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FZU Institute of Physics of the Czech Academy of Sciences

PIERRE AUGER OBSERVATORY

Extraction of the muon signals recorded by the Surface Detector of the Pierre Auger Observatory using Neural Networks

Master's thesis

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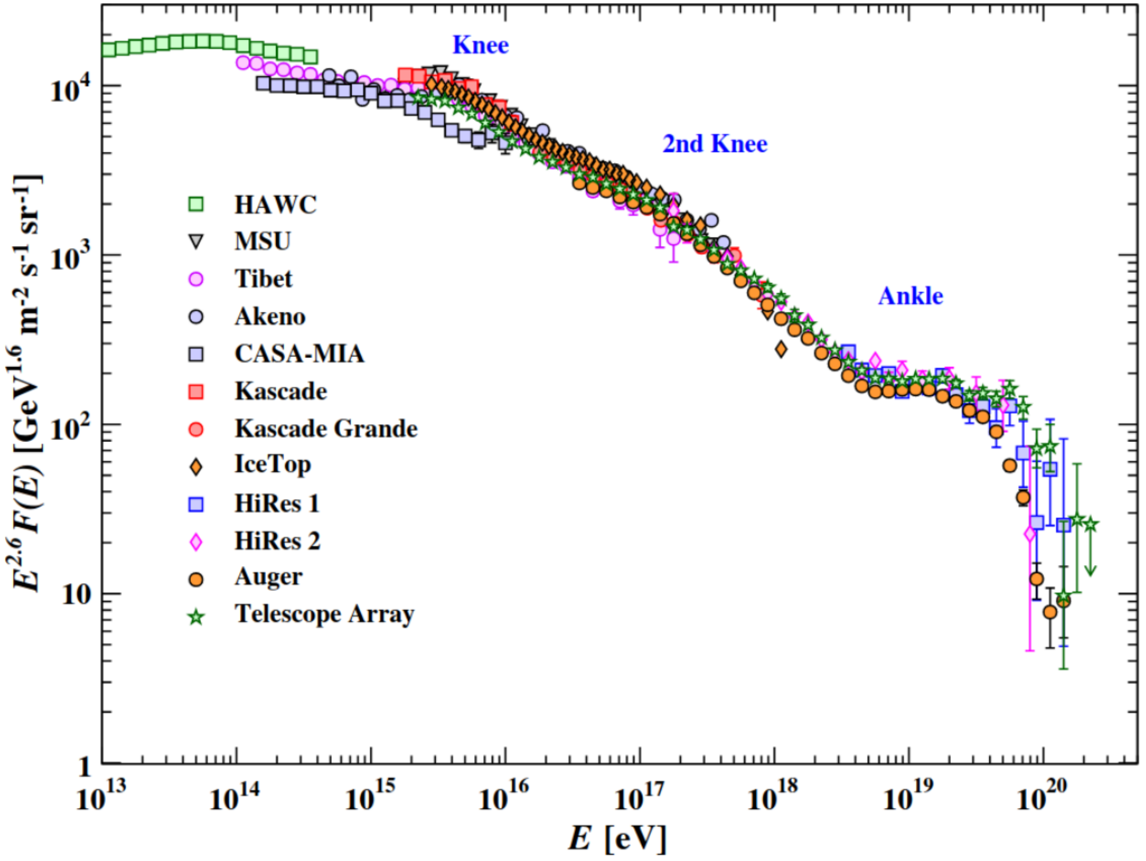
Cosmic rays

- Charged particles, mostly light ionized nuclei (protons) of galactic or extragalactic origin with various energies (from 10^8 to more than 10^{20} eV)
- Ultra high-energy cosmic rays (UHECRs) are defined as those with energies above 10^{18} eV

The flux of cosmic rays

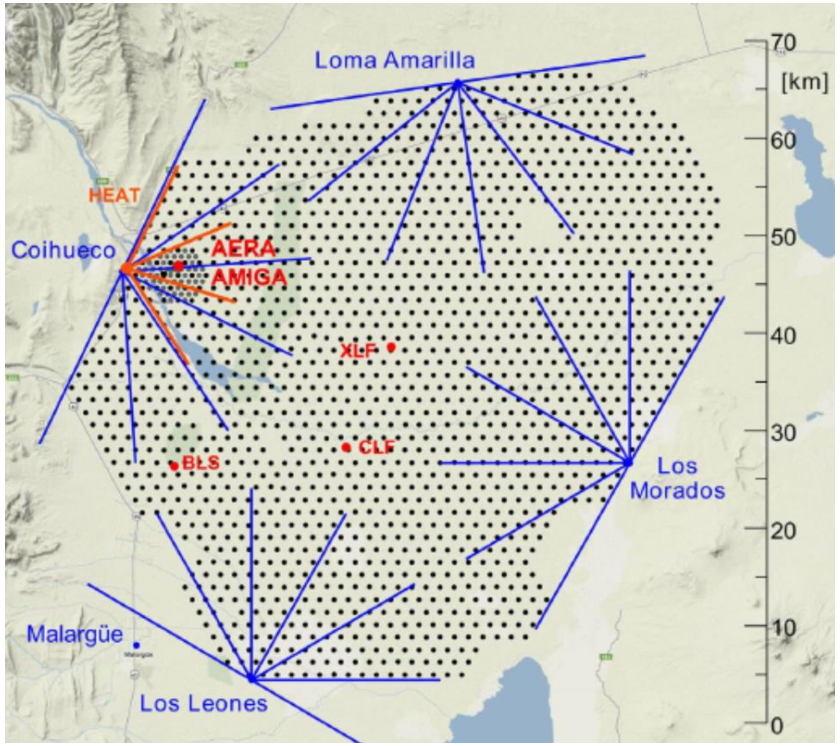
- $E^{-\gamma}$, the power law, with factor $\gamma \sim 3$ changing with the higlighted features:
- *The knee* steepening around $10^{15.5}$ eV, maximum proton energy accelerated in our galaxy
- *The second knee* 10^{17} eV, maximum for heavy nuclei within our galaxy
- *The ankle* flattening around $10^{18.7}$ eV – possibly maximum proton energy in extragalactic sources

Above 4 x 10^{19} eV - strong suppression, possibly due to propagation effects or to maximum acceleration potential of extragalactic sources



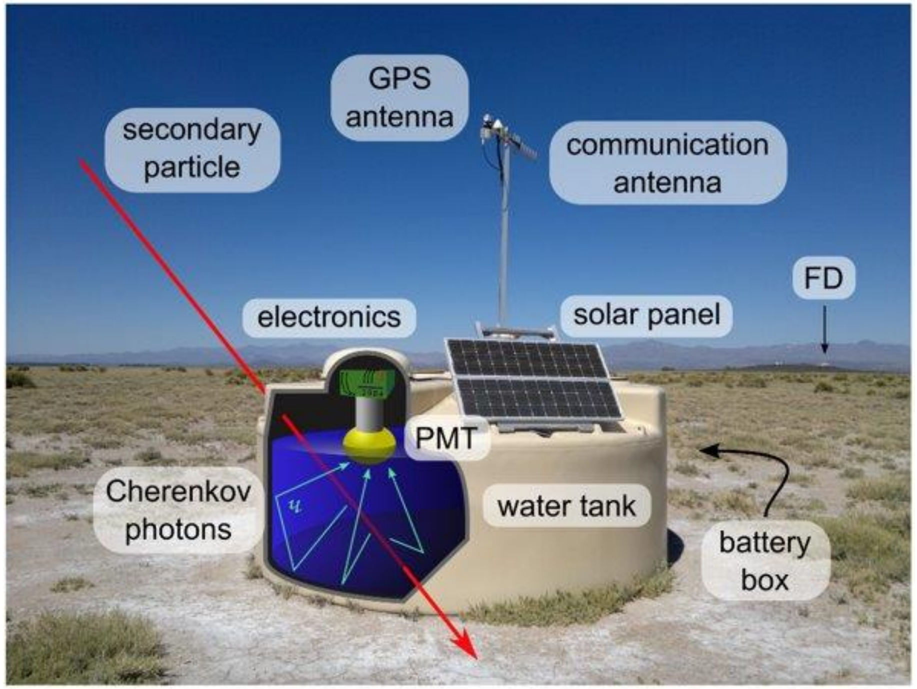
The Pierre Auger Observatory

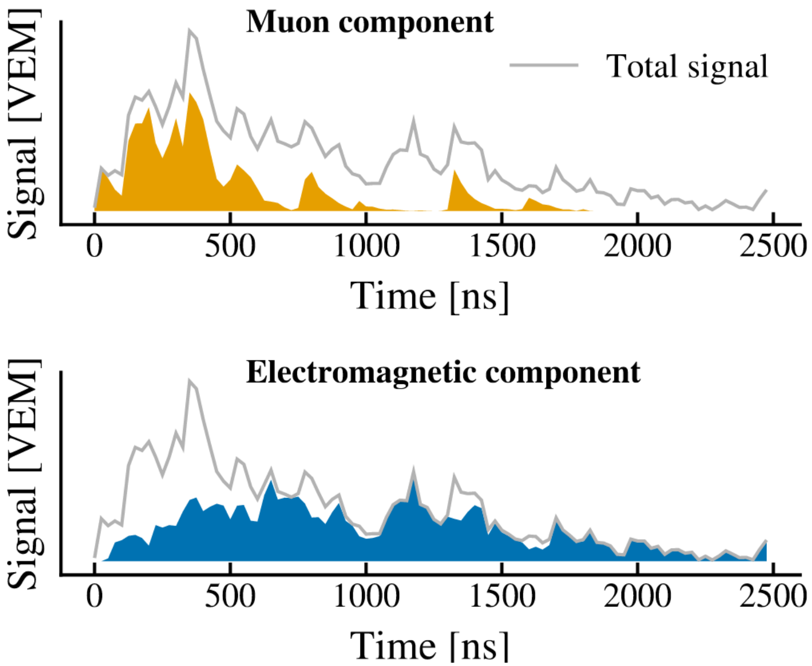
- A hybrid detector that combines multiple detection techniques to measure air showers, the main detectors are the Surface Detector (SD) and the Fluorescence Detector (FD)
- The SD is an array of 1660 water Cherenkov detectors (WCD) covering area of 3000 km^2
- The FD is composed of 27 fluorescence telescopes, installed in 4 sites that overlook the SD, detecting the fluorescence light emitted by particles as the shower develops in the atmosphere – directly observes X_{max} (disadvantage is a low duty cycle ~ 12%)



The surface detector

- Three PMTs record the Cherenkov light generated by relativistic charged particles traversing the water
- The signal is provided in two outputs, one from the anode (**low gain**) and the other from the last dynode, multiplied by a factor of 32 (**high gain**)
- The amplified signal is used if the station is far away from the shower core. In the case that the SD station is close to the core, this signal can be saturated => anode output is used





Motivation

Why muons?

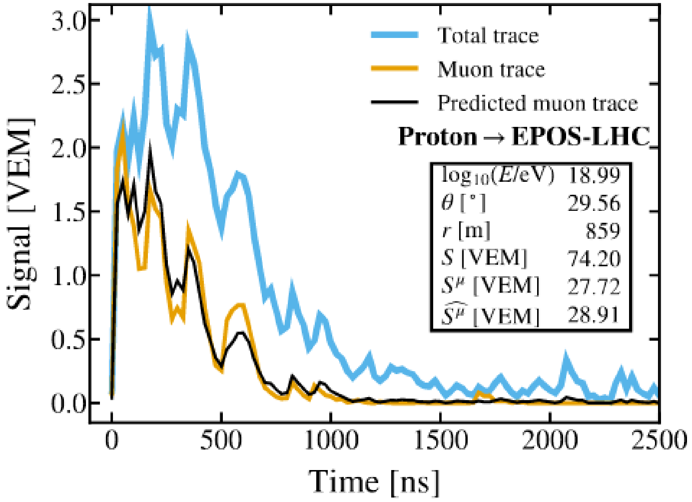
- Mass composition: more muons from heavier nuclei
- Hadronic interactions: modern models do not describe well the muon shower component

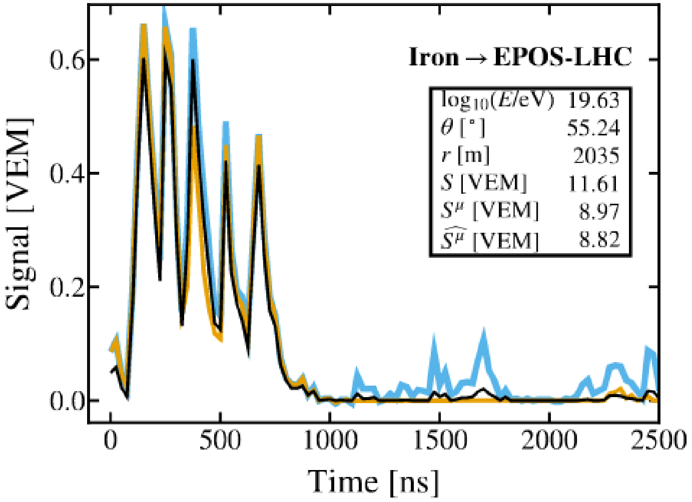
Why neural networks?

SD trace – too difficult to disentangle EM and muons -> machine learning methods could find patterns

- 2021 published paper "Extraction of the Muon Signals Recorded by the Surface Detector of the Pierre Auger Observatory using Recurrent Neural Networks"

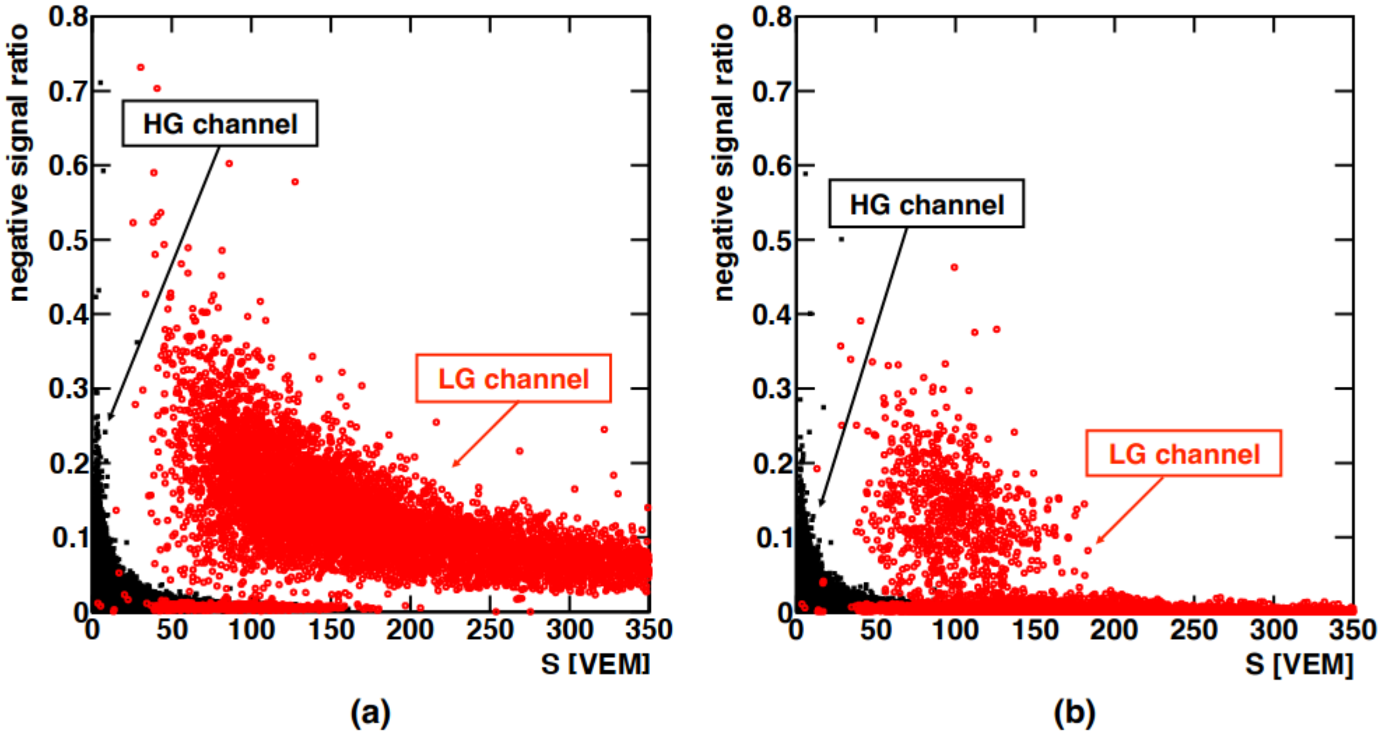
- Estimating total muon signal by integration of the predicted muon trace



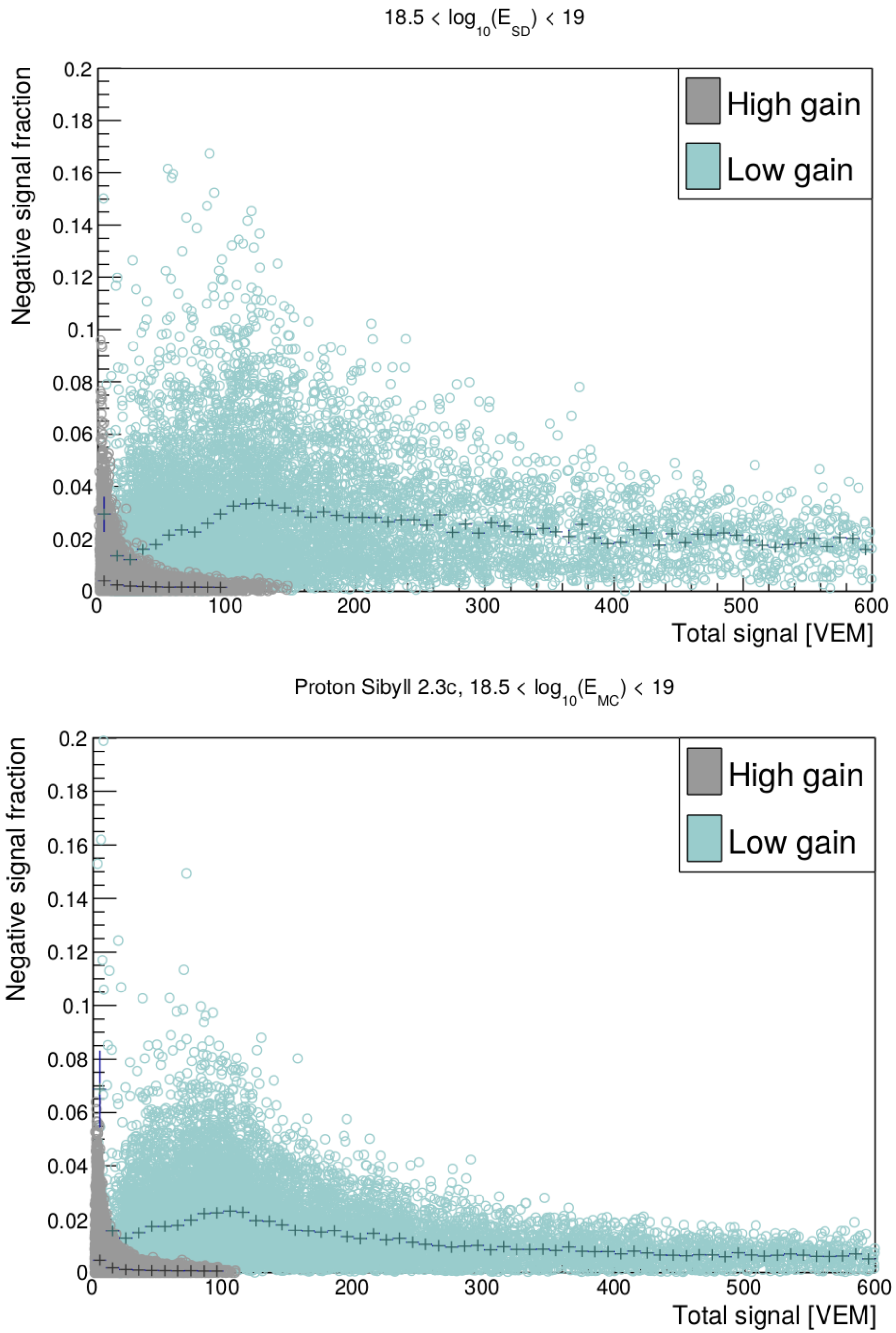


Including high gain saturated stations

- Negative signal fractions are small now: no particular reasons for excluding HG-saturated stations

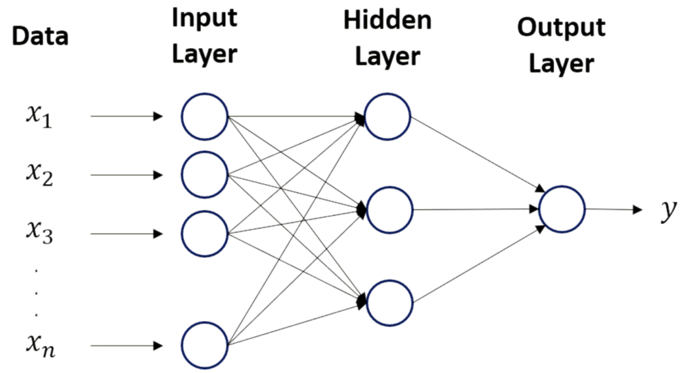


Events with energies 10 < E < 15 EeV and zenith 1.00 < sec θ < 1.45, (a) before Ronald's correction, (b) after, Internal Auger notes - GAP2017_005.



The FeedForward Neural Network

- Input variables:
  MC energy, MC zenith angle
  station: total signal, distance from the core, azimuth
  trace: length, area over peak, signal rise and fall times



- The output is **total muon signal**

- Software used: Keras, Tensorflow

- Trained on only iron, only proton, mix 50%, final = mix 25% (p, He, O, Fe)

- **Best performance: training on mixed compositions**

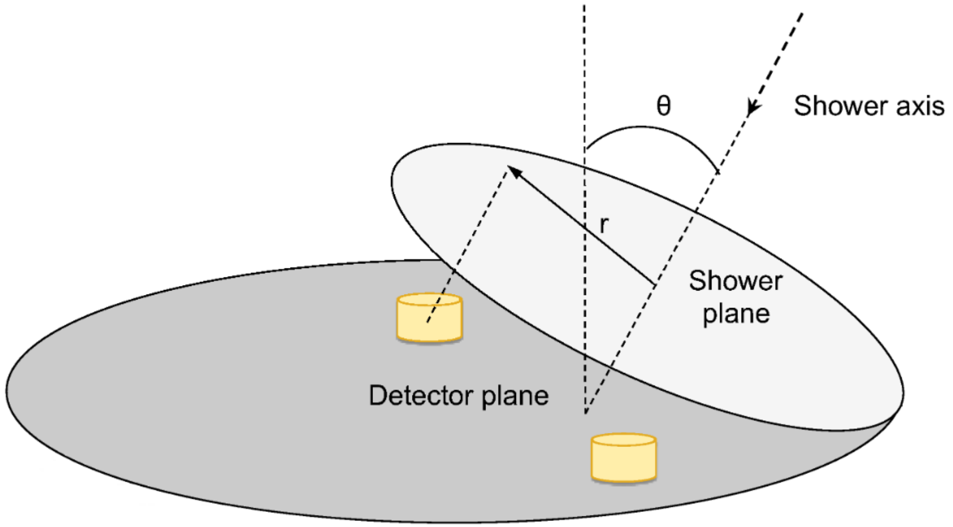
- Biases depend on mass
- Difference proton-iron is up to 13%

Biases on the reconstructed muon signal

Non-saturated stations		
Training sample	$\langle \widehat{S^\mu} - S^\mu \rangle / S^\mu$ **(p)**	$\langle \widehat{S^\mu} - S^\mu \rangle / S^\mu$ **(Fe)**
Proton	-0.042	-0.145
Iron	0.144	0.002
Mix 50% (p, Fe)	-0.030	-0.093
Mix 25% (p, He, O, Fe)	0.034	-0.041
HG saturated stations		
Proton	-0.025	-0.178
Iron	0.332	-0.015
Mix 50% (p, Fe)	0.038	-0.077
Mix 25% (p, He, O, Fe)	0.046	-0.086

Extraction of muon traces

- **Using Recurrent Neural Network to extract the muon trace**
- Input variables:
  zenith angle
  station: distance to the core, total trace (first 200 bins)

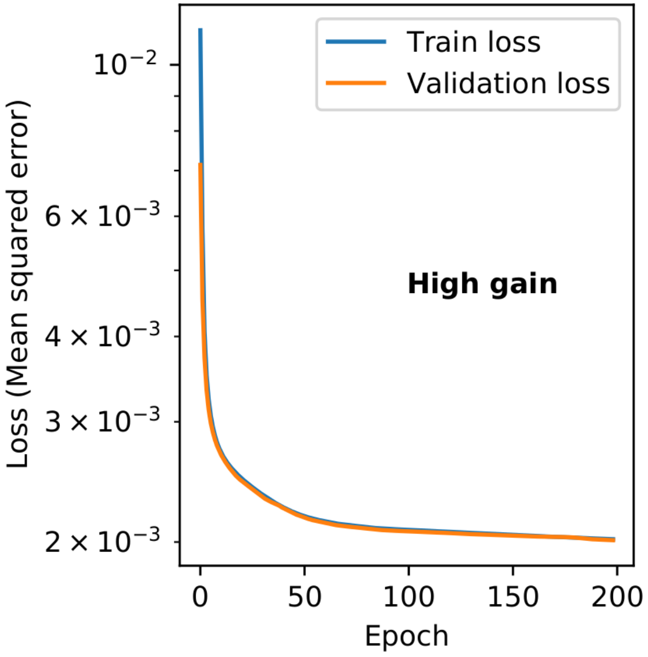


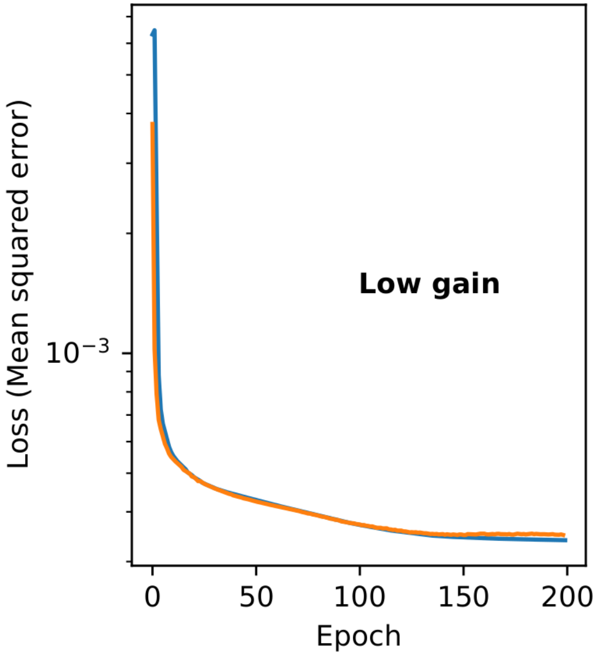
- Software used: PyTorch 1.11.0

$$L = \frac{1}{200}\sum_{i=1}^{200}(\widehat{S_i^{\mu}} - S_i^{\mu})^2$$

- Dataset:
  - Training: 420000, validation: 20000 traces, test: 10000 for each primary
- Epochs: 200, batch size: 512

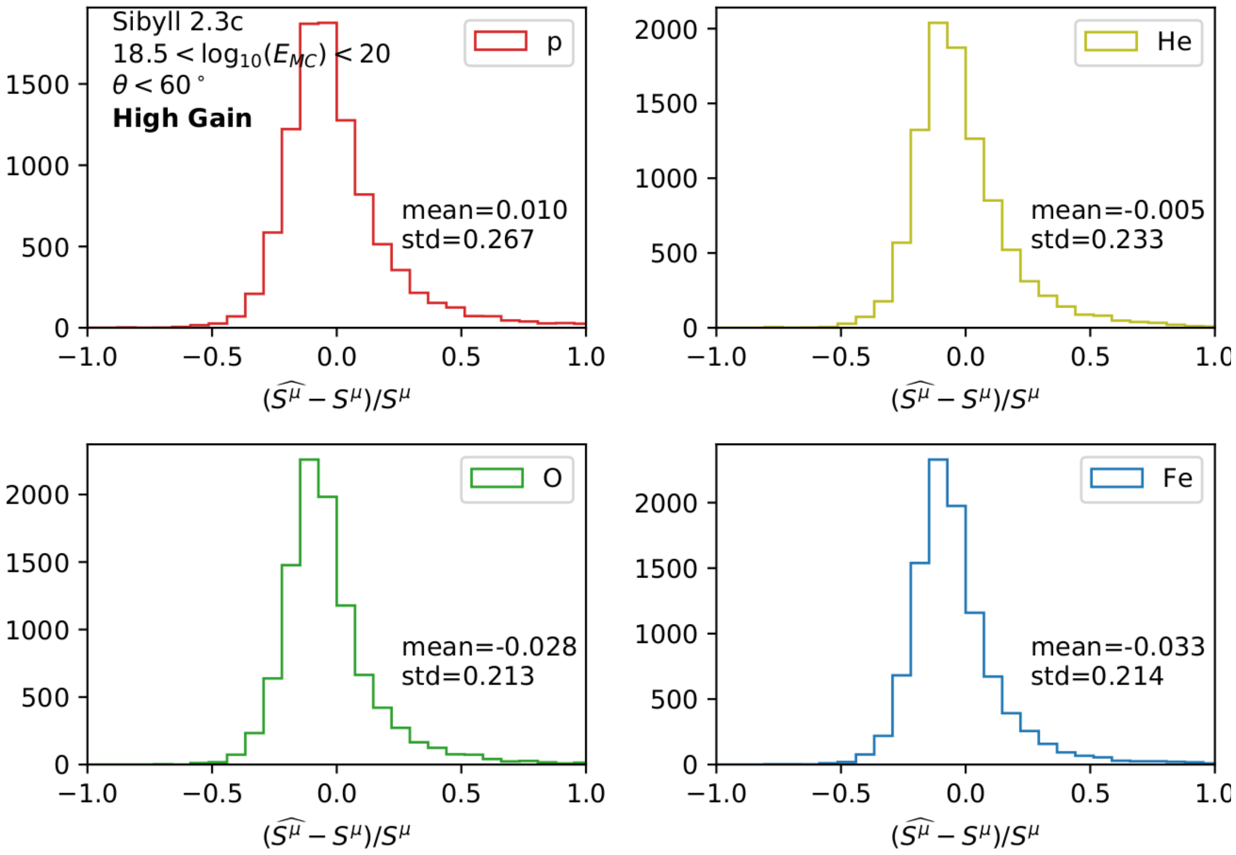
Output is the muon component for each of the first 200 trace bins



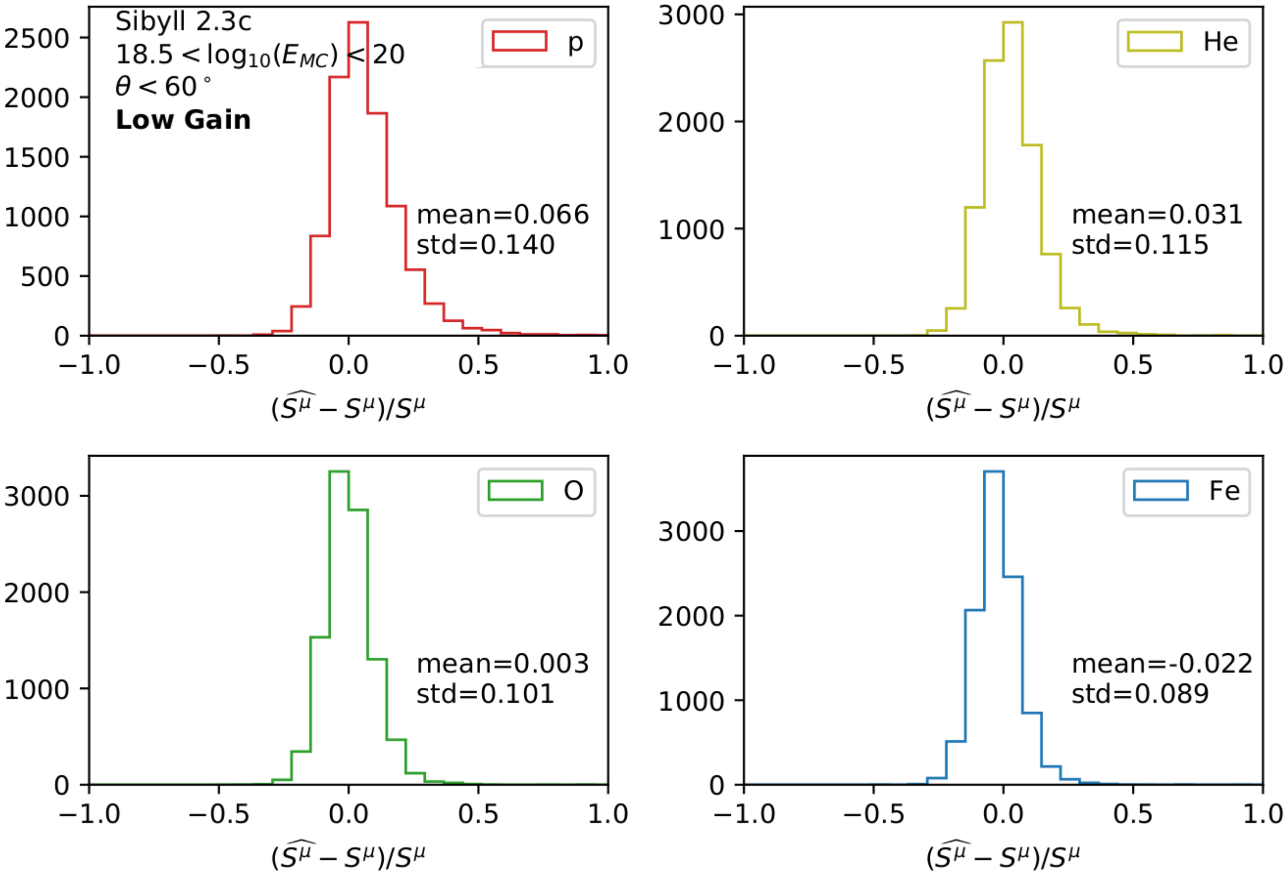


Relative biases

- **Biases are slightly worse for LG stations which are closer to the shower core and have a larger EM contamination**
- Difference in biases between proton and iron within 5% (HG) and 9% (LG)

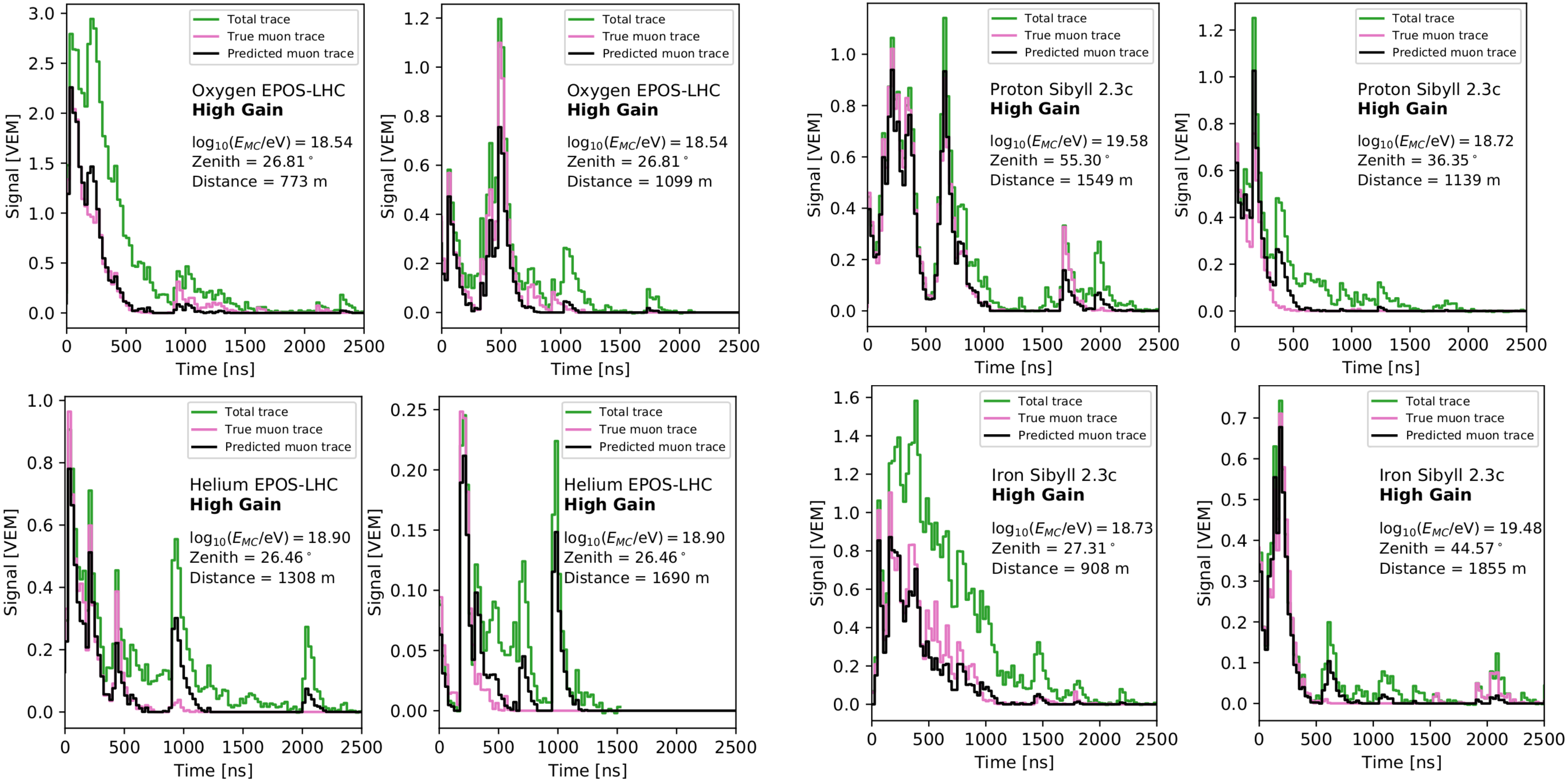


High Gain non-saturated stations



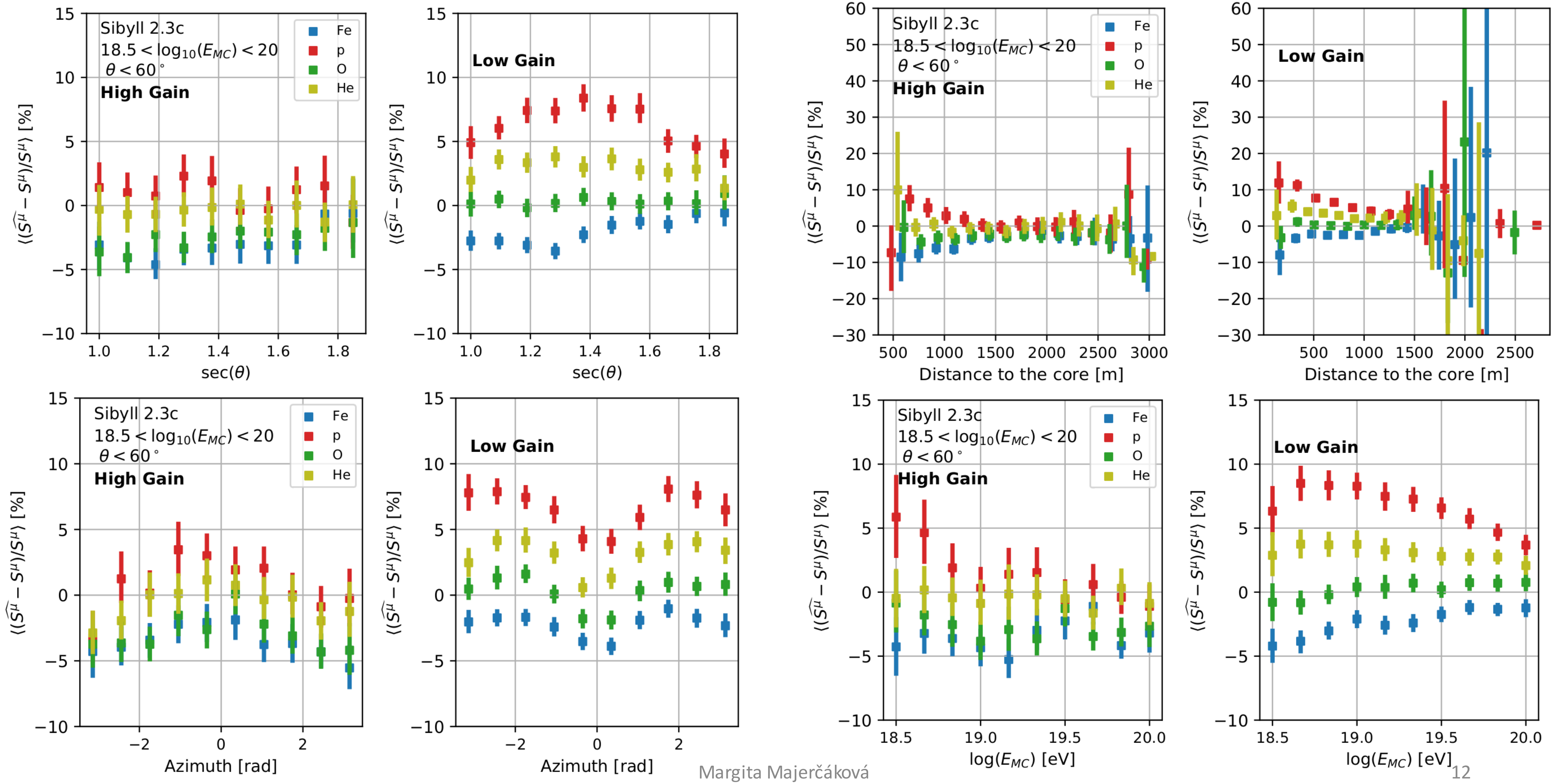
High Gain saturated stations

Examples of extracted muon traces



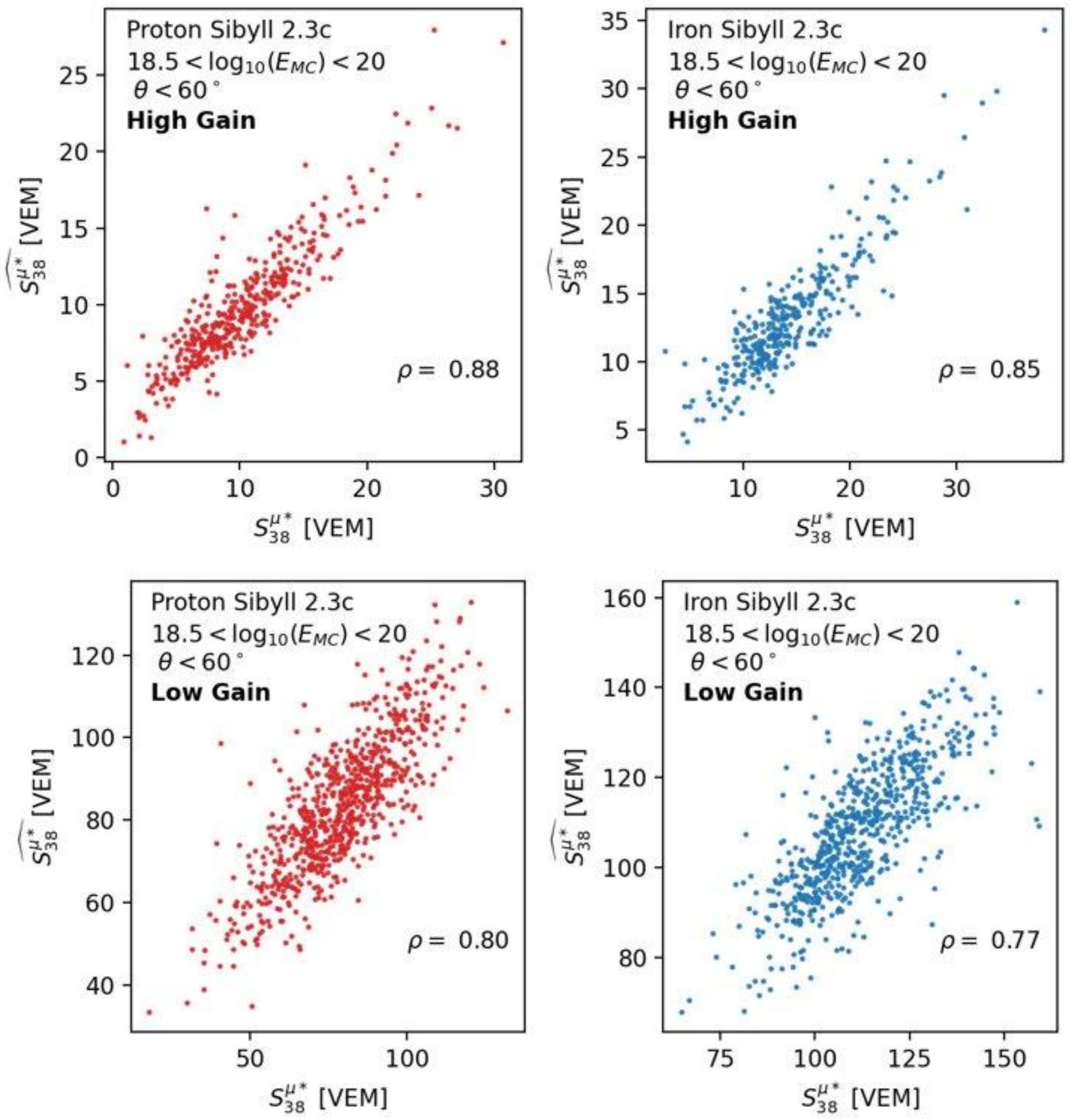
Relative biases

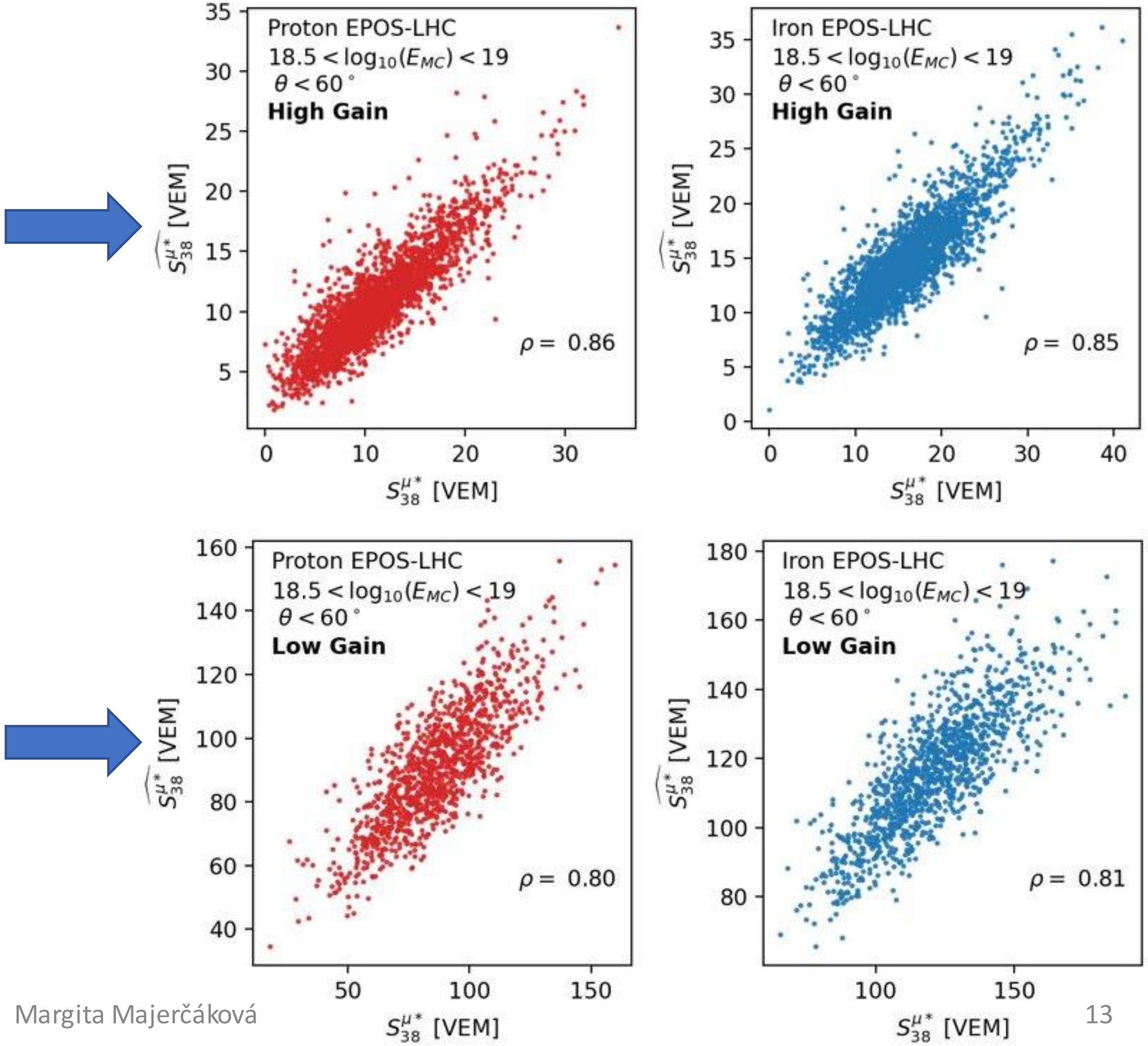
- **Biases are larger for smaller core distances and smaller for higher energies**



Are the results of neural network independent of the hadronic interaction model?

- NN trained on Sibyll 2.3c also tested on a different model (EPOS-LHC): **similar performance**



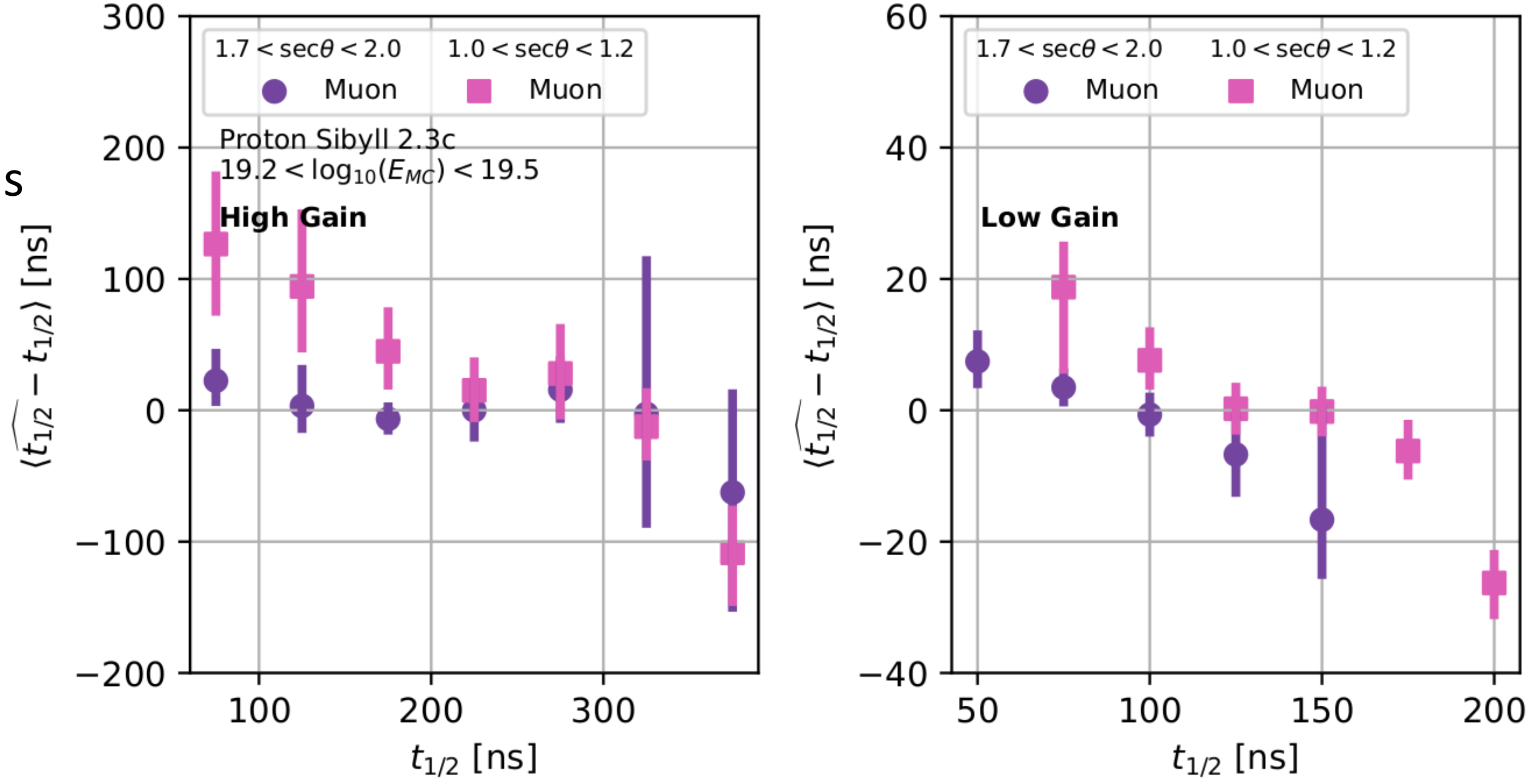


Risetimes

- The rise time $t_{1/2}$ - the length of a time slot during which the signal increases from 10% to 50% of its amplitude

- The muon trace has a faster rise time than the electromagnetic one -> electrons can undergo multiple scattering in the atmosphere and therefore be more dispersed in time

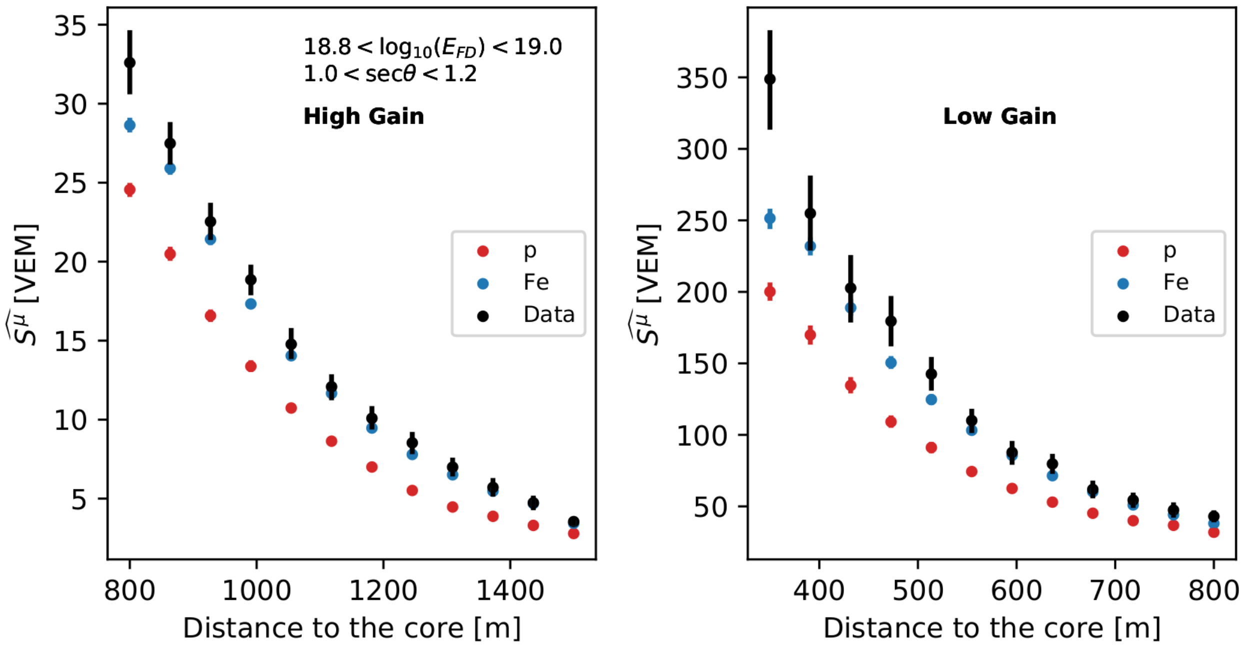
- The muons produced at the beginning of the shower development arrive earlier than those produced later

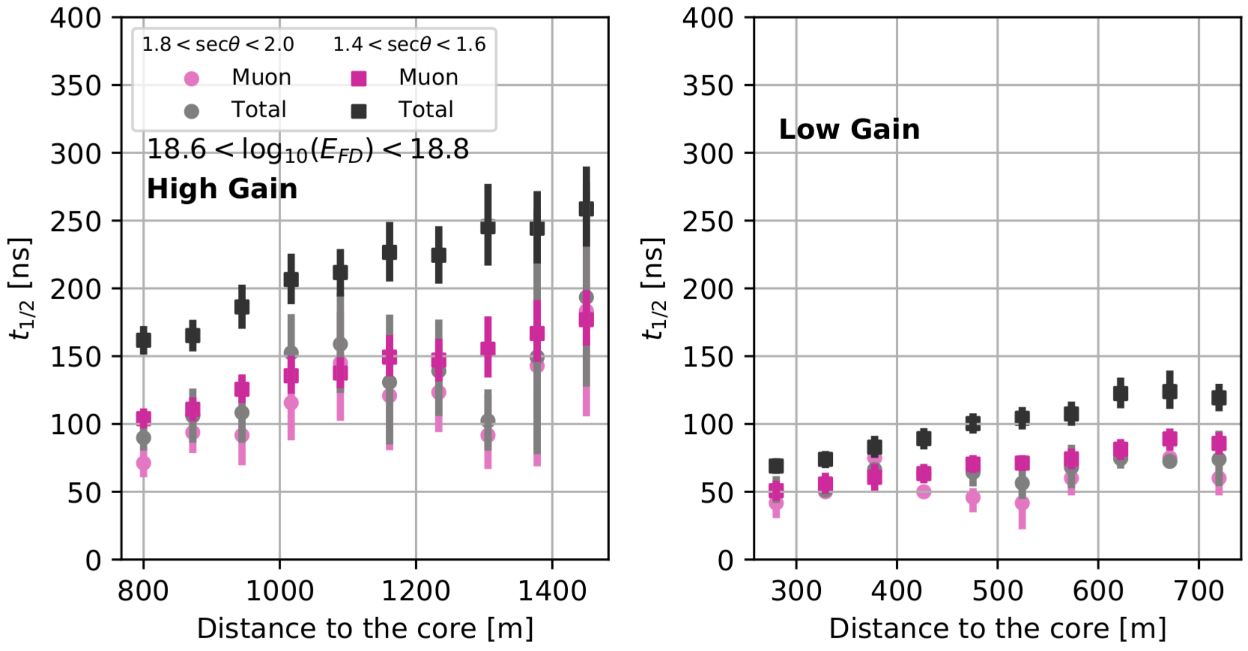


- The biases are higher for more vertical events and are decreasing for the larger values of risetime

Application to data

- Muon signal vs the distance to the shower core, predicted value for data compared to simulations
- Total and muon signal risetimes vs distance to the shower core, for more inclined and more vertical showers





Conclusions

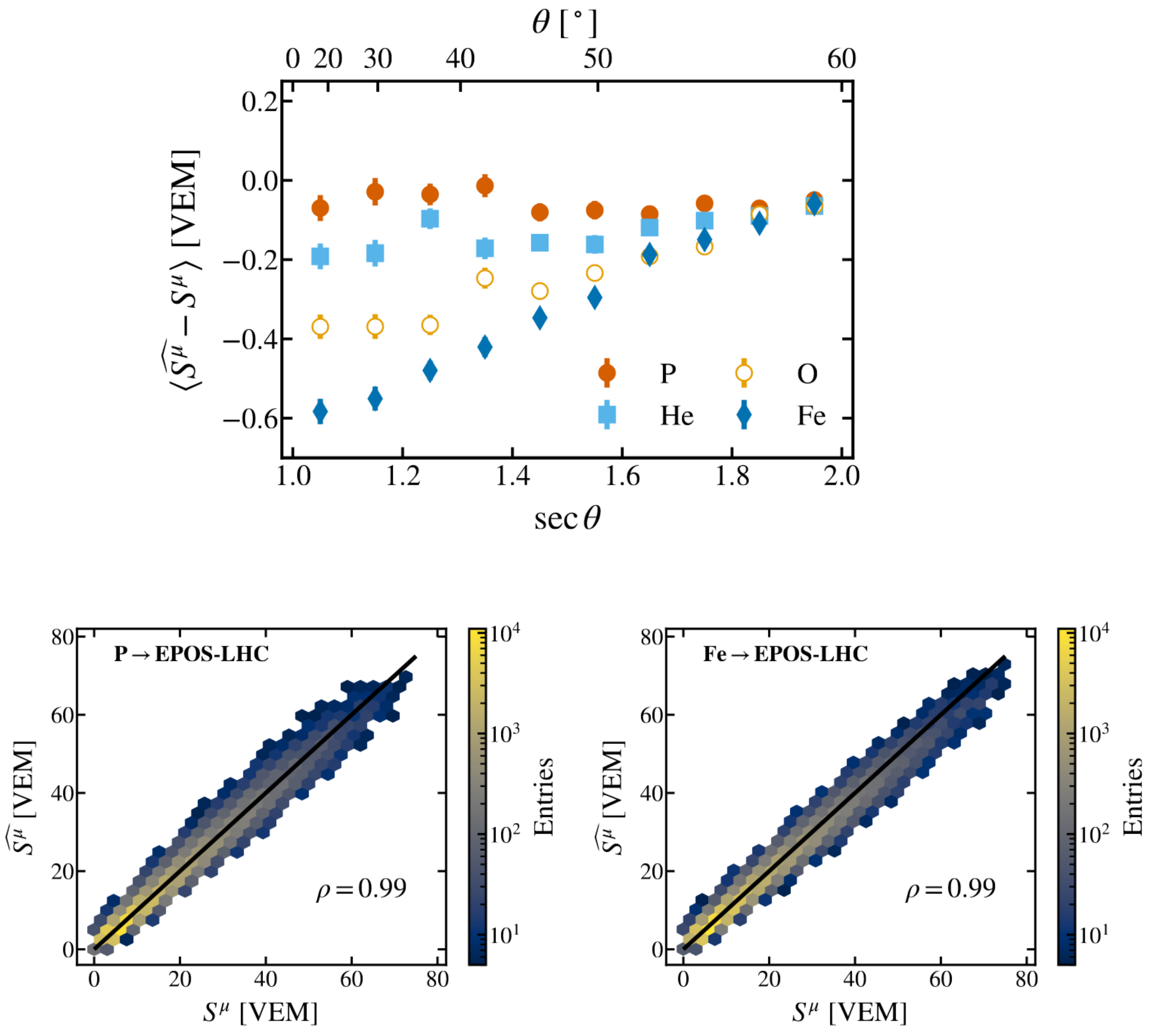
- Two types of neural networks were used to extract muon signal from Auger SD stations– FeedForward and Recurrent
- The largest biases on muon signal come from the stations at small distances to the shower core, dominated by an electromagnetic component producing smooth traces
- NN trained on Sibyll 2.3c was also tested on a different model (EPOS-LHC), no change in the muon signal biases was found
- **Muon signal and risetime can be extracted with a good accuracy for a certain ranges of distances to the shower core and zenith angles**
- The preliminary data application suggests the muon deficit in simulations (well-known problem)

Future plans

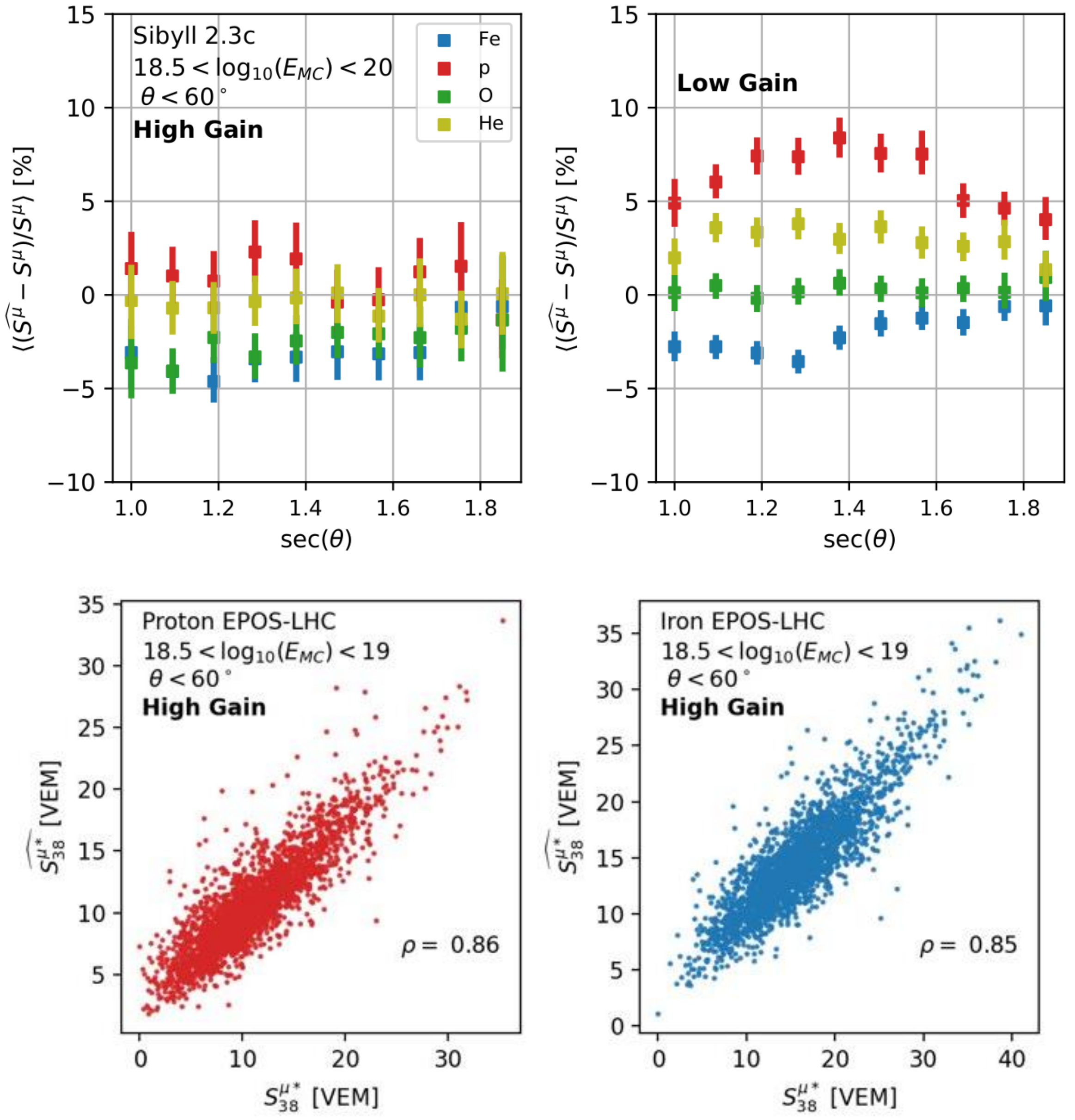
- Optimization of the network performances: architecture, input variables, application phase space
- Study of systematic uncertainties
- Application to the Auger and Auger upgrade (AugerPrime) data with the aim of publishing of the results on behalf of the Collaboration
- ...

Thank you for your attention!

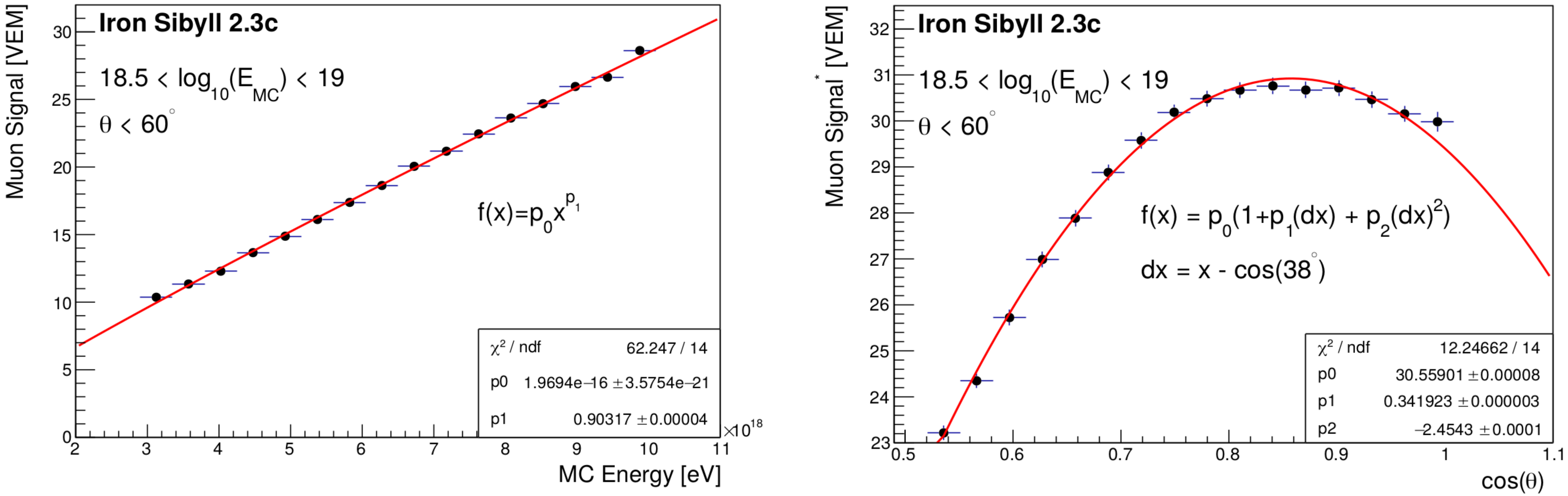
Published results



Thesis results



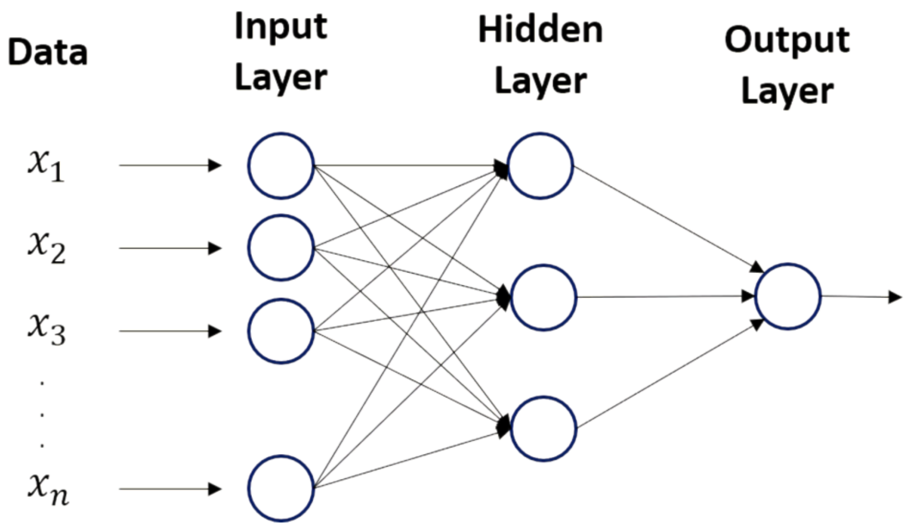
Backup

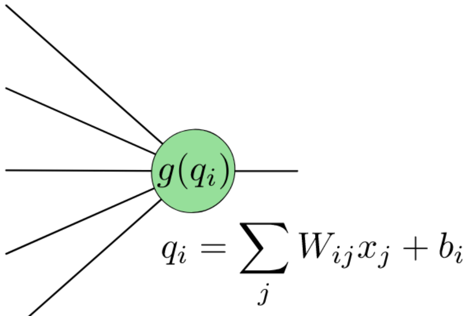


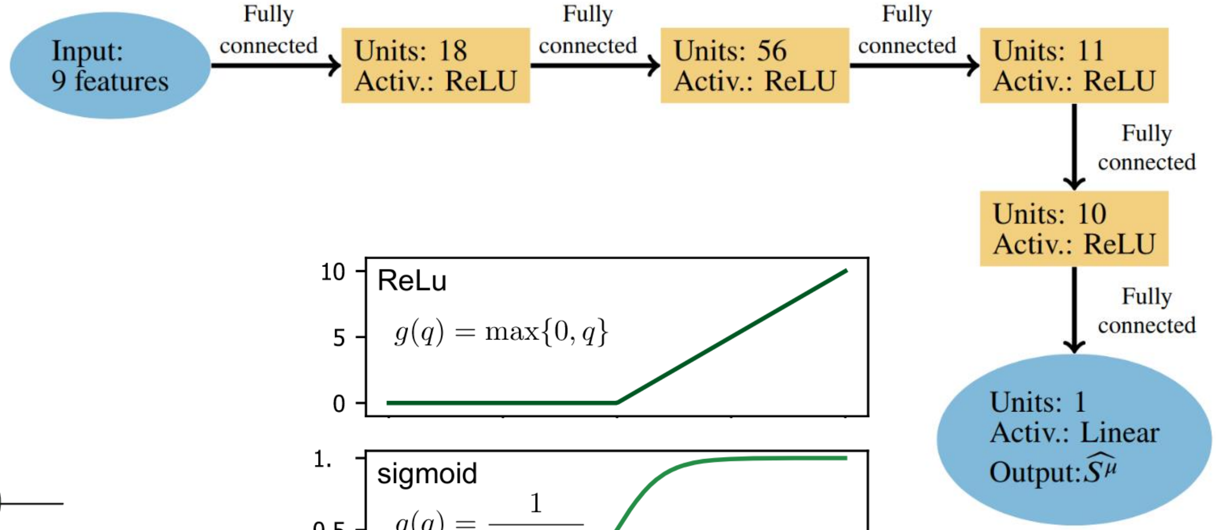
Iron Sibyll 2.3c
18.5 < log10(EMC) < 19
θ < 60°
f(x)=p0x^p1
χ2 / ndf 62.247 / 14
p0 1.9694e−16 ±3.5754e−21
p1 0.90317 ±0.00004
Muon Signal [VEM]
MC Energy [eV]
×10^18
Iron Sibyll 2.3c
18.5 < log10(EMC) < 19
θ < 60°
f(x) = p0(1+p1(dx) + p2(dx)2)
dx = x - cos(38°)
χ2 / ndf 12.24662 / 14
p0 30.55901 ±0.00008
p1 0.341923 ±0.000003
p2 −2.4543 ±0.0001
Muon Signal* [VEM]
cos(θ)

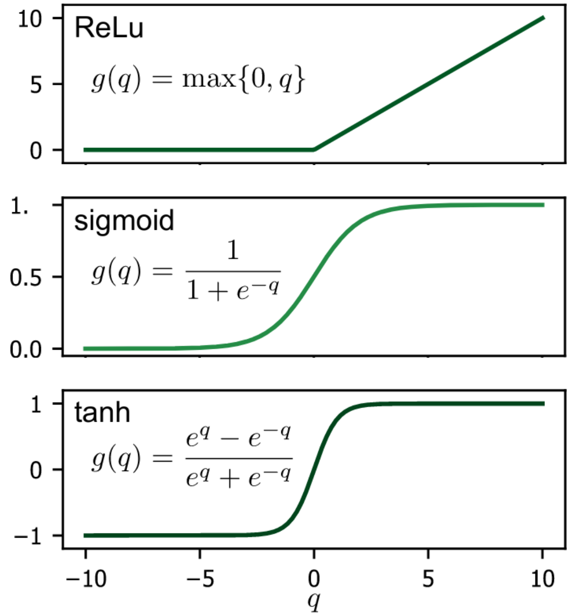
FeedForward neural network

Artificial Neural Networks

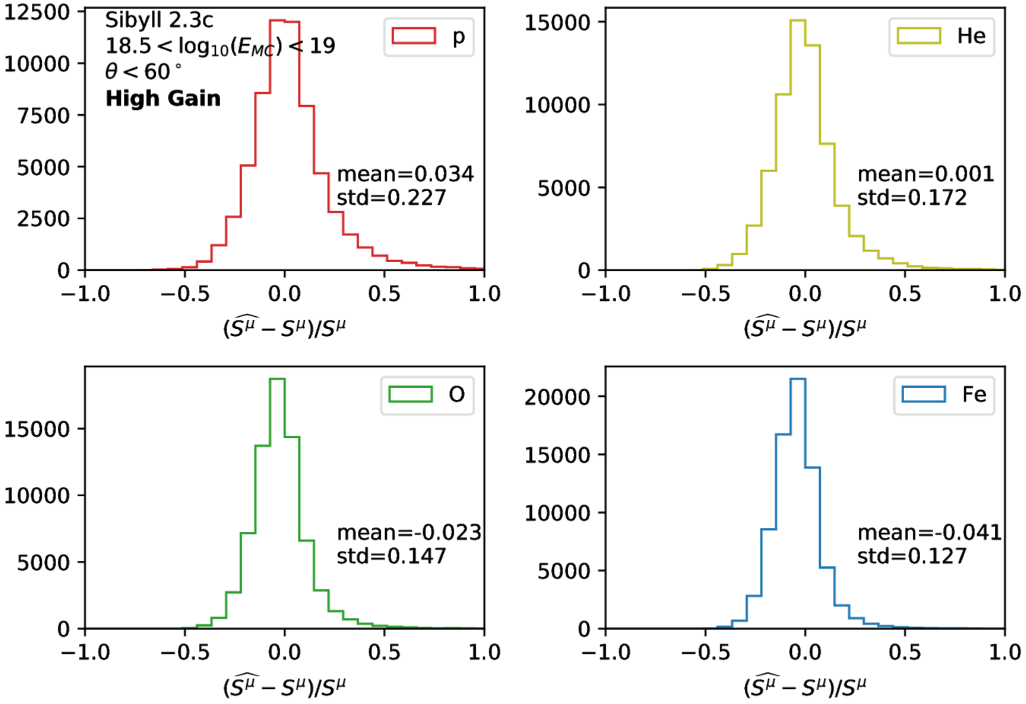


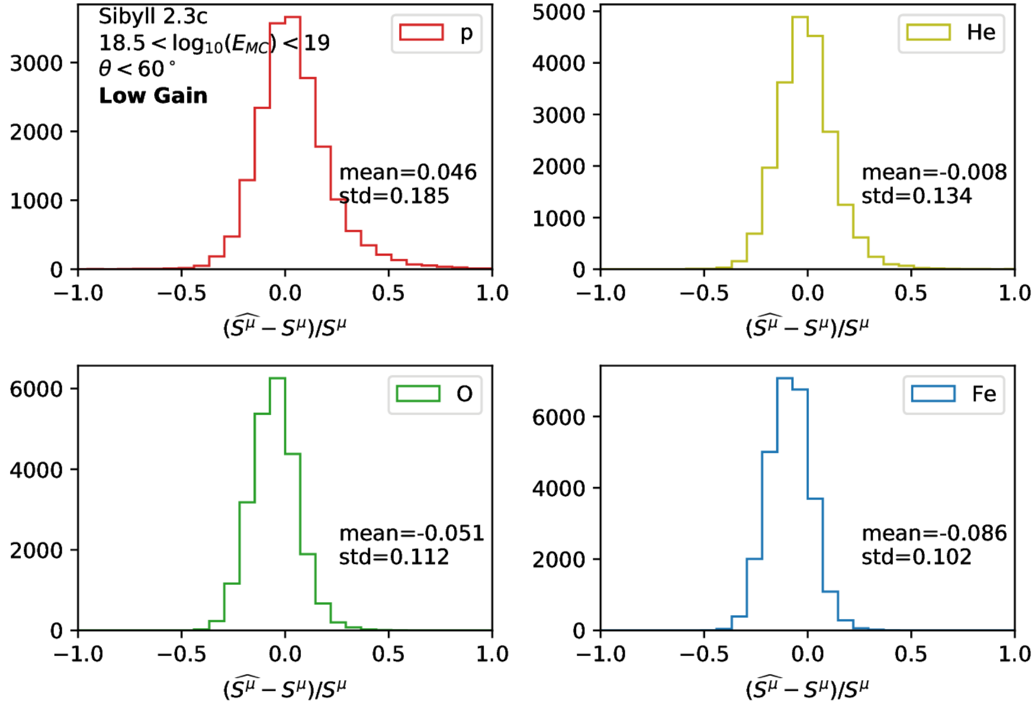






Histograms of biases (FeedForward)

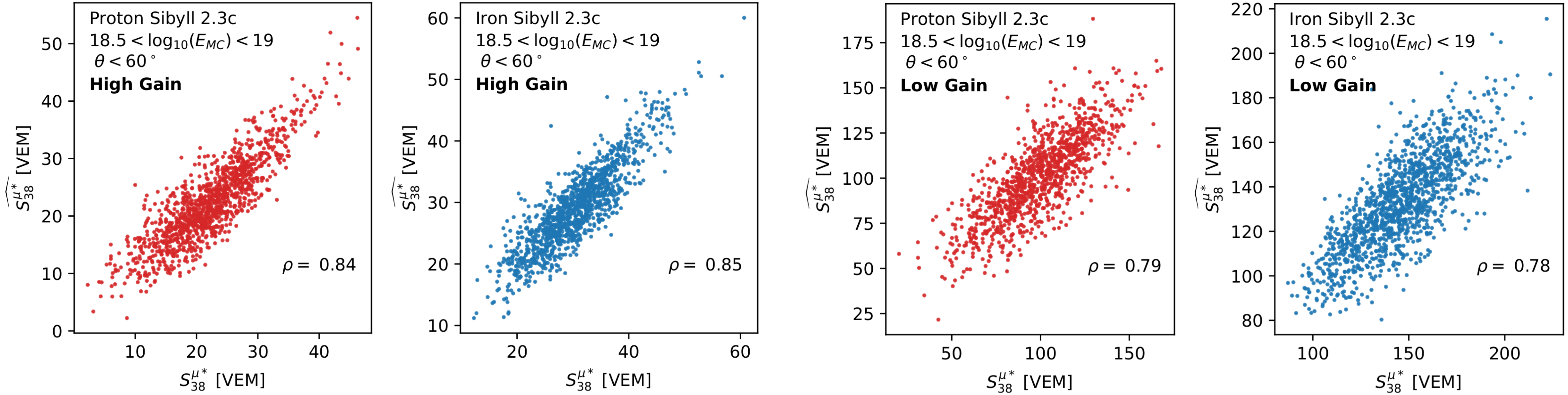




High Gain – Non saturated stations

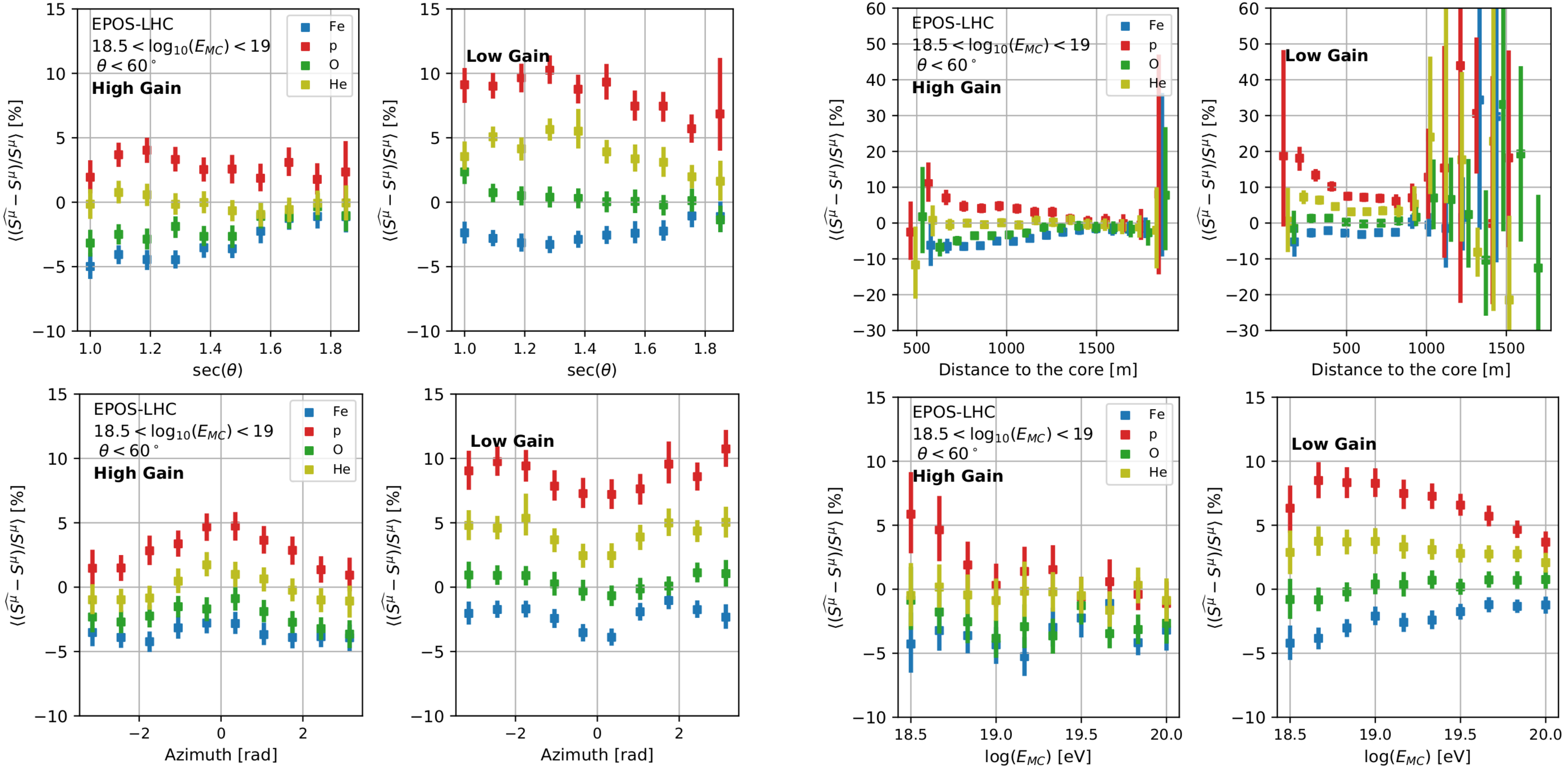
Low Gain – HG saturated stations

Predicted and true muon signal correlation

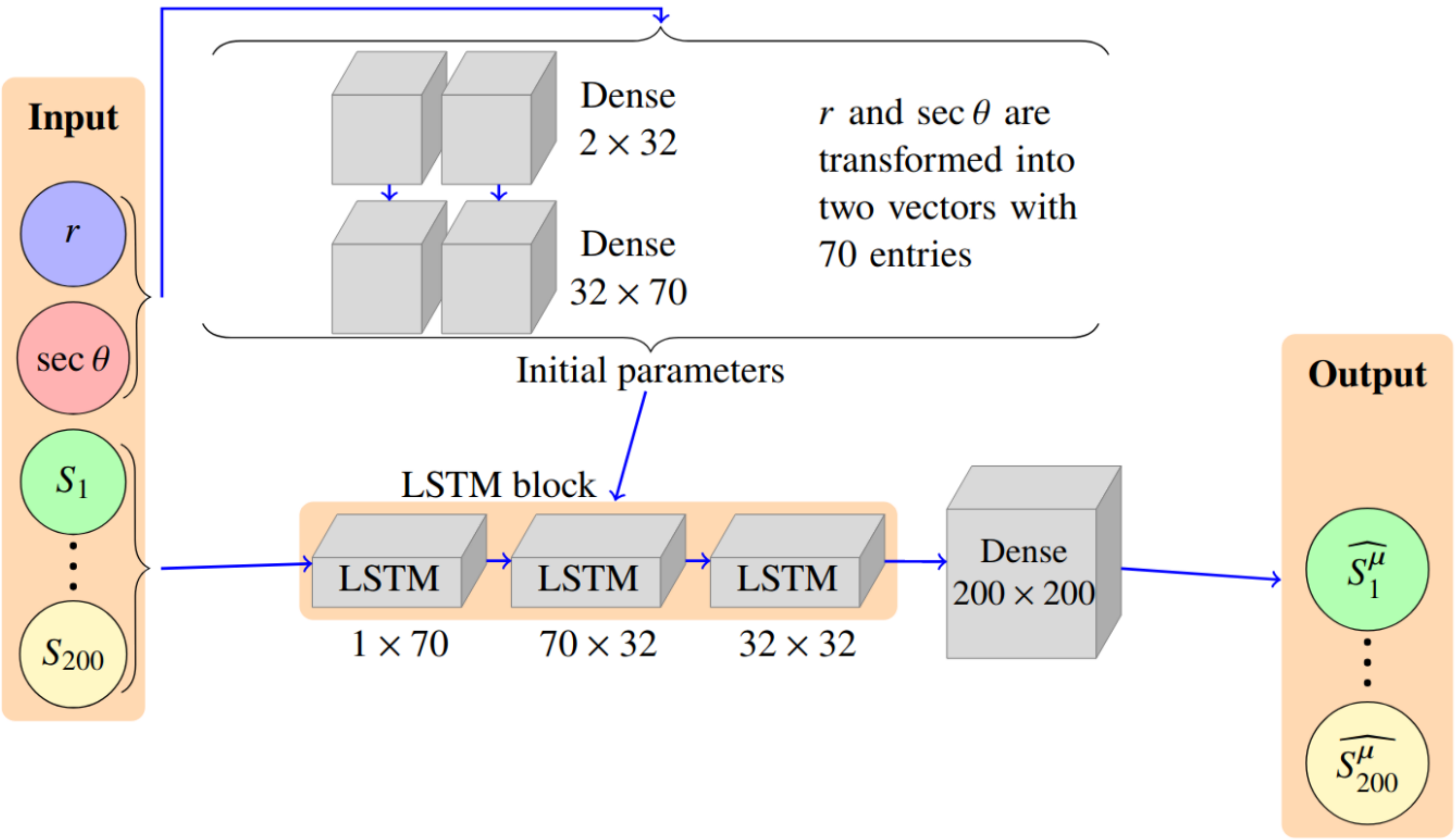


Extraction of muon traces with RNN

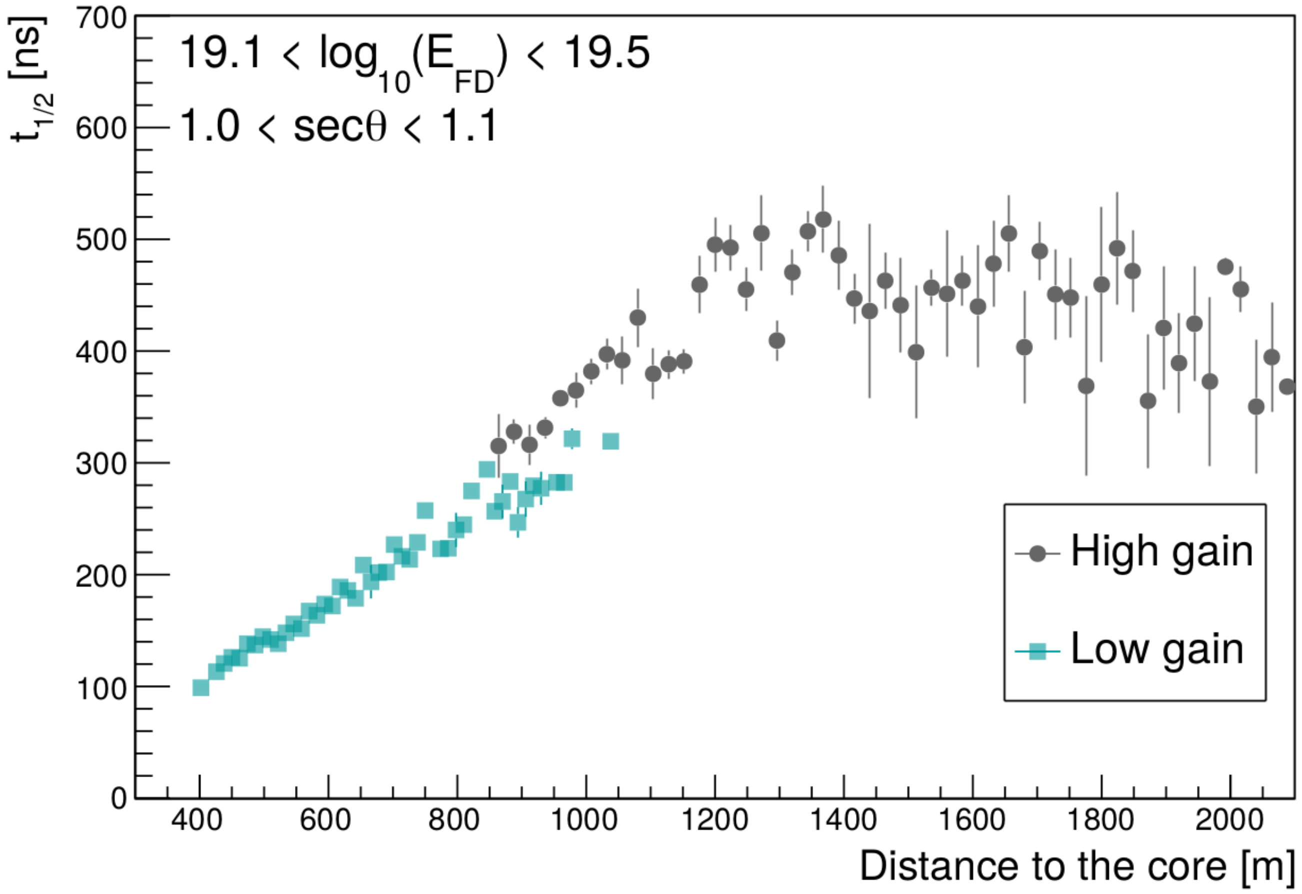
Relative biases (EPOS-LHC)



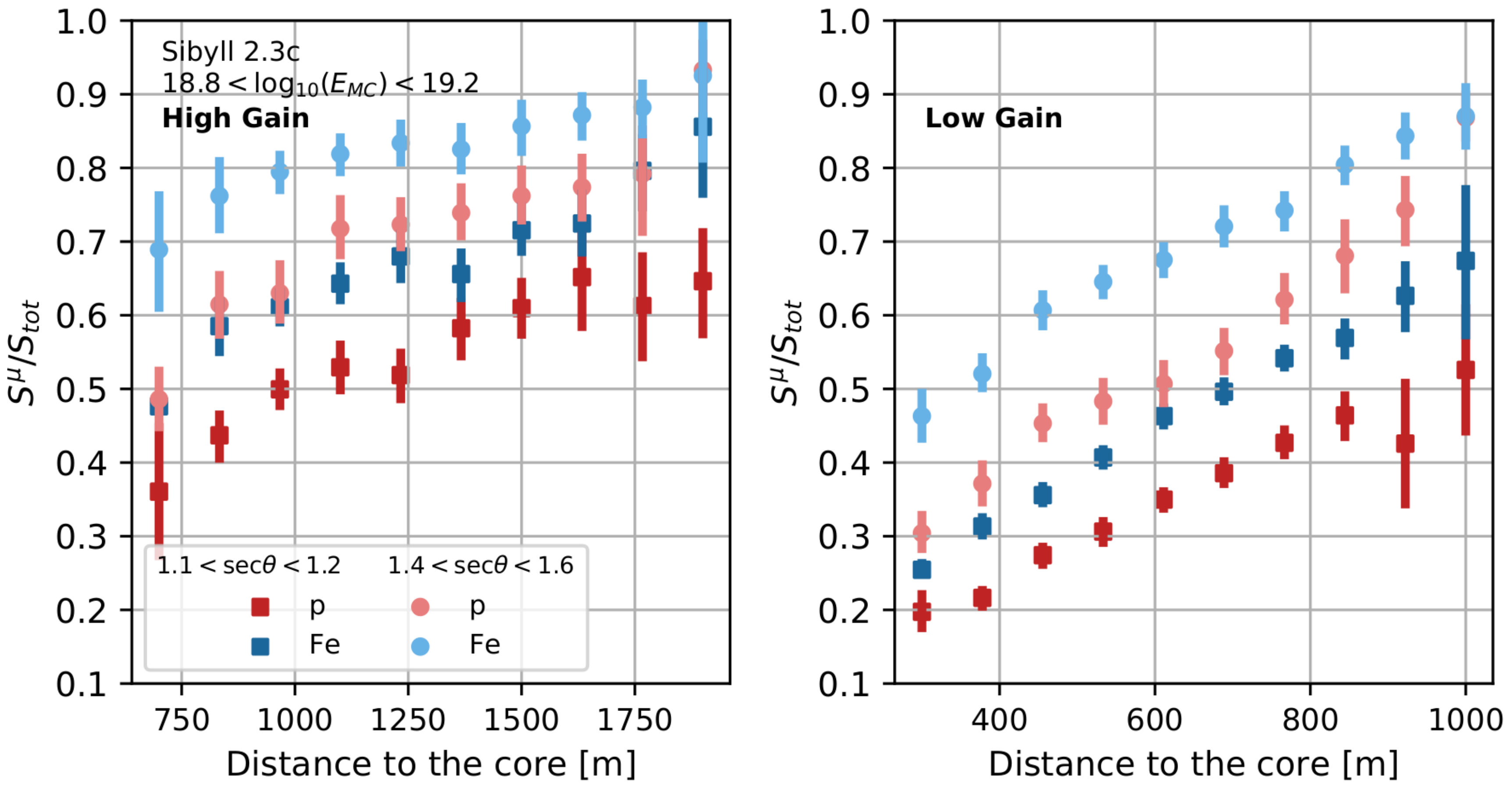
Architecture of the RNN



The risetimes for HG and LG channels



The fractions of muon signal as a function of the distance of the SD station to the shower core for more inclined and more vertical showers



- For vertical showers and LG stations close to the core the muon fraction is the smallest