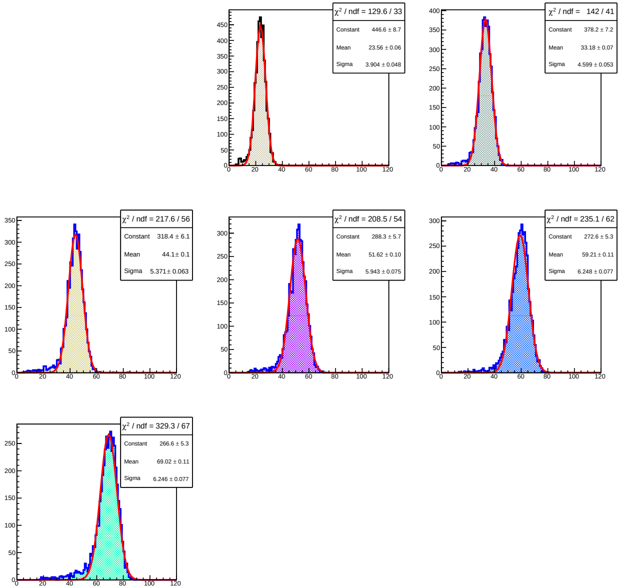
Distribution of hit Numbers



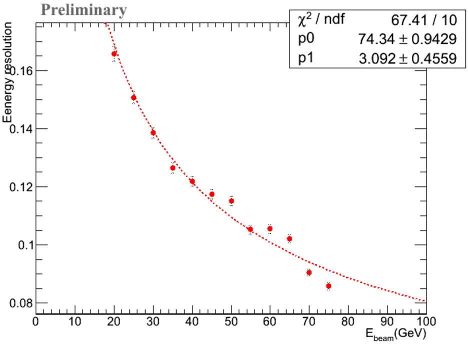
Data Samples

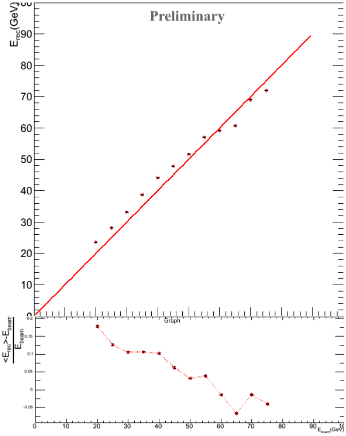
- Architecture of the ANN : One hidden layer of 5 neurons.
- The input variables: $\mathrm{N_1,N_2,N_3}$.
- The output variable is the reconstructed energy: $\mathrm{E_{rec}}$.
- Data SPS H6 2014
  - Training Samples(4500 events per energy point): Even energies(10,20,30,...80 GeV)
  - Test Samples(4500 events per energy point): Energies(20,25,30,35...75 GeV)

Neural Networks Results: Data December 2014

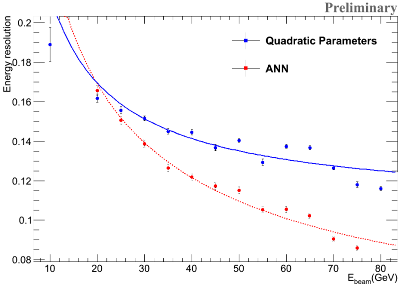


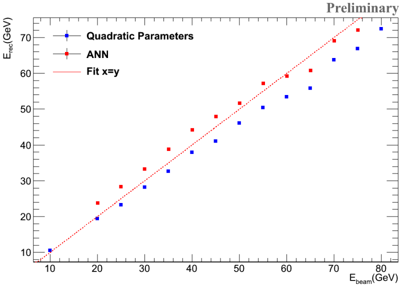
Neural Networks Results





ANN results comparison with Quadratic parametrisation



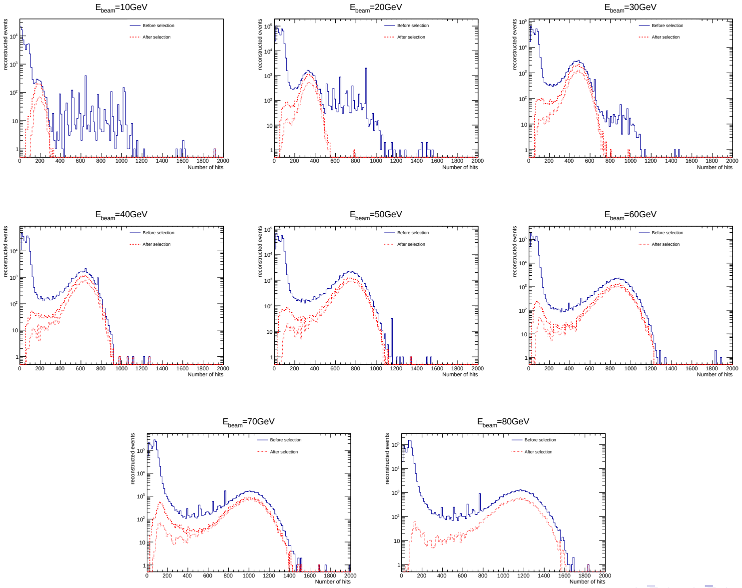


Conclusion

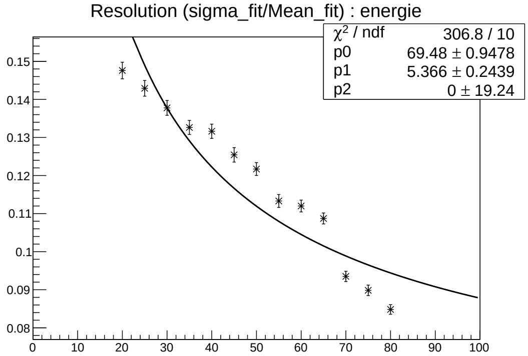
- The ANN is used in energy reconstruction study for both Simulation and data.
- The ANN technique is compared to the analytic quadratic parametrisation method of energy reconstruction.
- ANN show better results in energy resolution and linearity.
- Ongoing study
  - ANN with more input variables: Shower Start, Center of Gravity, Mean shower Radius, Lengh of the hadronic shower ...

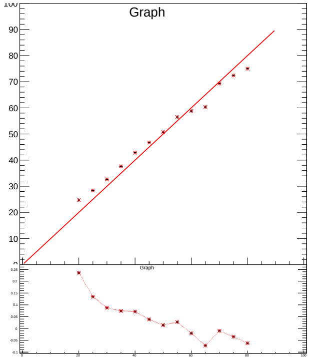
Back-up

Distribution of hit Numbers

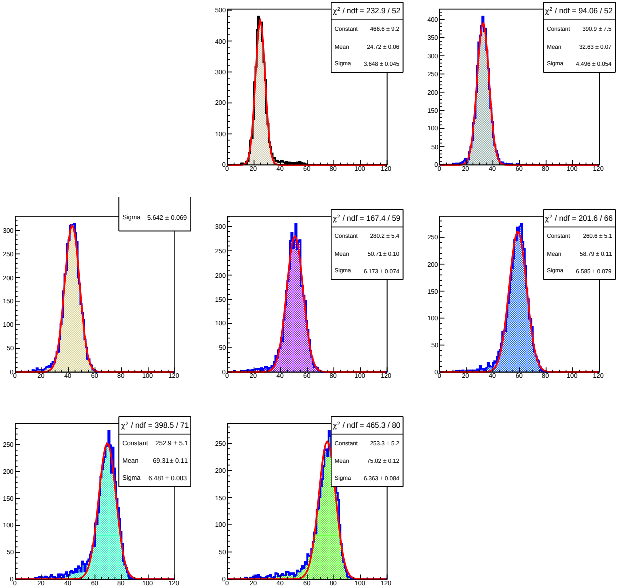


ANN results with 8 variables

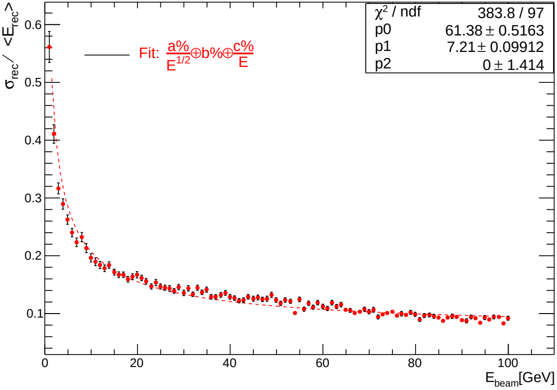




ANN results with 8 variables



Quadratic parametrisation



Quadratic parametrisation

$$\mathrm{E}_{\mathrm{rec}} = A(N_{\mathrm{tot}}) \times N_1 + B(N_{\mathrm{tot}}) \times N_2 + C(N_{\mathrm{tot}}) \times N_3 (1)$$

$$\mathrm{A}(\mathrm{N}_{\mathrm{tot}}) = A_1 + A_2 \times N_{\mathrm{tot}} + A_3 \times N_{\mathrm{tot}}^2 (2)$$

$$\mathrm{B}(\mathrm{N}_{\mathrm{tot}}) = B_1 + B_2 \times N_{\mathrm{tot}} + B_3 \times N_{\mathrm{tot}}^2 (3)$$

$$\mathrm{C}(\mathrm{N}_{\mathrm{tot}}) = C_1 + C_2 \times N_{\mathrm{tot}} + C_3 \times N_{\mathrm{tot}}^2 (4)$$