Energy reconstruction methods for ANTARES - From hit counts to PDF modelling

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

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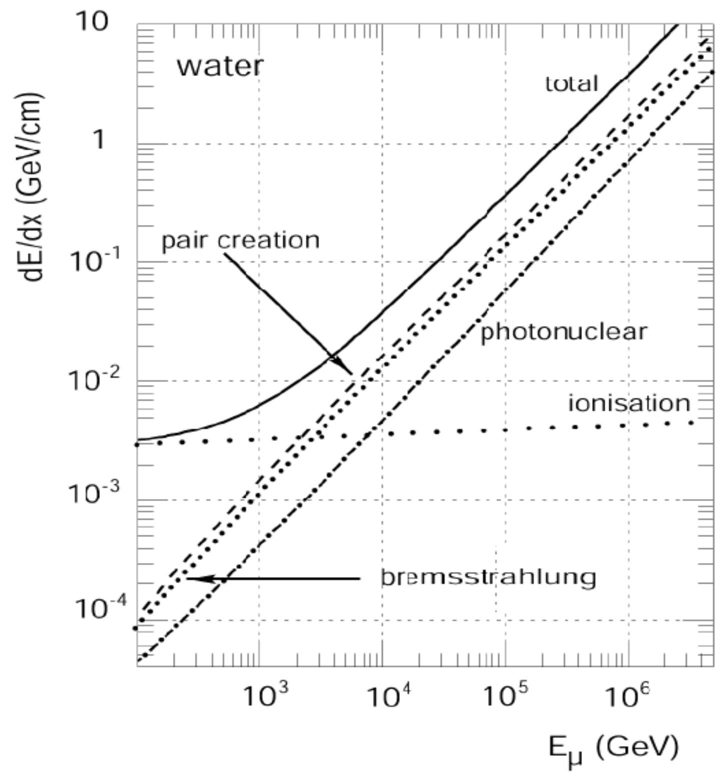
Task and Tools

What there is

$$-dE/dx = a(E) + b(E)E$$

Muon energy loss

- is highly stochastic,
- consists of almost constant ionization loss a(*E*)
- and energy dependent radiative losses b(*E*)*E,* dominant above 1 TeV.



What we have

Muon energy is correlated to

- number of photons emitted per unit length,
- total charge measured by the detector,
- distribution of photons in the detector
- time residuals of photons

$$E(A, N, x, t)$$

The four ways towards energy

Energy reconstruction generally needs

- track reconstruction
- hit selection, to supress K40 and bioluminescence background (mostly achieved by using all hits within a certain distance and time residual relative to the track)

For ANTARES four different energy reconstruction methods exist, using various features of the muon energy loss processes and reaching different levels of complexity.

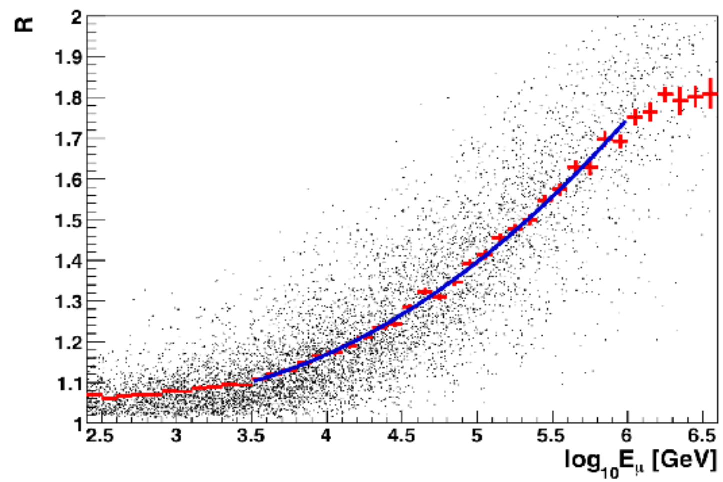
R-Estimator	dE/dx	ANN	Max. Likelihood
hit counting	charge estimate	PDF modelling machine based	PDF modelling analytical
N, t	*A*	*A, N, x, t*	*A, N, x, t*

R-Estimator

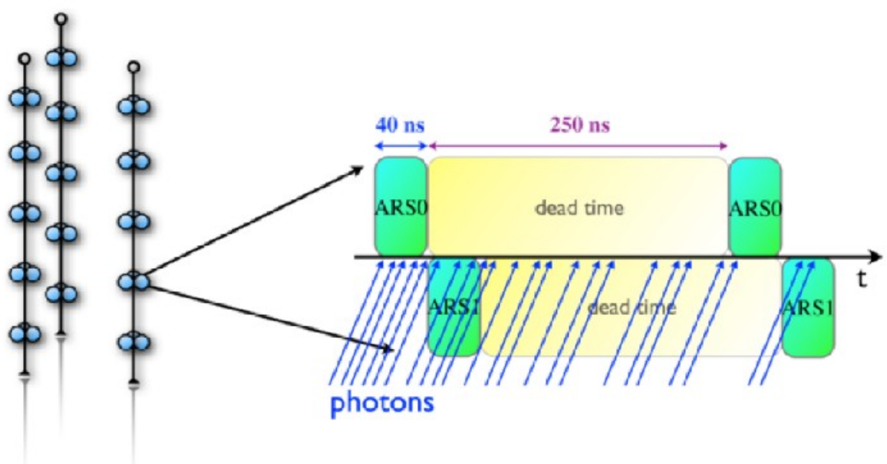
$$E(A, N, x, t)$$

R = number of hit repetitions per OM

- within 100m from the track
- with time residuals < 500ns



Parameter correlated to energy
(measure of hits with large time residual)
used for polynomial fit on MC to find *E(R)*



- specialized to E > 10 TeV
- used for Diffuse Flux analysis (Phys.Lett.B696:16-22,2011)

dE/dx estimator

$\boxed{E(A, N, x, t)}$

Estimate energy loss from total charge

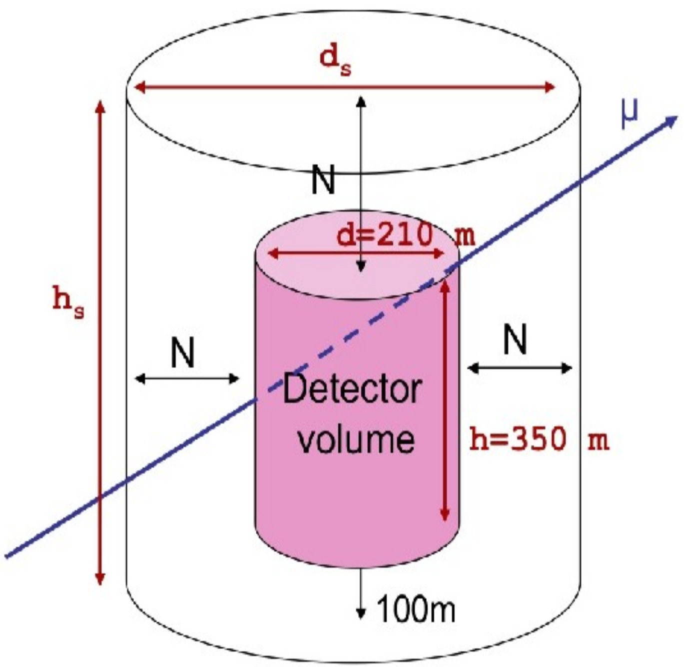
$$\left\langle \frac{dE}{dx} \right\rangle \approx \rho = \frac{1}{L_{Det}} \frac{\sum A}{p_{acc}}$$

Weighted by

L_{Det} track length in sensitive volume

p_{acc} total detector acceptance

E(ρ) derived from fit on MC



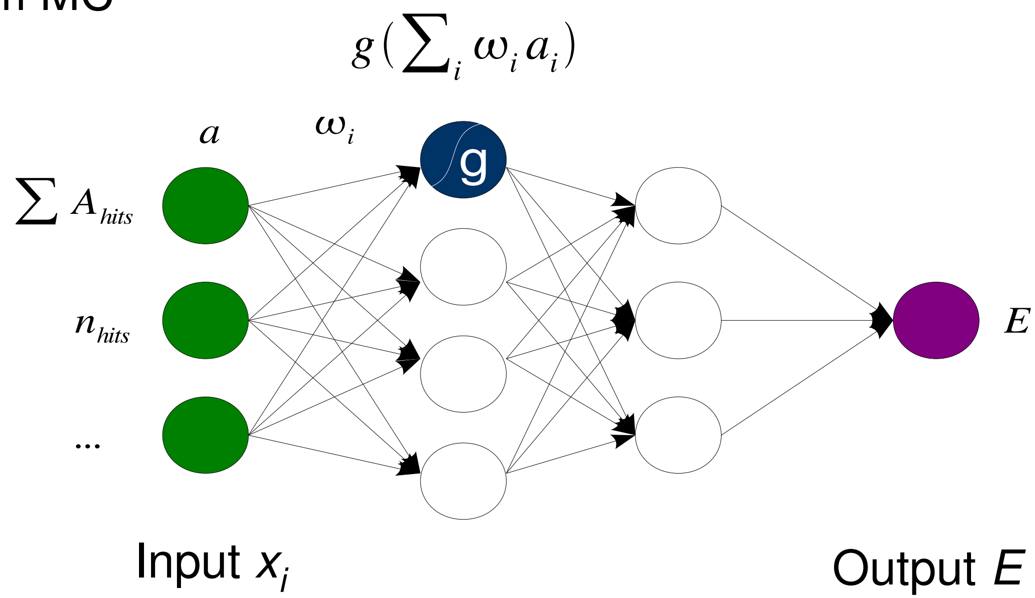
Artifical Neural Nets (ANN)

$$E(A, N, x, t)$$

PDF modelling by machine learning

- 56 parameters x_i describe location, charge and time of hits and track
- preprocessing performed to distinguish independent features
- training sets of (x_i , E) derived from MC

- Modelling of PDF by applying learning algorithm to ANN (adjusting connection weights for error minimization on training set)



Maximum Likelihood method

$$E(A, N, x, t)$$

Likelihood of energy from analytical PDF

$$L_{Det}(E) = \prod_i^{N_{OM}} P_i(E)$$

For each hit OM, the probability of seeing a given amplitude is multiplied

$$P(A; \langle n \rangle) = \sum_{n=1}^{n_{max}} P_p(n; \langle n \rangle) P_g(A; n)$$

$P_p(n; \langle n \rangle)$ Poissonian probability to measure *n* photons if average is <*n*>

$P_g(A; n)$ Gaussian probability of *n* photons to produce amplitude *A*

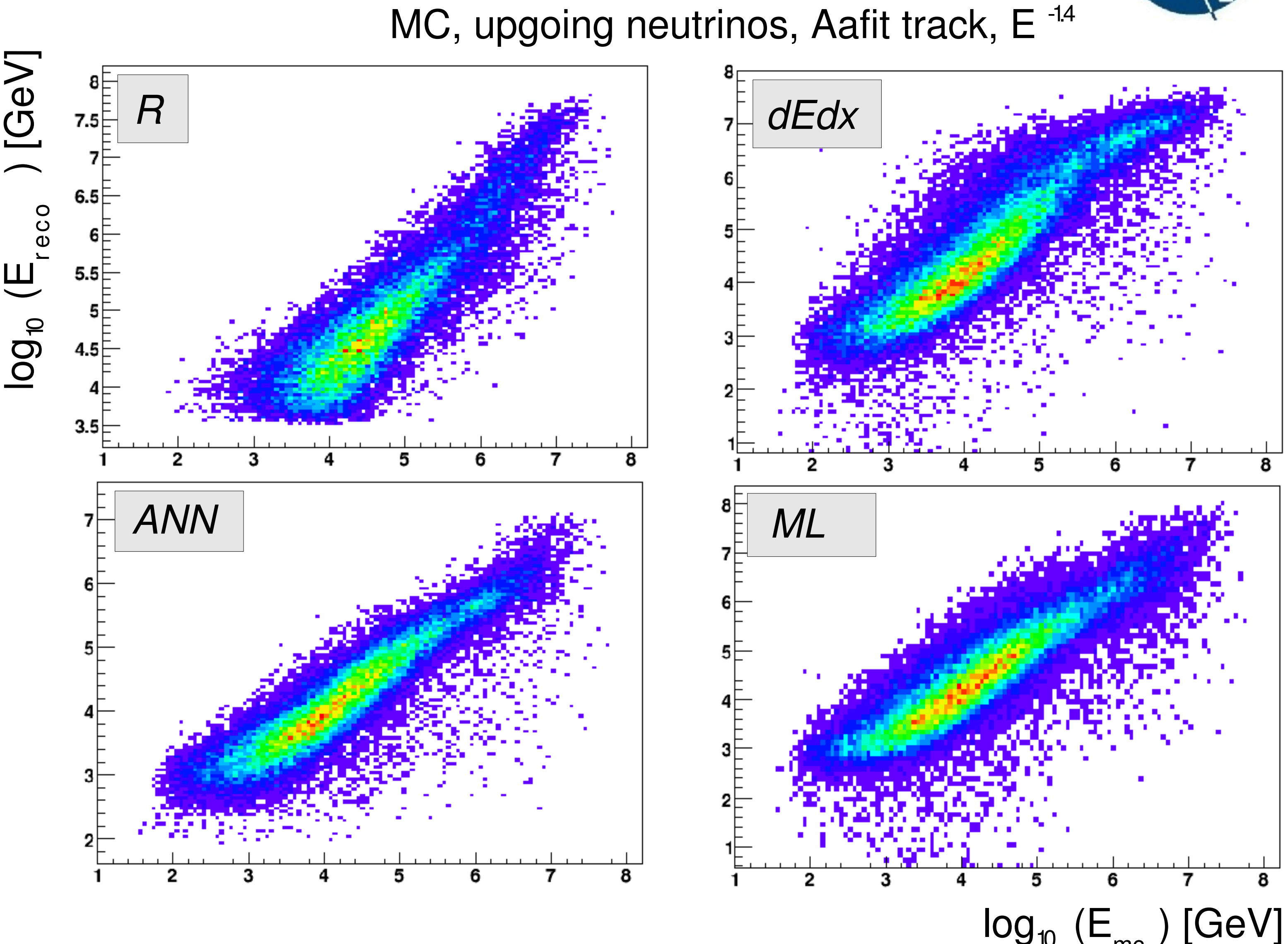
For each OM without hit, the probability to see nothing is used

$$P(0, \langle npe \rangle) = e^{-\langle n \rangle} + P_{threshold}(\langle n \rangle)$$

$P_{threshold}(\langle n \rangle)$ Probability to have a photon below the PMT threshold

The energy is derived from minimizing $-\log(L_{Det}(E))$ using $\langle n \rangle(E)$ of the PDF.

Overall performance



Comparison of Performance

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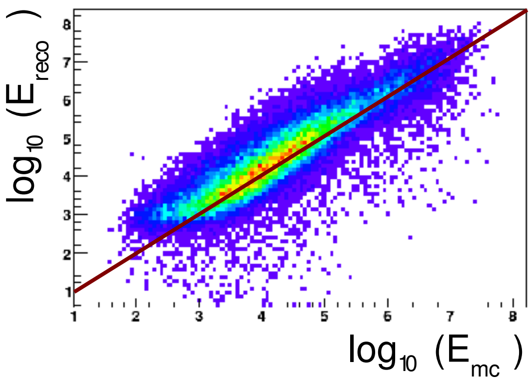
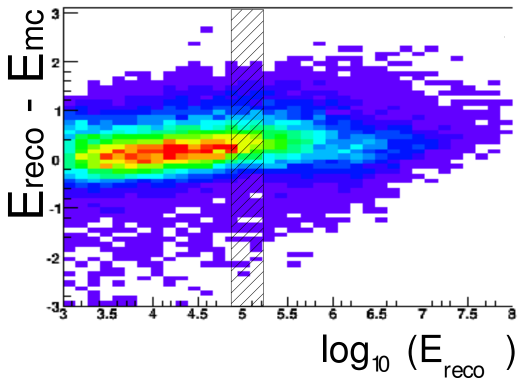
Resolution is measured by a Gaussian fit of $\log_{10}(E_{reco}) - \log_{10}(E_{mc})$ in bins over reconstructed or MC energy axis.

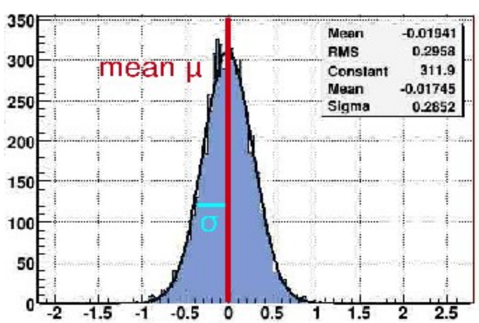


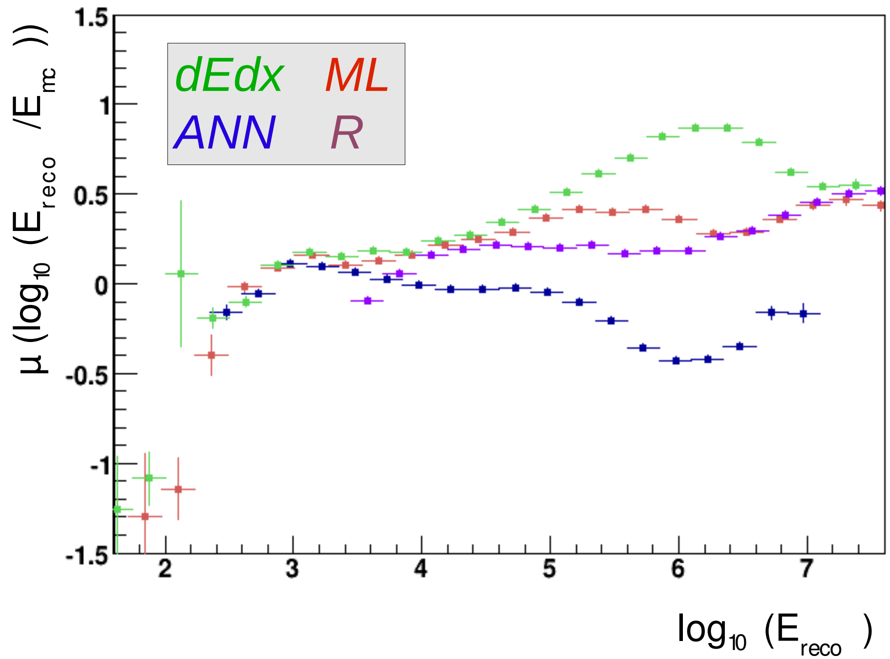
$\log_{10}(E_{reco})$

$- \log_{10}(E_{mc})$



Fitting Gaussian in bins in x

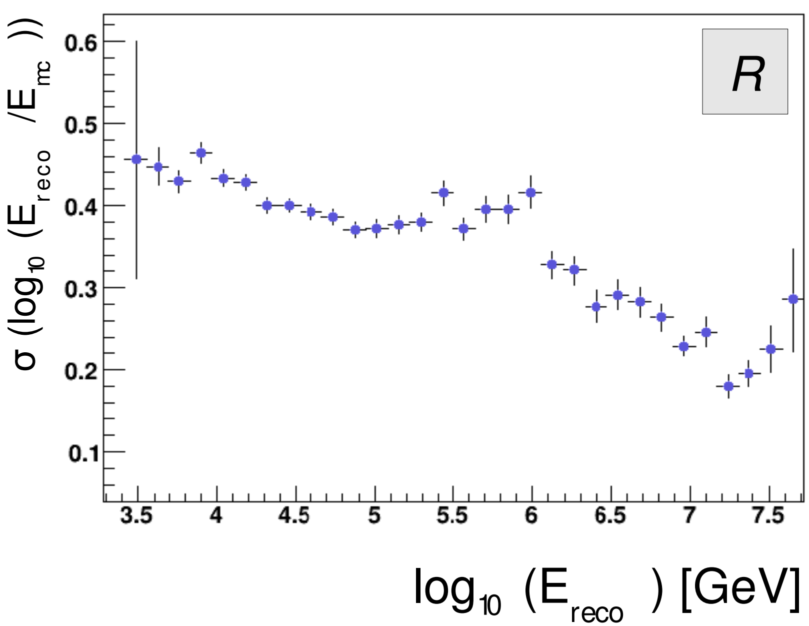


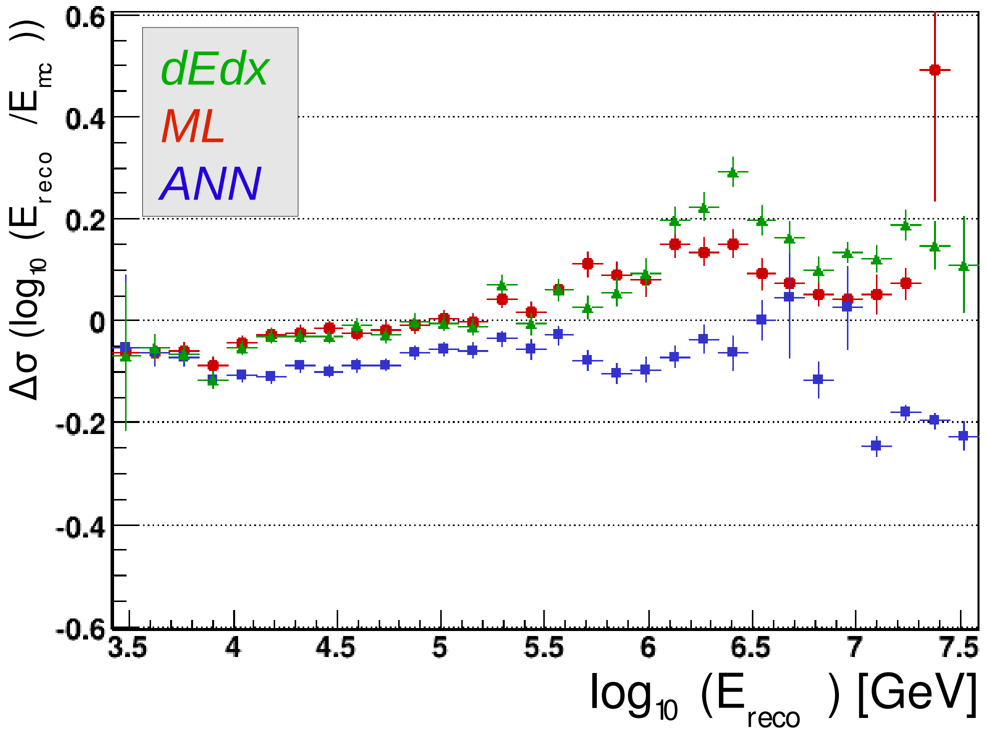


Performance on neutrino induced muons

$$\Delta\sigma = \log_{10}(E_{reco}/E_{MC})_{method} - \log_{10}(E_{reco}/E_{MC})_R$$

R-Estimator has already been used for diffuse flux analysis
→ taken as reference for newer methods

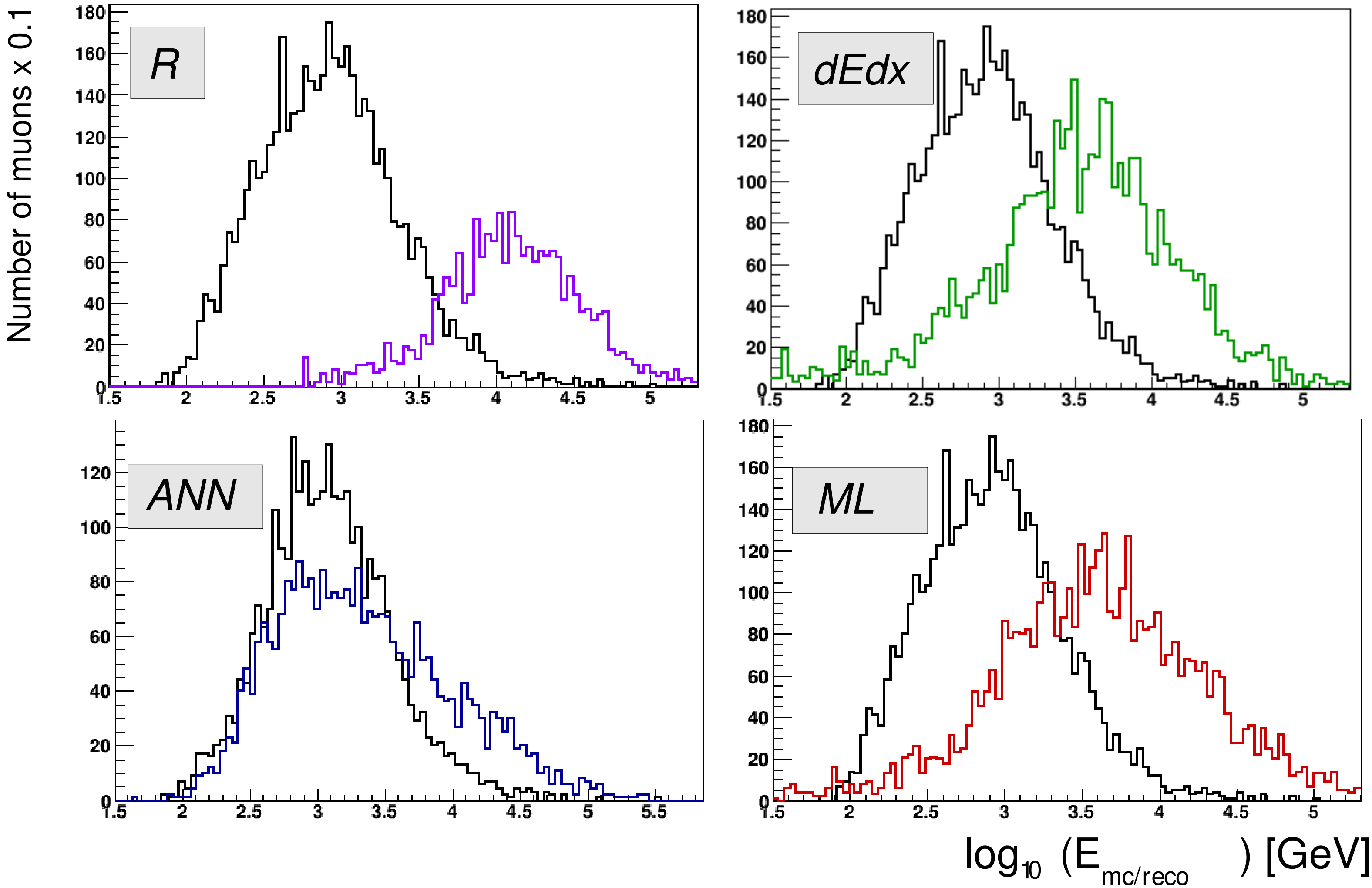




Good resolution of factor 2 can be reached above 10 TeV

Reconstructing atmospheric muons

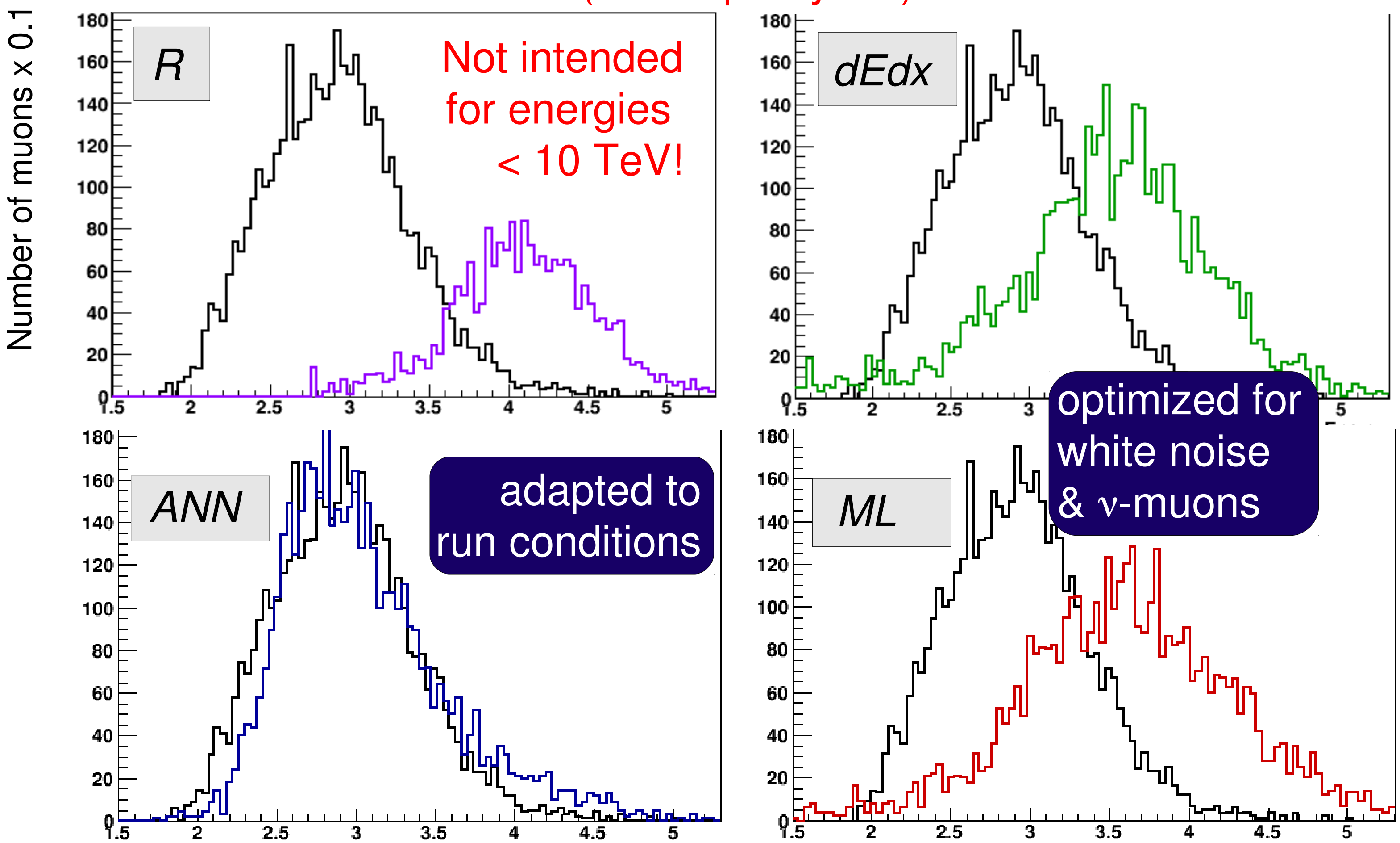
MC, run by run simulation, atmospheric muons, 1 run (36906)



Reconstructing atmospheric muons

MC, run by run simulation, atmospheric muons, 1 run

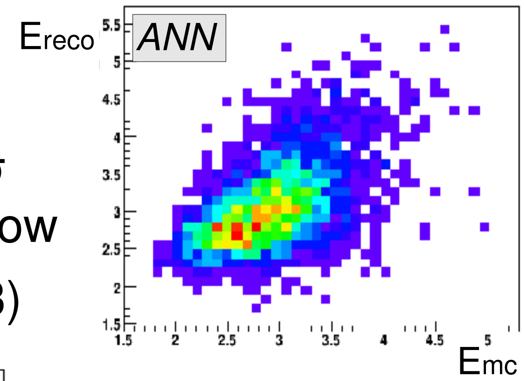
Λ > -7 (loose quality cut)

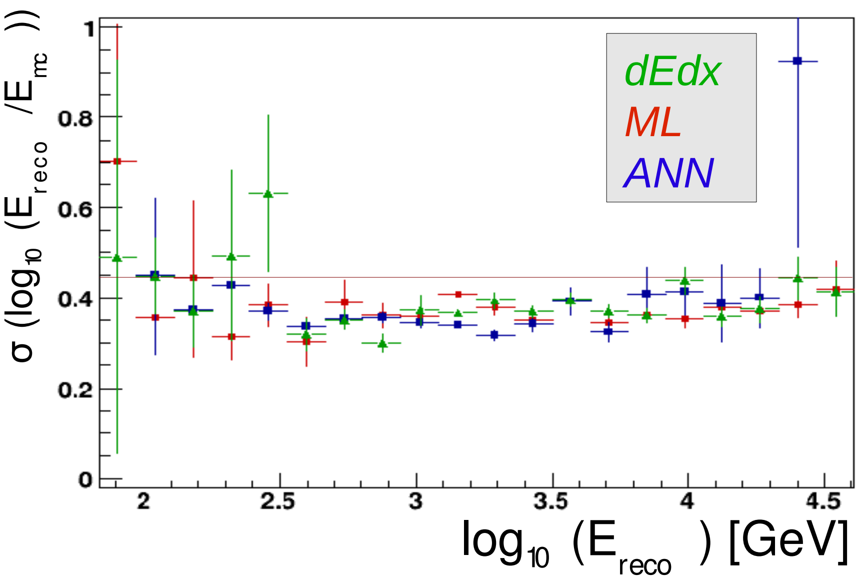


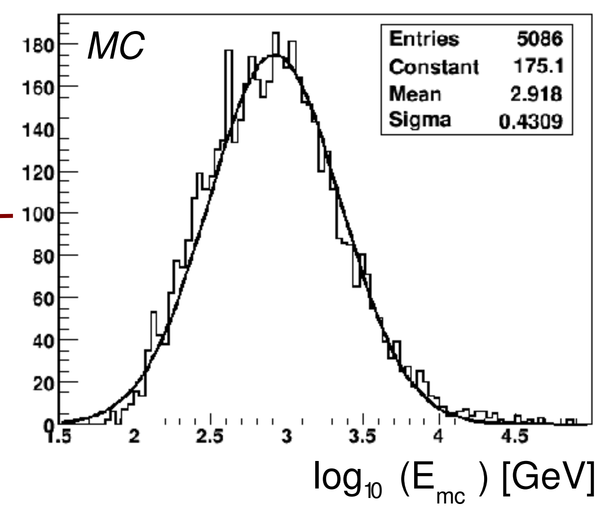
Strong variation of run conditions have to be considered for reconstruction of atmospheric muon energy → adaptation necessary!

Performance for atmospheric muons

- Estimators reach only a poor resolution for amospheric muon reconstruction
- have a common resolution of roughly 0.4 in σ ($\log_{10}(E_{reco}/E_{mc})$), which is only slightly below the width of the true muon spectrum (σ= 0.43)

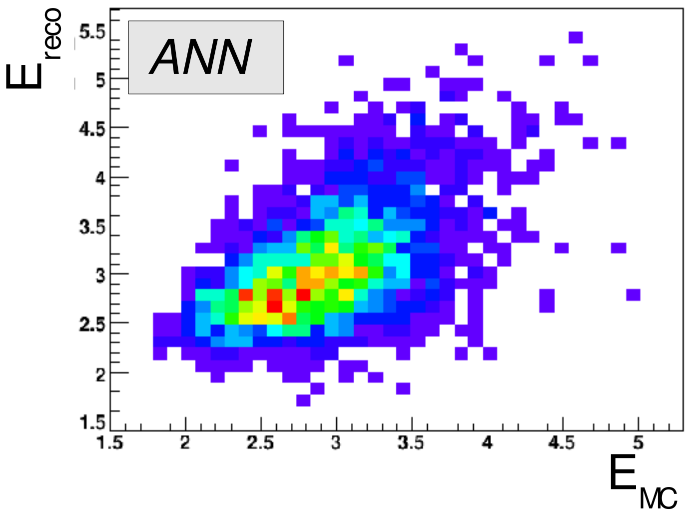


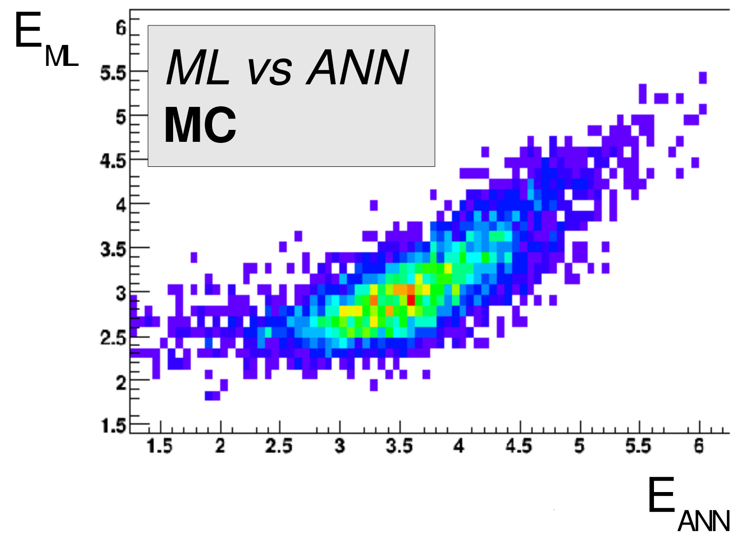




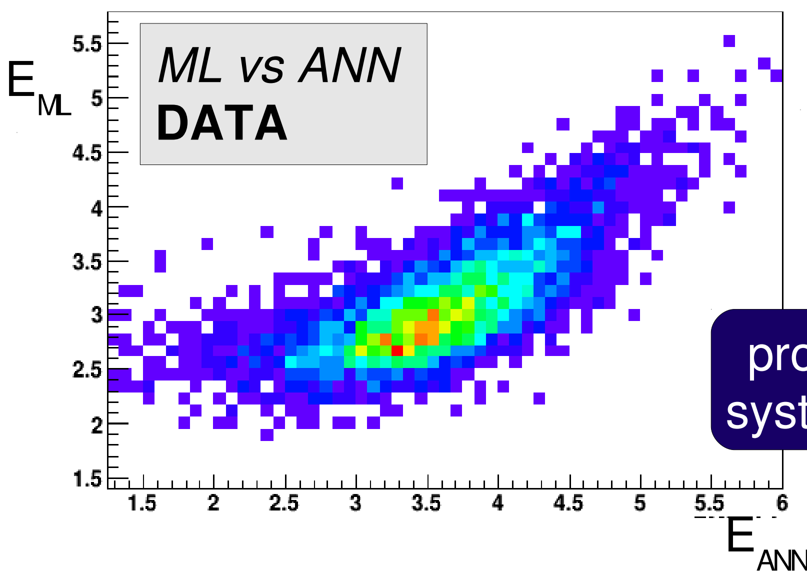
→ Reconstruction influenced by track reco systematics and signature in detector has weak energy dependence below a few TeV.

Different methods – different errors?





Limited resolution for each reco

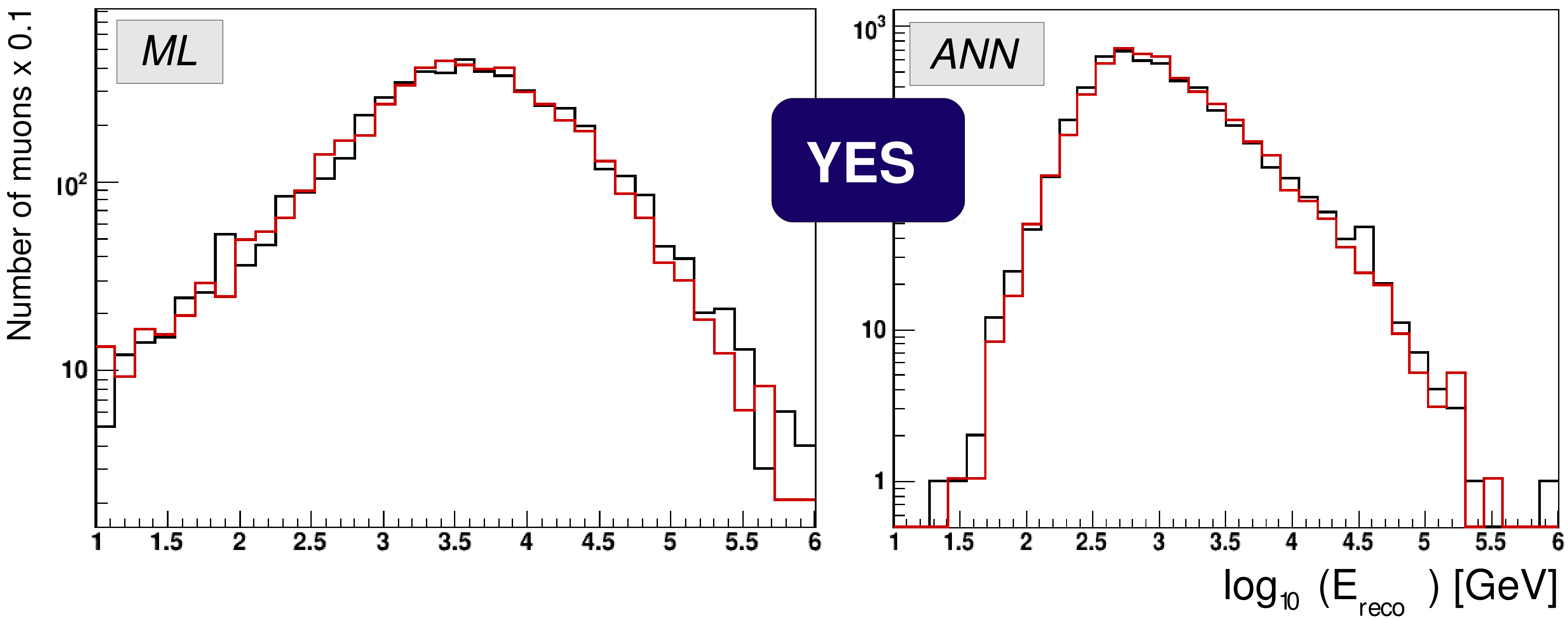


correlation between reco errors

projecting same systematic effects

Does it work on data?

Data and MC reconstructed, atmospheric muons, 1 run (36906)



Summary and Outlook

Four energy reconstruction methods are used at ANTARES and have been presented.

- Using different approaches to estimate the energy,
- Reaching a resolution between 0.25 – 0.4 in log10(ΔE) for upgoing muons above 10 TeV.
- Varying detector conditions have to be considered for atmospheric muon reconstruction to correctly reconstruct the shape of the spectrum
- Poor resolution for atmospheric muons due to limited detector size and energy loss characteristics at 1 TeV
- PDF based methods show correlated behaviour in reconstruction errors.
- Data-MC comparison works well for ML and ANN