

Cosmic-ray mass composition study
and ultra-high-energy neutrino search
with the Telescope Array experiment data

Yana Zhezher

ICRR, 2019

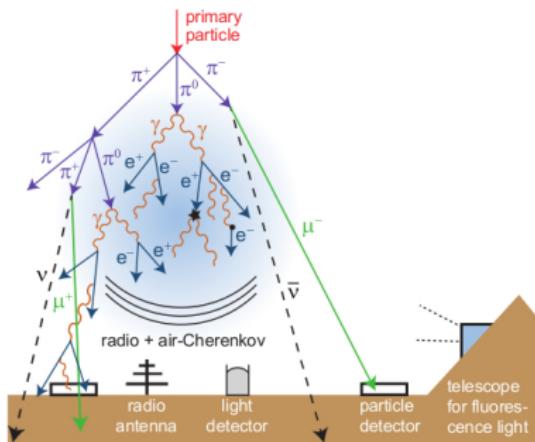
Overview

1. Ultra-high-energy cosmic-ray mass composition study with the Telescope Array surface detector data
2. Determination of a lower limit on the ultrahigh-energy proton-to-helium ratio from the measurements the X_{max} distribution
3. Ultra-high-energy neutrino search with the Telescope Array surface detector data

Open issues in UHECR physics:

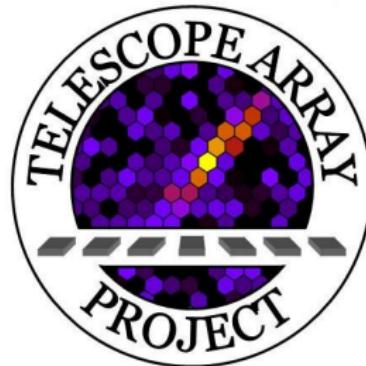
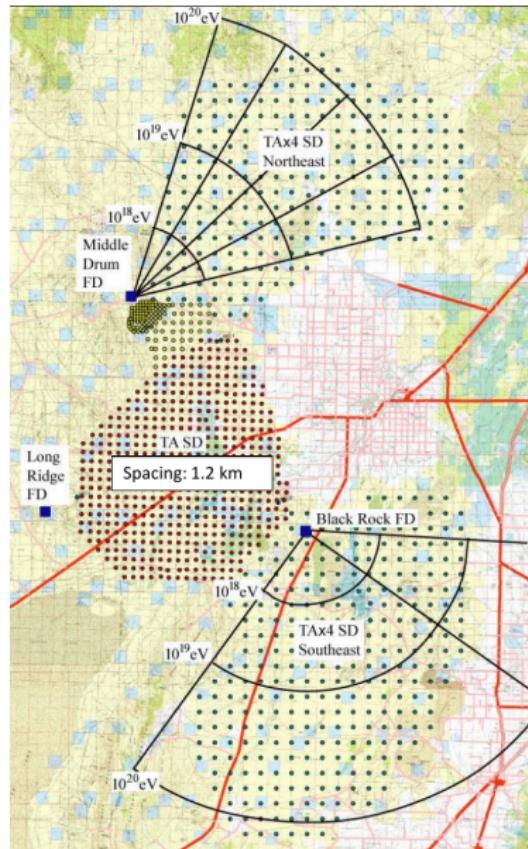
1. UHECR sources, UHECR production processes:
“bottom-up” vs “top-down” models
2. UHECR acceleration mechanisms, possible acceleration sites
3. UHECR propagation: medium parameters, magnetic field structure, etc.

Introduction: observation of UHECR



- ▶ Fluorescence light: air molecules excitation during the propagation of an EAS.
- ▶ Registration of particle distribution at the ground.
- ▶ Radio-emission caused by the propagation of the EM component of a shower.

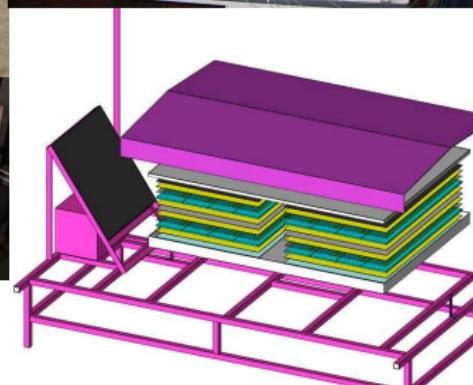
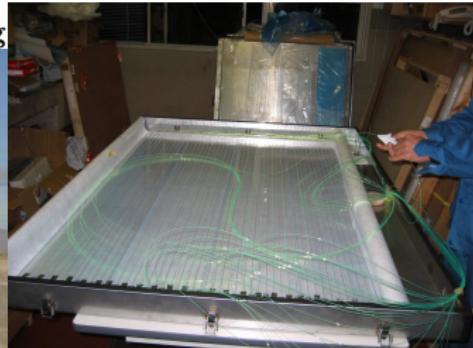
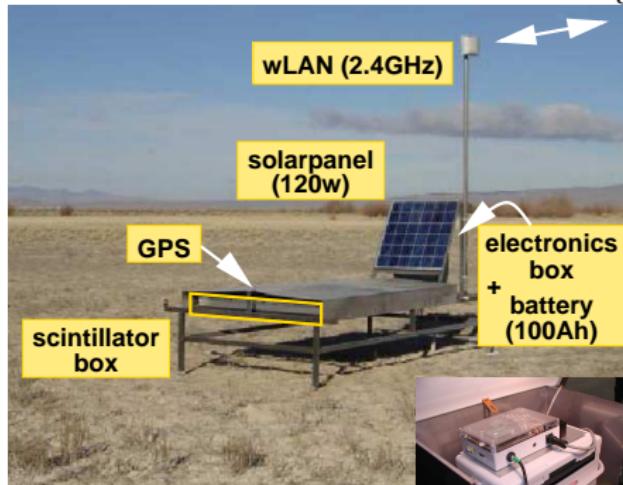
Introduction: the Telescope Array experiment



- Utah, USA
- 507 surface detectors, $S = 3 \text{ m}^2$, 1.2 km distance
- 3 fluorescence detectors
- > 10 years of operation

Telescope Array surface detector

< Surface Detector >



- WLSF: $1.0\text{mm}\phi$
(2cm separation)
- PMTs: ET 9123SA $\times 2$
- 3m^2 (12mm \times 2 layers)

Part 1: UHECR mass composition with the TA SD

Motivation:

- ▶ One can directly determine the mass composition of cosmic rays from the observed EAS.
- ▶ Mass composition is directly connected with the UHECR acceleration mechanisms, accelerator density in the Universe and with the CR propagation processes.
- ▶ Mass composition of UHECR is the main source of uncertainties in the expected flux of cosmogenic photons and neutrinos. UHECR mass is important in the precise tests of Lorentz-invariance violation.

UHECR mass composition $\gtrsim 10^{18}$ eV

Experiment	Detector	Observables
HiRes	fluorescence stereo	X_{MAX}
Pierre Auger	fluorescence + SD (hybrid)	X_{MAX}
Telescope Array	stereo	X_{MAX}
Telescope Array	hybrid	X_{MAX}
Yakutsk	muon	ρ_μ
Pierre Auger	SD	X_{MAX}^μ
Pierre Auger	SD	risetime asymmetry

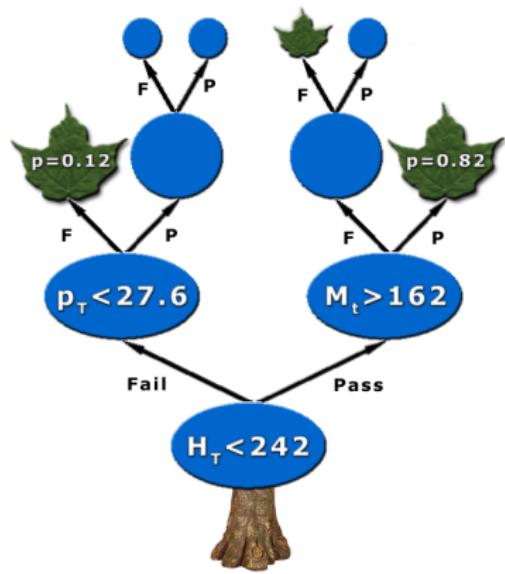
X_{MAX} – depth of shower maximum

X_{MAX}^μ – depth of muon component development

risetime – time from 10% to 50% for the total integrated signal

Mass composition study with the TA SD

p-Fe classifier (BDT)



SD detector array: > 90 %
duty cycle, larger data
statistics compared to FD

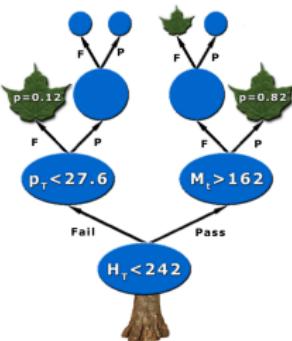
Comparison of ξ distributions for data with Monte-Carlo modelling

$$\langle \ln A \rangle (E)$$

$$(a, AoP, \dots) \rightarrow \xi$$

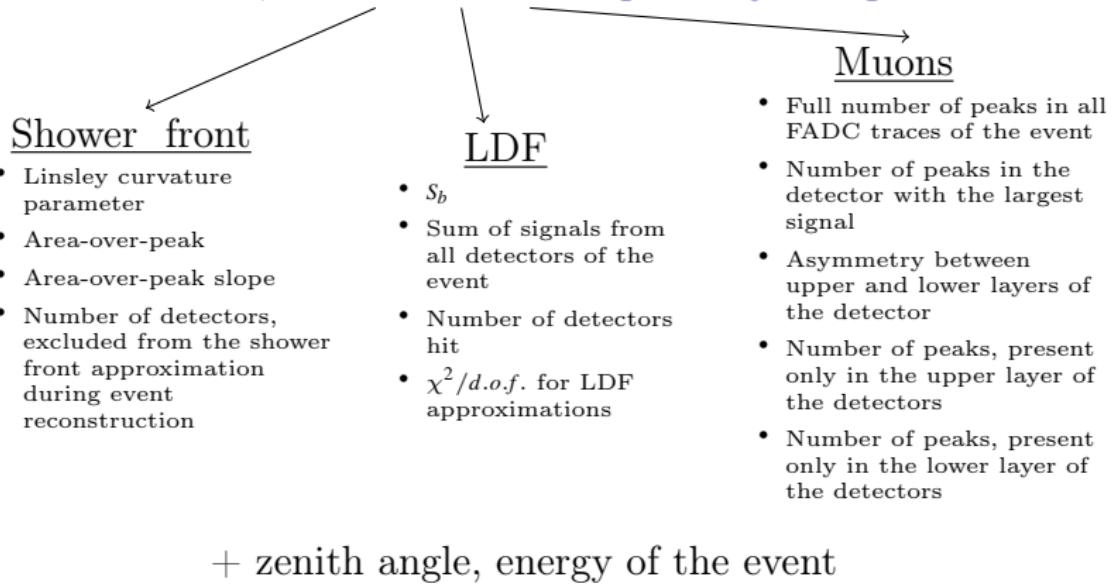
TA, Phys. Rev. D 99, 022002 (2019)

Boosted decision trees (shortly)



1. Find a splitting value for an observable, which gives the best separation: mostly signal events in one branch, mostly background in the other;
2. Repeat step 1 recursively, may use a new observable or re-use the same one;
3. Iterate until the stopping criterion is reached. Terminate node – “leaf”;
4. Boosting: use a number of weak classifiers to build a strong one (“forest”).

Observables, sensitive to the primary composition



Dataset

- ▶ 9-year TA SD dataset:

2008-05-11 — 2017-05-11

Quality cuts:

1. event includes 7 or more triggered stations;
2. zenith angle is below 45° ;
3. reconstructed core position inside the array with the distance of at least 1200 m from the edge of the array;
4. $\chi^2/d.o.f.$ doesn't exceed 4 for both the geometry and the LDF fits;
5. $\chi^2/d.o.f.$ doesn't exceed 5 for the joint geometry and LDF fit.
6. an arrival direction is reconstructed with accuracy less than 5° ;
7. fractional uncertainty of the S_{800} is less than 25 %.

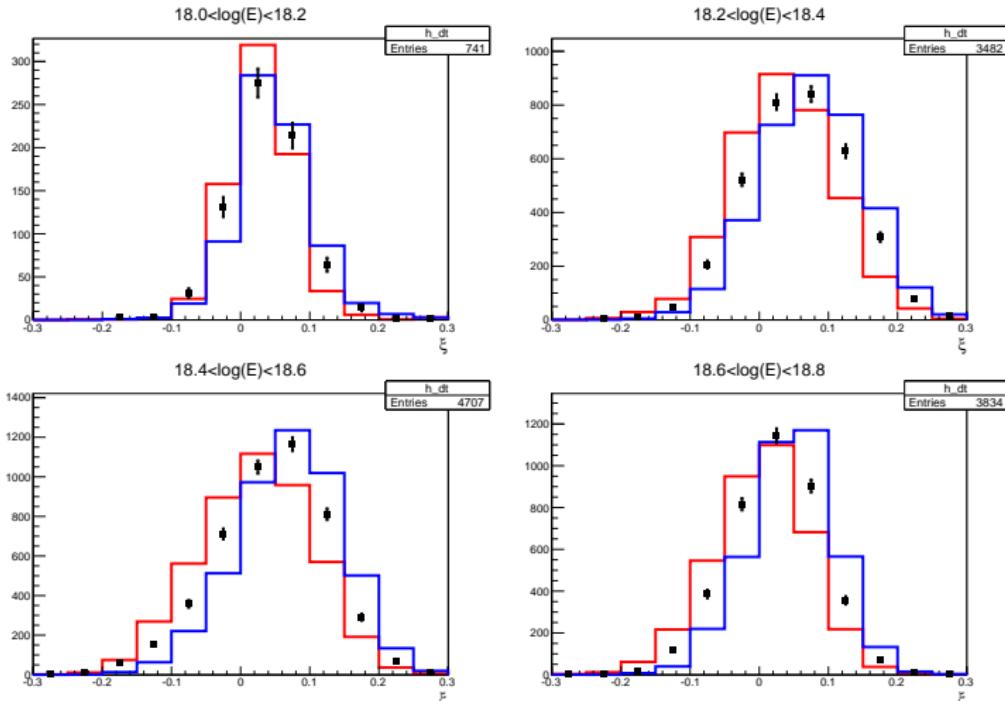
18077 events

Monte-Carlo sets

p, He, N and Fe Monte-Carlo sets with QGSJETII-03

Note: MC-sets are split into three parts with equal statistics: (I) for classifier training, (II) to calculate fractions of protons and iron nuclei, (III) for $\langle \ln A \rangle$ bias correction.

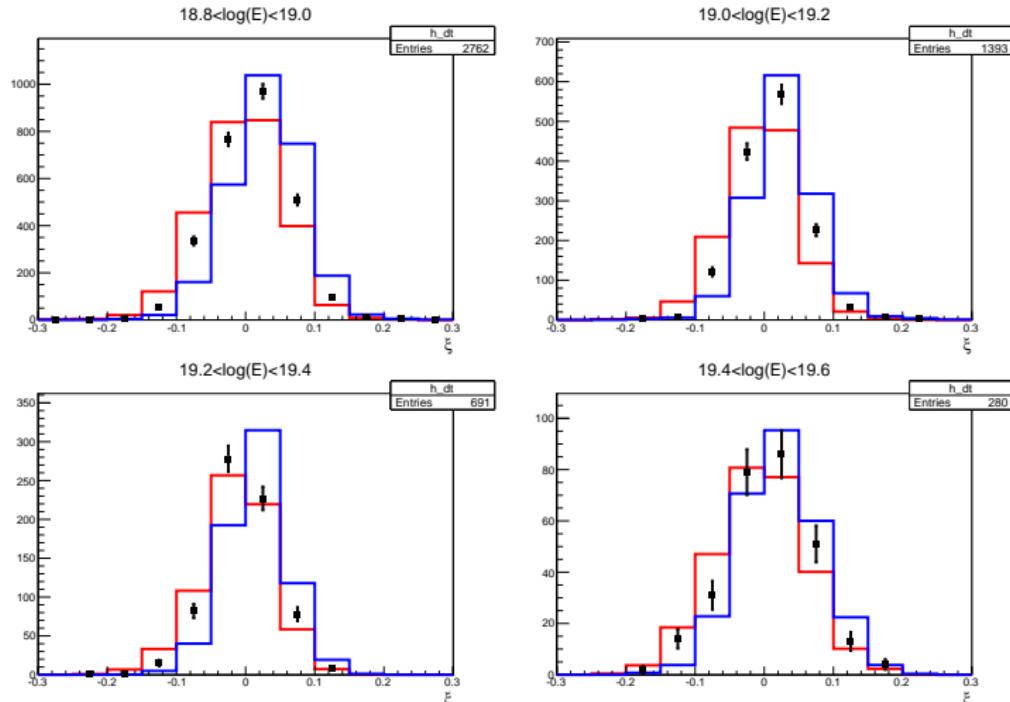
$\langle \ln A \rangle$ first estimate



proton, iron, data

$$\langle \ln A \rangle^{(1)} = \epsilon_p \times \ln(M_p) + \epsilon_{Fe} \times \ln(M_{Fe})$$

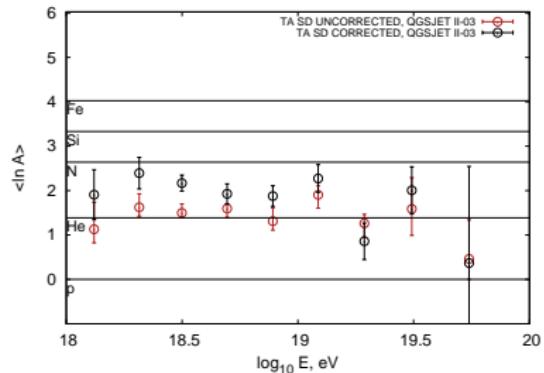
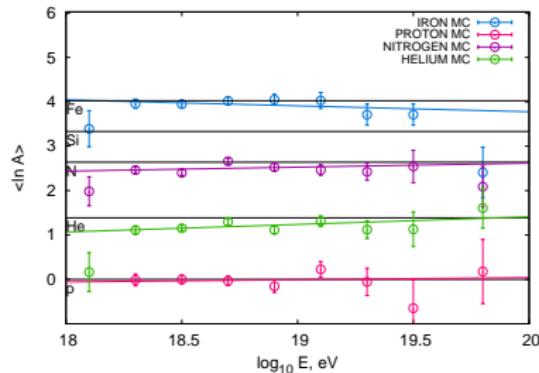
$\langle \ln A \rangle$ first estimate



proton, iron, data

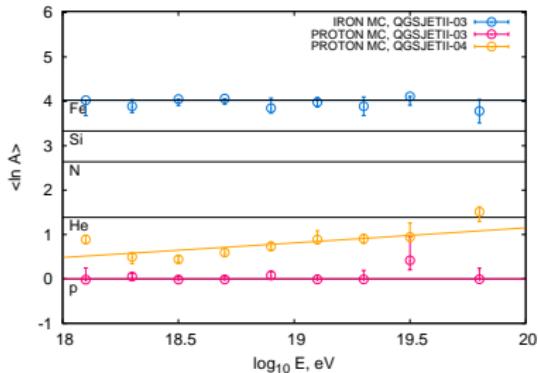
$$\langle \ln A \rangle^{(1)} = \epsilon_p \times \ln(M_p) + \epsilon_{Fe} \times \ln(M_{Fe})$$

$\langle \ln A \rangle$ bias correction



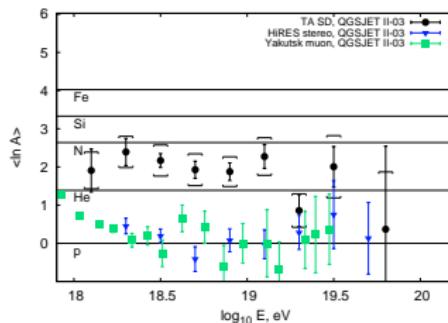
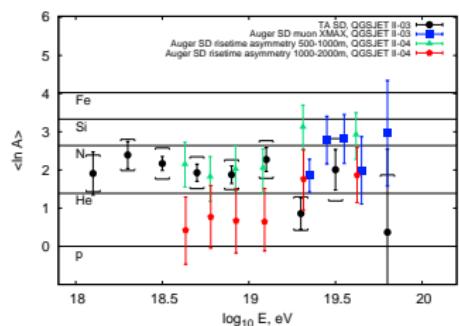
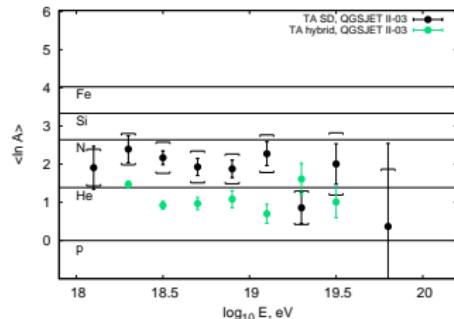
Assume that CR flux is monochromatic. In each energy bin, $\ln A_{true}$ ($\langle \ln A \rangle$) is constructed, which relates derived masses with “true” MC ones.

Hadronic model uncertainty



- All contemporary hadronic interaction models are phenomenological and use approximations.
- EAS muon excess problem: hadronic interaction models fail to correctly describe experimental data.
- Comparison of QGSJETII-03 и QGSJETII-04: $\delta \ln A_{hadr.} = 0.4$.

TA SD composition results



$$\langle \ln A \rangle = 2.0 \pm 0.1(\text{stat.}) \pm 0.44(\text{syst.})$$

R. U. Abbasi et al. [Telescope Array Collaboration]. PRD, 2019

Part 1: moving beyond

How to improve the analysis:

1. Better discrimination between primary particles.
2. Do not rely on “synthetic” variables (primary assumptions such as predefined functions, etc.).

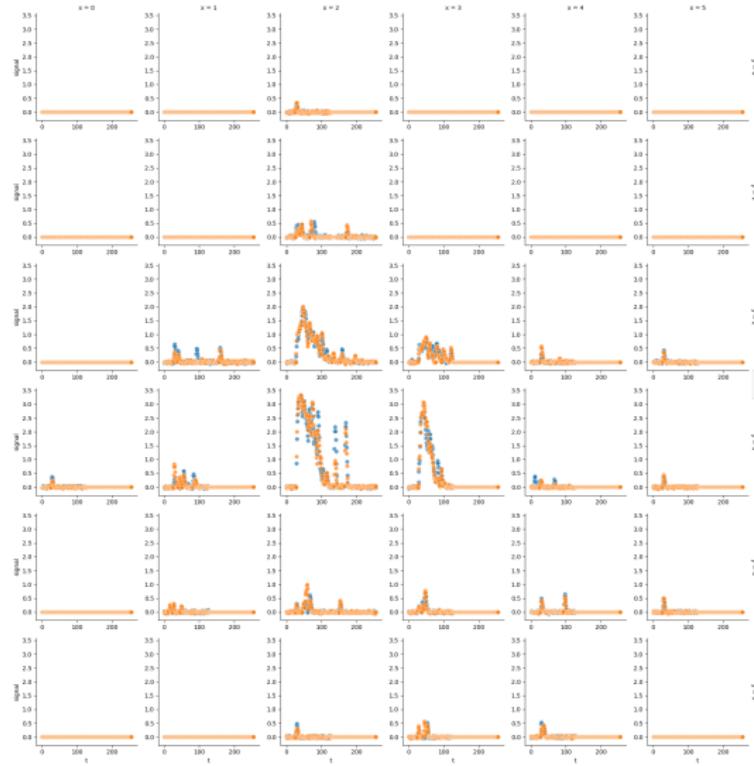
Part 1: moving beyond

How to improve the analysis:

1. Better discrimination between primary particles.
 2. Do not rely on “synthetic” variables (primary assumptions such as predefined functions, etc.).
- ▶ Instead: use “raw” observables, i.e. the time-resolved signals from detectors participating in the event.
 - ▶ Method: Artificial neural networks (NN).
 - ▶ Can describe any continuous function of input data.
 - ▶ Can be tuned using examples generated using Monte-Carlo.

Part 1: moving beyond

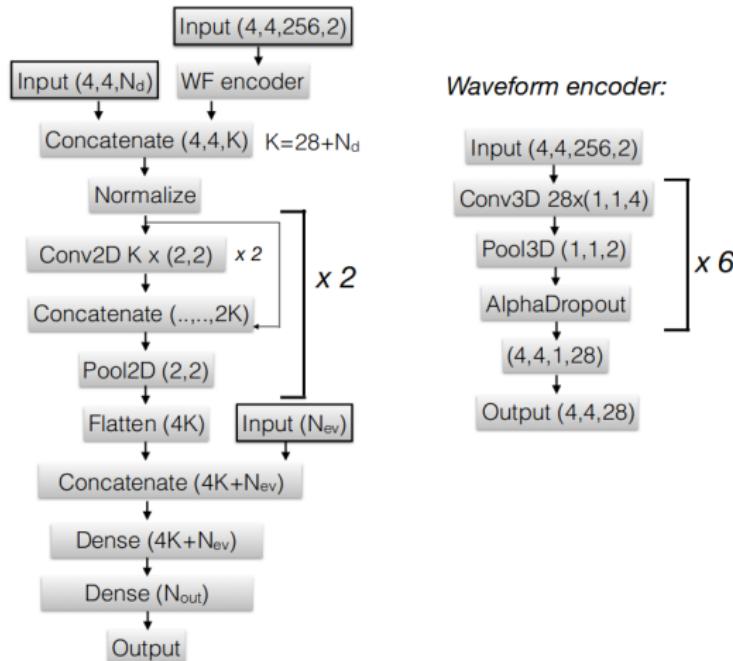
SD event: grid of 4×4 detectors with two separate signals for two layers each containing max. 256 points (total dim.: $4 \times 4 \times 256 \times 2$).



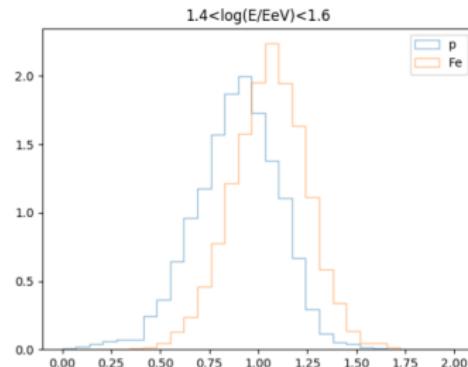
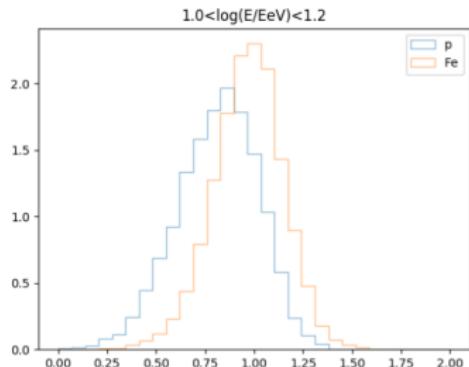
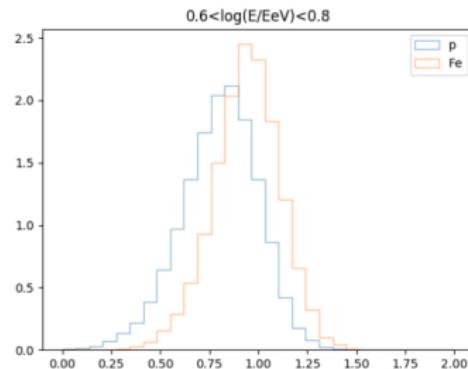
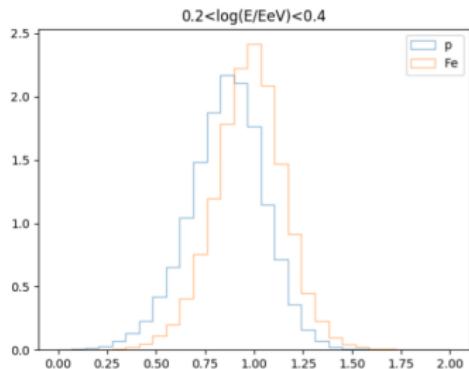
Part 1: moving beyond

Analysis using convolutional neural networks, widely used in image and sequence processing.

NN architecture (PoS(ICRC2019)304):

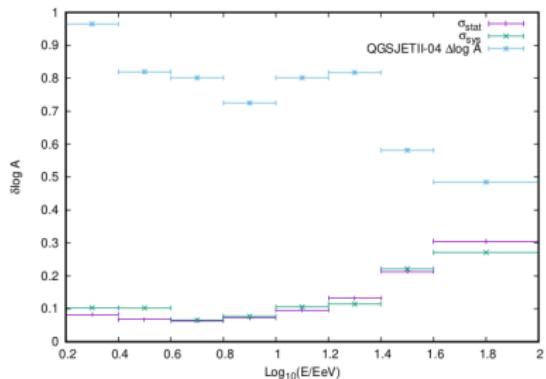
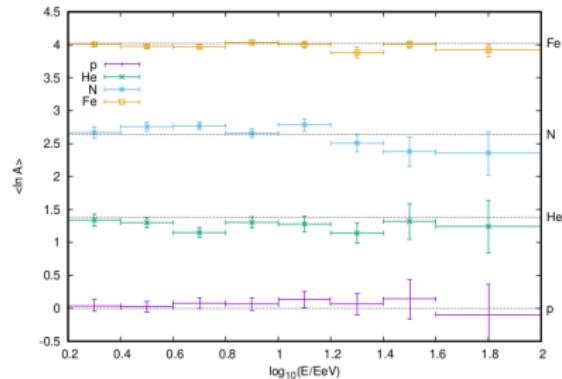


Part 1: moving beyond



NN preliminary result: separation between primaries improved.

Part 1: moving beyond



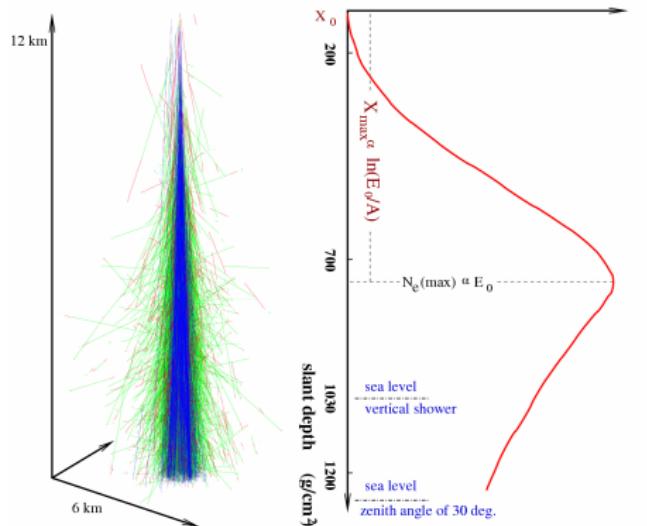
NN preliminary result: statistical and systematic uncertainties reduced.

Part 2: p/He ratio from the tail of X_{\max} distribution

Motivation:

- ▶ UHECR mass-composition-related characteristic, derived independently;
- ▶ Constraints on cosmic-ray source models;
- ▶ Investigations of future collider safety.

Tail of X_{\max} distribution



X_{\max} distribution tail may be used independently: $\exp(-X_{\max}/\Lambda)$, where Λ – attenuation length.

Λ is sensitive to the proton-air cross-section and to the proton-to-helium ratio p/He.

Lower limit on p/He: methodology

1. MC sets for EAS initiated by primary protons, helium and carbon nuclei with different hadronic interaction models.
2. Calculate Λ_i values for different mixtures of primary elements.
3. Compare Λ_i with experimental data.

Experimental Λ

Pierre Auger observatory: $10^{18.0}$ eV $< E < 10^{18.5}$ eV
 $\Lambda = 57.4 \pm 1.8_{stat.} \pm 1.6_{syst.}$ g/cm 2

(R. Ulrich. PoS(ICRC2015). – 2016. – № 401.)

Telescope Array experiment: $10^{18.3}$ eV $< E < 10^{19.3}$ eV
 $\Lambda = 50.47 \pm 6.26$ g/cm 2

(R. U. Abbasi et al. [Telescope Array Collaboration]. Phys. Rev. D – V. 92. – № 3. – P. 032007.)

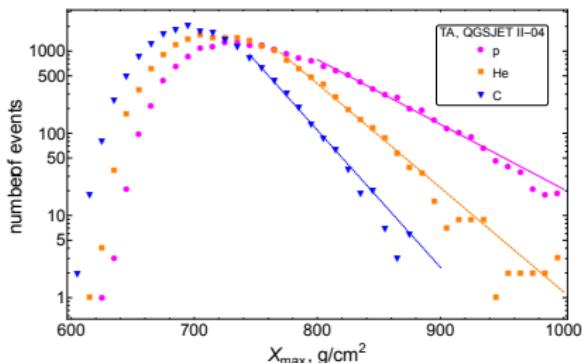
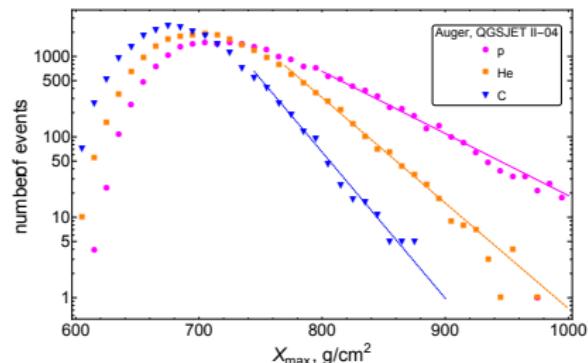
Monte-Carlo sets

Monte-Carlo sets with QGSJETII-04 and EPOS-LHC hadronic interaction models for both experiments.

Auger: 17 098 for each primary in the energy range
 $10^{18.0}$ eV $< E < 10^{18.5}$ eV spectral index -3.293 .

Telescope Array: 17 354 for each primary in the energy range from $10^{18.3}$ eV to $10^{19.3}$ eV with spectral index -3.226 for $E < 10^{18.72}$ eV and -2.66 for $E > 10^{18.72}$ eV.

X_{\max} distribution (QGSJETII-04)

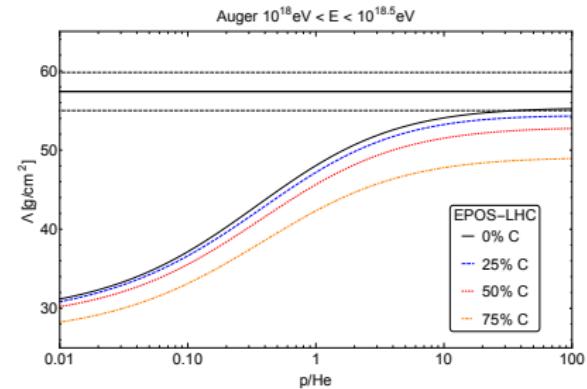
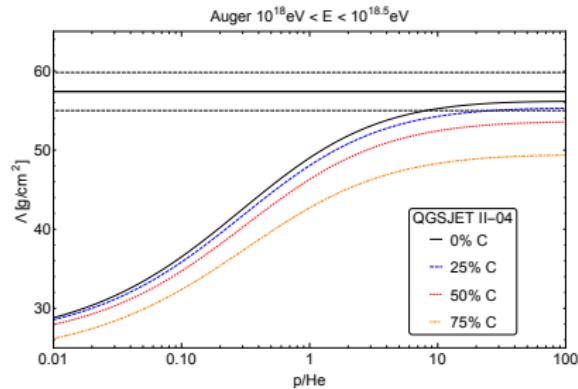


proton

helium

carbon

Results: p/He, Auger

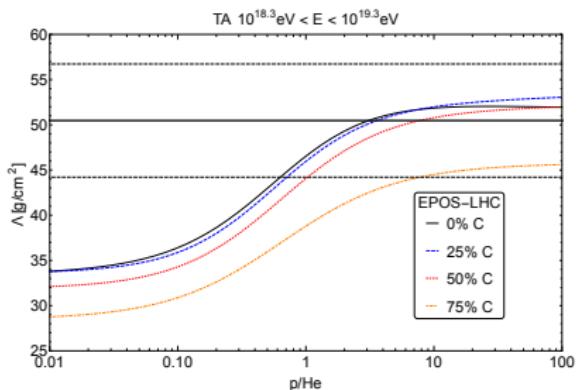
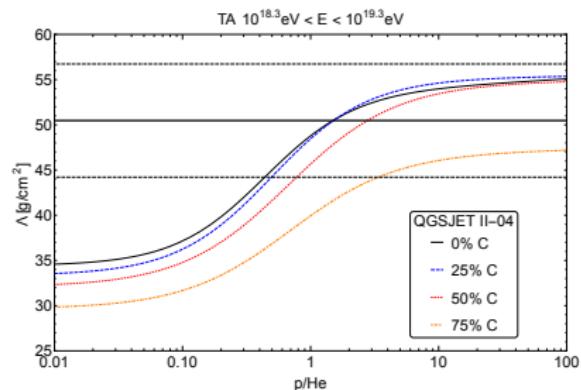


$p/\text{He} > 7.3$ (68% CL)
 $p/\text{He} > 24.0$ (68% CL)

QGSJET II-04,
EPOS-LHC.

I. I. Karpikov, G. I. Rubtsov and Y. V. Zhezher. PRD, 2018.

Results: p/He, TA



$p/\text{He} > 0.43$ (68% CL)

$p/\text{He} > 0.63$ (68% CL)

QGSJET II-04,

EPOS-LHC.

I. I. Karpikov, G. I. Rubtsov and Y. V. Zhezher. PRD, 2018.

Contamination by heavier elements

Proton ratio constraints w.r.t. the three-component mixture:

Auger:

$$p/(p + He + C) > 0.8 \text{ (68\% CL)} \quad \text{QGSJET II-04}$$

$$p/(p + He + C) > 0.96 \text{ (68\% CL)} \quad \text{EPOS-LHC.}$$

Telescope Array:

$$p/(p + He + C) > 0.20 \text{ (68\% CL)} \quad \text{QGSJET II-04,}$$

$$p/(p + He + C) > 0.23 \text{ (68\% CL)} \quad \text{EPOS-LHC.}$$

Part 2 conclusions

Source models

Dip model
(R. Aloisio et al., Astropart. Phys., 2007)

- Power-law injection spectrum.
- Proton primary composition.
- Uniformly-distributed sources.
- Describes the observed spectrum.
- Predicts cosmogenic photon and neutrino fluxes.

Disappointing model

(V. Berezinsky et al., Phys. Rev. D, 2006)

- Power-law injection spectrum.
- Proton composition up to (1 – 3) eV.
- CR energy depends on charge: $E_{max}^{acc} = Z E_0$.
- Predicts Auger mass composition.
- Doesn't predict cosmogenic neutrinos.
- No correlation with sources due to large deflection in magnetic fields.

Part 2 conclusions

Model	Composition	Resolution
Dip model <small>(R. Aloisio et al., Astropart. Phys., 2007)</small>	proton	consistent
Modified dip model <small>(R. Aloisio, V. Berezinsky, arXiv:1703.08671)</small>	$p/\text{He} = 5$	excluded by Auger
Disappointing model <small>(V. Berezinsky et al., Phys. Rev. D, 2006)</small>	mostly proton	consistent
Helium disappointing model	helium	excluded by Auger

Part 3: UHE neutrino search with the TA SD

Motivation:

- ▶ Neutrinos are almost not absorbed during their propagation due to small cross-sections and aren't deflected in magnetic fields – pointing to the sources.
- ▶ Indication to the UHECR source types.
- ▶ Constraints on UHECR acceleration mechanisms.
- ▶ UHECR mass composition study – if primary UHECR flux is not purely protons, neutrino production is strongly suppressed.

UHE neutrino production mechanisms

1. **Astrophysical** neutrinos are produced in UHE hadron interactions with radiation and matter close to their astrophysical sources.
2. **Cosmogenic** neutrinos are born in interactions of primary protons and nuclei with background radiation during their propagation to Earth.
3. Neutrinos may be born in “top-down” models in decays of massive objects in the processes such as $D \rightarrow \nu + \text{all}$, or a possible rare decay $D \rightarrow 3\nu$.

Observation of UHE neutrino

1. “Down-going” neutrino: interaction in Earth’s atmosphere through charged-current (CC) and neutral-current (NC) interactions

$$\begin{aligned}\nu_{\text{lepton}} + X &\rightarrow \text{lepton} + X, \\ \nu_{\text{lepton}} + X &\rightarrow \nu_{\text{lepton}} + X.\end{aligned}$$

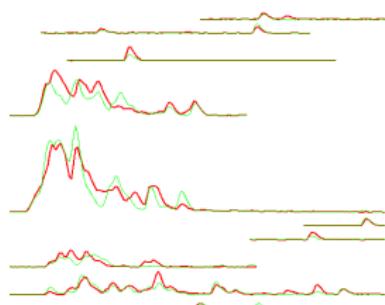
2. “Earth-skimming” neutrino: EAS invoked in the CC interactions with the minerals in the Earth’s crust.
3. Radio-emission from neutrino passing through dense matter, such as ice or lunar regolith, caused by the Askaryan effect.

Down-going neutrino search with the TA SD

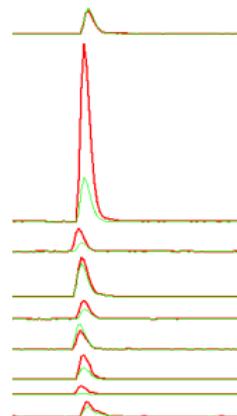
- ▶ Small interaction cross section -> search in highly-inclined showers (V. S. Berezinsky, G. T. Zatsepin. Phys. Lett., 1969).
- ▶ Neutrino-invoked EASes are “young” – develop deep, EM component is not absorbed.
- ▶ Time-resolved signals contain many peaks.

Down-going neutrino search with the TA SD

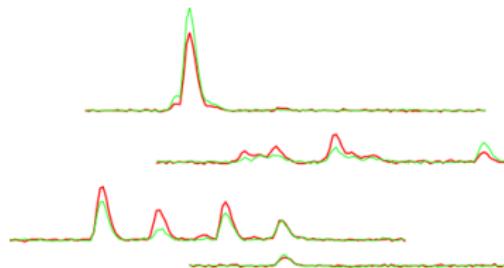
“young” EAS, $\theta = 19.5^\circ$



“old” EAS, 78.3°

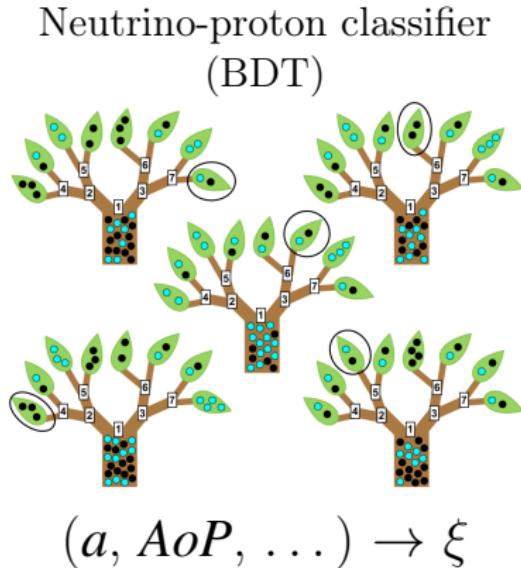


neutrino EAS (MC), $\theta = 78.6^\circ$

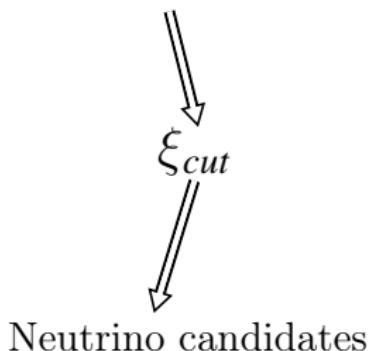


upper layer lower layer

UHE neutrino search pipeline



$\xi(\theta)$ distribution for
Monte-Carlo sets



Dataset

- ▶ 9-year TA SD dataset:

2008-05-11 — 2017-05-11

Quality cuts:

1. 5 or more triggered stations;
2. zenith angle $\theta \in [45^\circ; 90^\circ]$;
3. reconstructed core position not less than 1200 m from the boundary of the array;
4. $\chi^2/d.o.f.$ not more than 5 for the joint approximation of shower geometry and LDF.

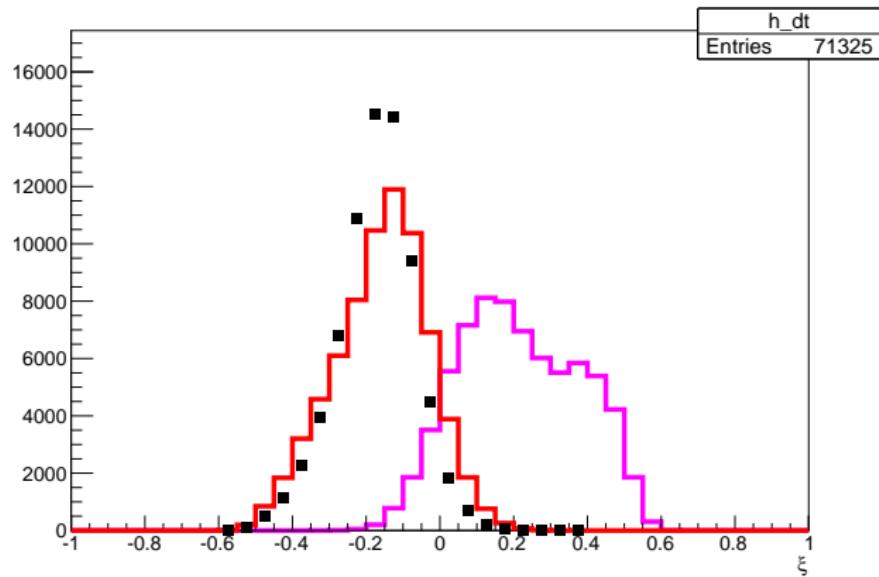
197250 events

Neutrino MC

- ▶ 3000 CORSIKA shower, primary neutrino interactions with HERWIG;
- ▶ Uniform neutrino flavour flux
 $\nu_e : \bar{\nu}_e : \nu_\mu : \bar{\nu}_\mu : \nu_\tau : \bar{\nu}_\tau = 1 : 1 : 1 : 1 : 1 : 1$; neutrino type randomly assigned for each event;
- ▶ Energies: $3 \times 10^{17} - 3 \times 10^{20}$ eB;
- ▶ Zenith angles: $\theta \in [0; 90^\circ]$;
- ▶ Neutrinos don't interact in CORSIKA, point of first interaction calculated independently and fixed within CORSIKA:
 - ▶ Interaction depth: $T_{int} \sim 1/\sigma_{CC+NC}$;
 - ▶ Cross-sections: A. Cooper-Sarkar and S. Sarkar, JHEP, 2008.

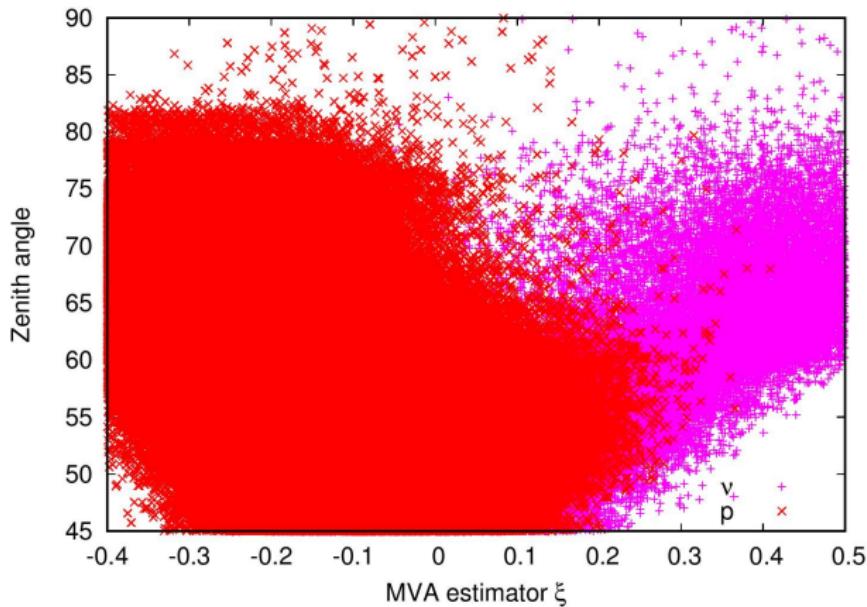
Note: MC set split into three parts. (I) to train the classifier, (II) to optimize the cuts, (III) to calculate the exposure.

ξ distribution histogram



neutrino MC proton MC data

Cut optimization



neutrino MC proton MC

Cut optimization

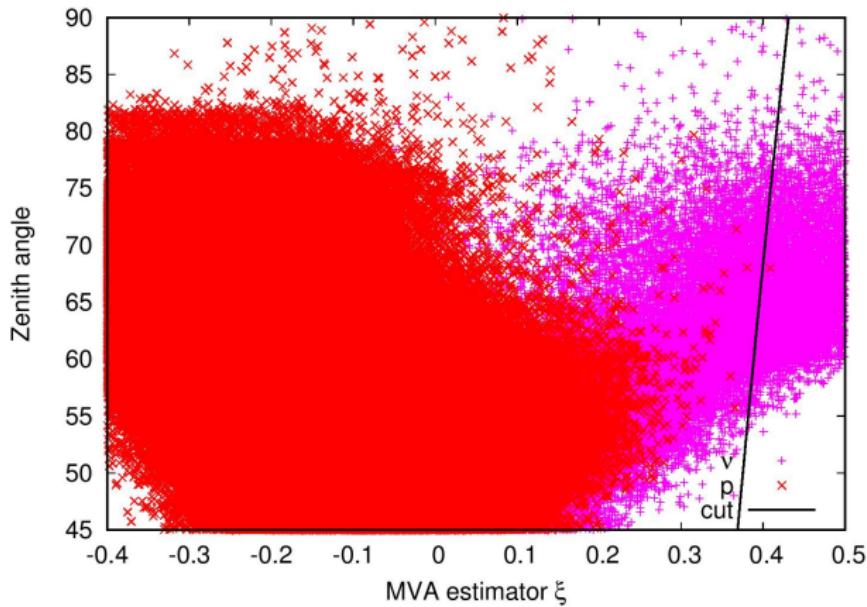
Neutrino candidate: $\xi > \xi_{cut}(\theta) = \xi_0 + \xi_1 \times \theta + \xi_2 \times \theta^2$.

Merit function: mean expected value of the upper limit on neutrino flux.

$\langle n_p \rangle_{90\% \text{ C.L.}}$ – upper limit on the mean value of the Poisson random variable with observed number of events n_p (Feldman-Cousins statistics).

$$f_{merit}(\xi_0, \xi_1, \xi_2, \theta) = \frac{\langle n_p \rangle_{90\% \text{ C.L.}}}{n_\nu}.$$

Cut optimization



$$\xi_{cut} = 0.302 + 0.046 \times \theta - 0.006 \times \theta^2$$

neutrino MC proton MC

Exposure estimate

Geometric exposure for 9 years of observations and zenith angle range $0^\circ < \theta < 90^\circ$:

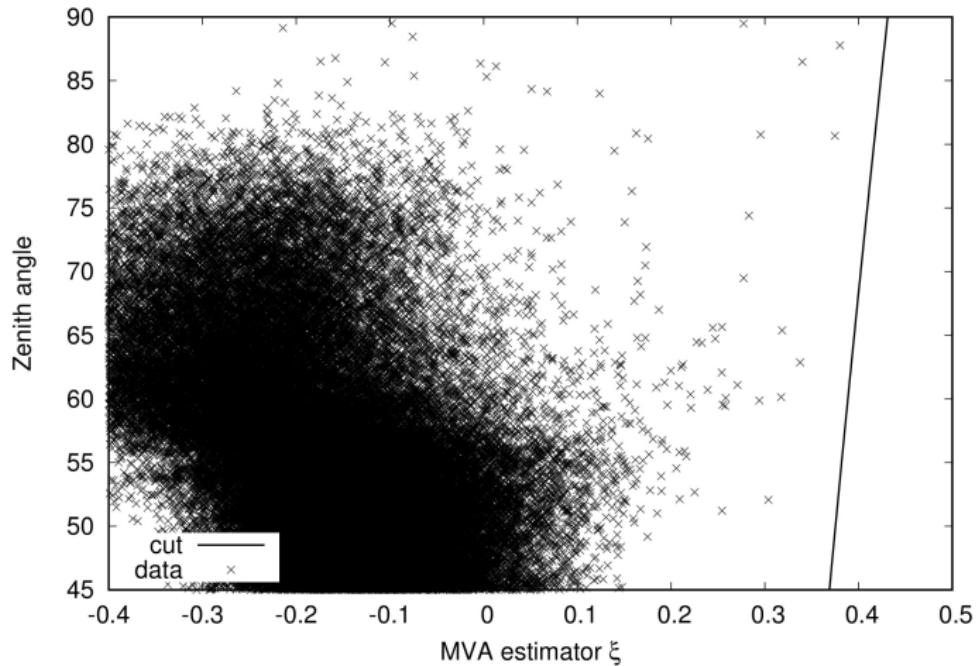
$$A_{geom}^{MC} = \int_0^{\pi/2} \sin \theta \cos \theta S T d\theta = 55500 \text{ km}^2 \text{ sr yr}$$

$$A_{eff}^\nu = A_{geom}^{MC} \times \frac{N_{pass}}{N_{thrown}} \times N_{flavor}$$

$$N_{pass} = 8278, \quad N_{thrown} = 2.81 \times 10^{11}$$

$$A_{eff}^\nu = 1.6 \times 10^{-3} \text{ km}^2 \text{ sr yr}$$

Part 3 results



0 neutrino candidates

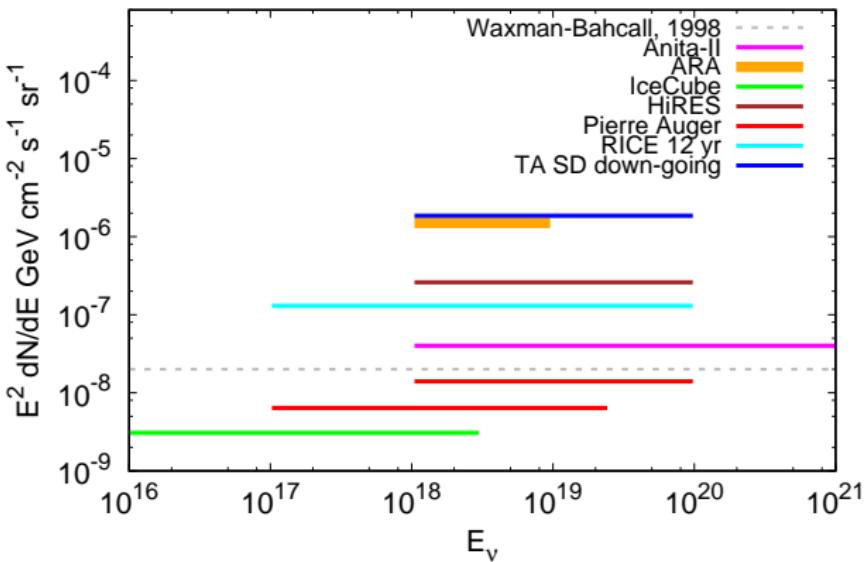
Part 3 results

0 neutrino candidates in dataset. Upper limit on number of neutrino events of all flavours: $\bar{n}_\nu = 2.44$ (90% C.L.).

Upper limit on diffuse flux on one-flavour neutrino for $E > 10^{18}$ eV:

$$EF_\nu < 1.58 \times 10^{-6} \text{ GeV cm}^{-2} \text{ s}^{-1} \text{ sr}^{-1} \text{ (90\% C.L.)}.$$

Part 3 results



Backup

Linsley front curvature parameter

In TA, shower front is approximated as follows:

$$t_0(r) = t_0 + t_{plane} + \\ + \textcolor{blue}{a} \times 0.67 (1 + r/R_L)^{1.5} LDF(r)^{-0.5}$$

$$LDF(r) = S(r)/S(800 \text{ m})$$

$$S(r) = \left(\frac{r}{R_m}\right)^{-1.2} \left(1 + \frac{r}{R_m}\right)^{-(\eta-1.2)} \left(1 + \frac{r^2}{R_1^2}\right)^{-0.6}$$

$$R_m = 90.0 \text{ m}, R_1 = 1000 \text{ m}, R_L = 30 \text{ m}$$

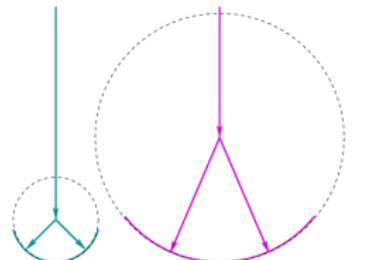
$$\eta = 3.97 - 1.79(\sec(\theta) - 1)$$

$$t_{plane}^i = \frac{1}{c} \vec{n} \left(\vec{R}_i - \vec{R}_{core} \right)$$

t_{plane} – flat front arrival time

a – Linsley front curvature parameter

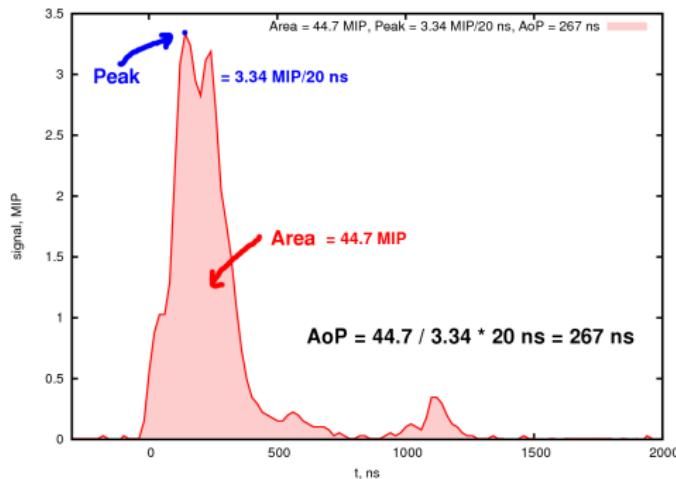
LDF – lateral distribution function



The deeper the shower develops \rightarrow the more curved front it has.

Area-over-peak and area-over-peak slope

- Time-resolved signal from a given station:



- $AoP(r)$ is approximated as follows:
 - $AoP(r) = \alpha - \beta(r/r_0 - 1.0)$
 - $r_0 = 1200$ m, α – it's value at 1200 m, β – AoP slope

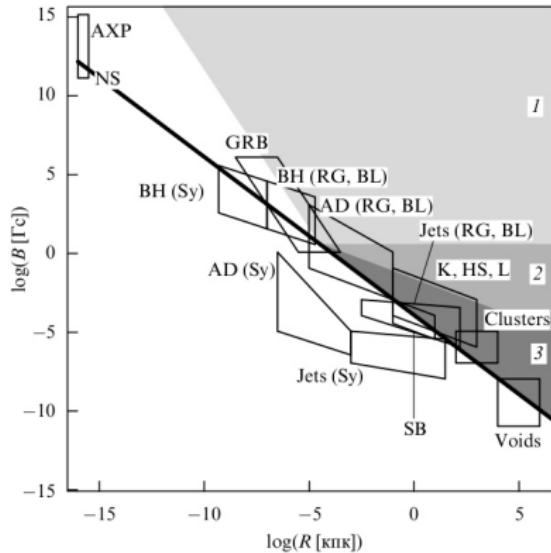
S_b parameter

$$S_b = \sum_{i=1}^N \left[S_i \times \left(\frac{r_i}{r_0} \right)^b \right],$$

S_i – signal of i-th detector, r_i – distance to the shower core in meters, $r_0 = 1200$ m – characteristic distance. $b = 3$ and $b = 4.5$ values chosen as giving the best separation between primaries.

G. Ros, A. D. Supanitsky, G. A. Medina-Tanco et al., Astropart. Phys., 2001

Hillas plot



Geometric criterion:

$$R_{ac} > \frac{E}{qB}$$

AdaBoost

Boosting – idea of making one good classifier from a number of weak ones (a forest).

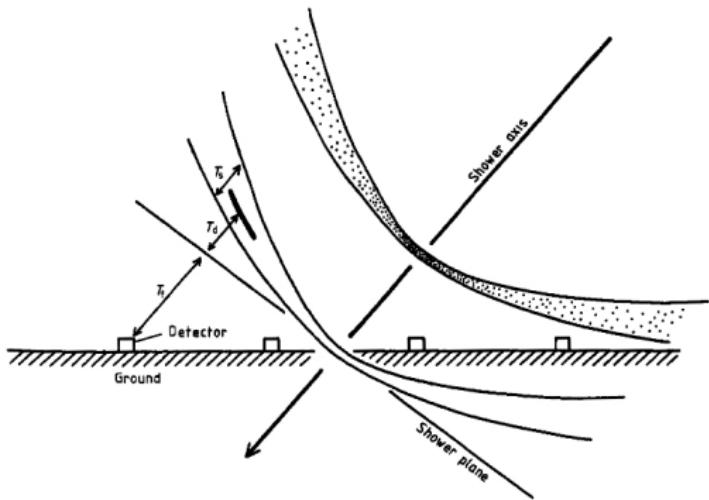
- ▶ Given a weak learner, run it multiple times on (reweighted) training data.
- ▶ On each iteration: misclassified events are assigned a new weight α

$$err = \frac{N_{misidentified}}{N_{all}}, \quad \alpha = \frac{1 - err}{err}.$$

- ▶ New tree with reweighted events is built and optimized.
Tree weight: $TW = \ln \alpha$.
- ▶ Average over all trees with their weights:

$$y_{boost} = \frac{1}{N_{trees}} \sum \ln \alpha_i \times h_i.$$

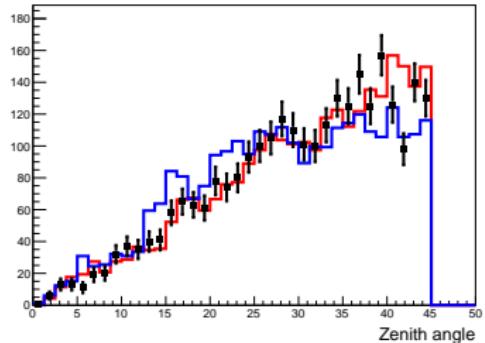
Shower front



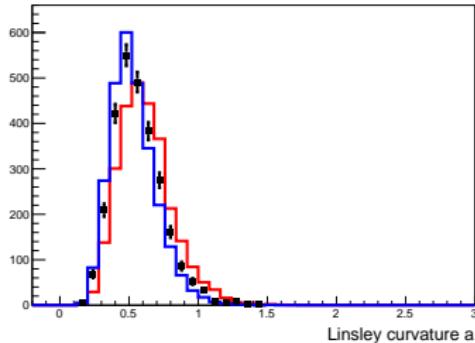
$$t_0(r) = t_0 + t_{plane} + a \times 0.67 (1 + r/R_L)^{1.5} LDF(r)^{-0.5}$$

Composition-sensitive observables distribution

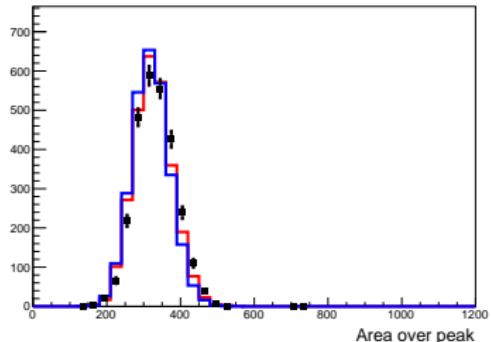
18.8< $\log(E)$ <19.0, chi2_p=44.383050, chi2_Fe=85.504708



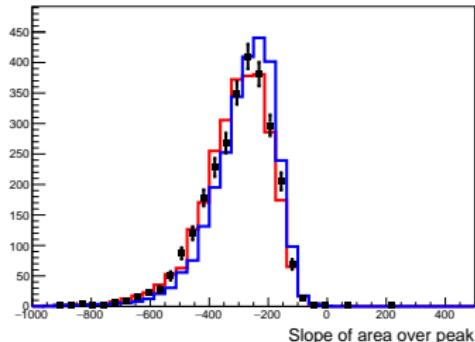
18.8< $\log(E)$ <19.0, chi2_p=195.988966, chi2_Fe=86.564301



18.8< $\log(E)$ <19.0, chi2_p=63.521131, chi2_Fe=156.167544



18.8< $\log(E)$ <19.0, chi2_p=29.471641, chi2_Fe=123.891251



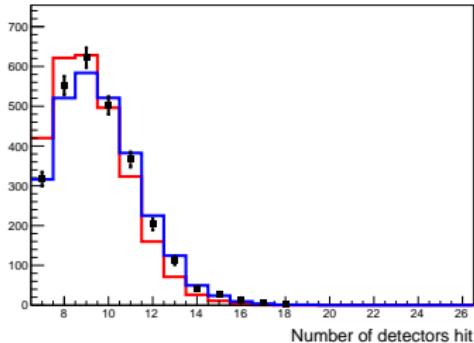
proton MC

iron MC

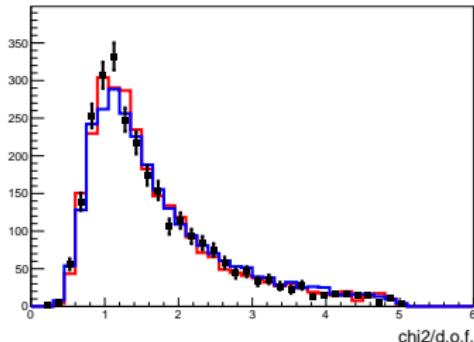
data

Composition-sensitive observables distribution

$18.8 < \log(E) < 19.0$, $\chi^2_p = 105.250446$, $\chi^2_{Fe} = 11.869181$



$18.8 < \log(E) < 19.0$, $\chi^2_p = 39.512367$, $\chi^2_{Fe} = 39.487245$

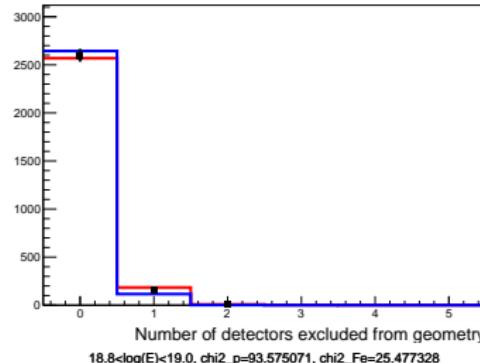


proton MC

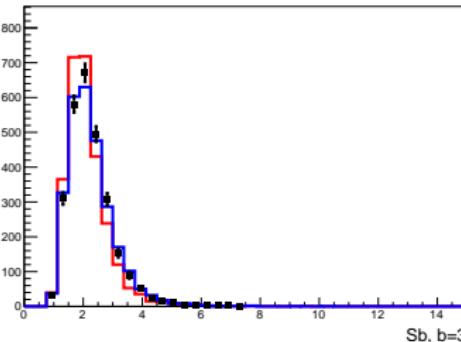
iron MC

data

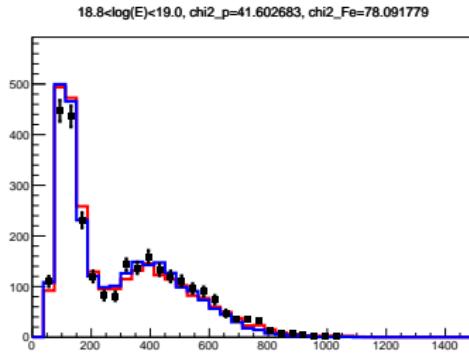
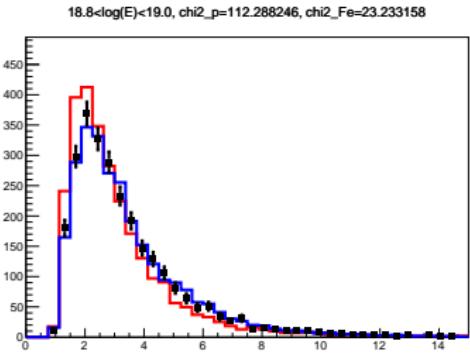
$18.8 < \log(E) < 19.0$, $\chi^2_p = 4.673748$, $\chi^2_{Fe} = 19.012361$



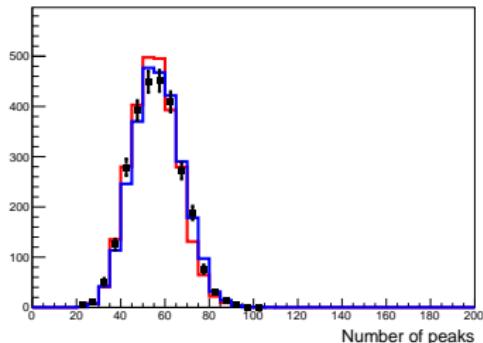
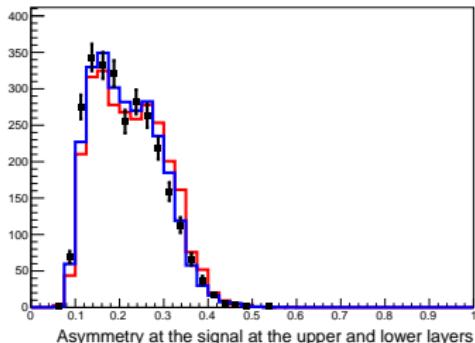
$18.8 < \log(E) < 19.0$, $\chi^2_p = 93.575071$, $\chi^2_{Fe} = 25.477328$



Composition-sensitive observables distribution



18.8<log(E)<19.0, chi2_p=61.703748, chi2_Fe=26.128389



Asymmetry at the signal at the upper and lower layers

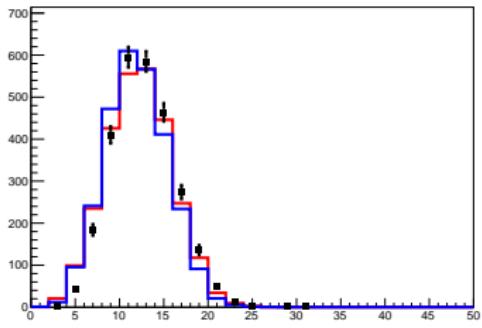
proton MC

iron MC

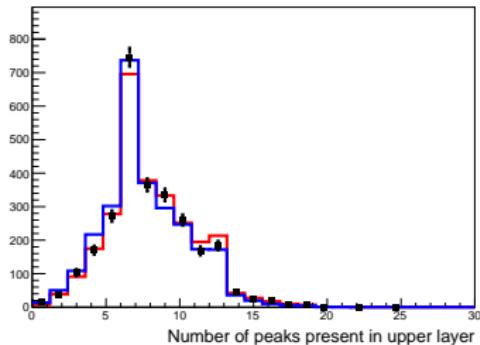
data

Composition-sensitive observables distribution

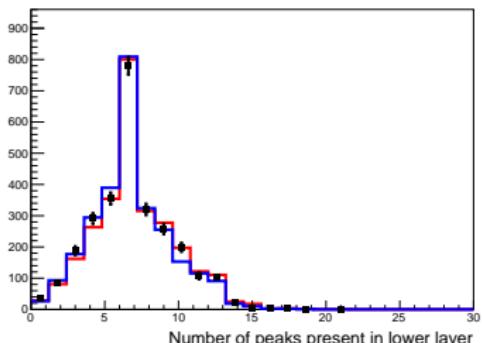
$18.8 < \log(E) < 19.0$, $\chi^2_{\nu} = 65.425385$, $\chi^2_{\nu, \text{Fe}} = 113.658717$



$18.8 < \log(E) < 19.0$, $\chi^2_{\nu} = 20.455666$, $\chi^2_{\nu, \text{Fe}} = 39.690790$



$18.8 < \log(E) < 19.0$, $\chi^2_{\nu} = 18.140512$, $\chi^2_{\nu, \text{Fe}} = 24.776133$

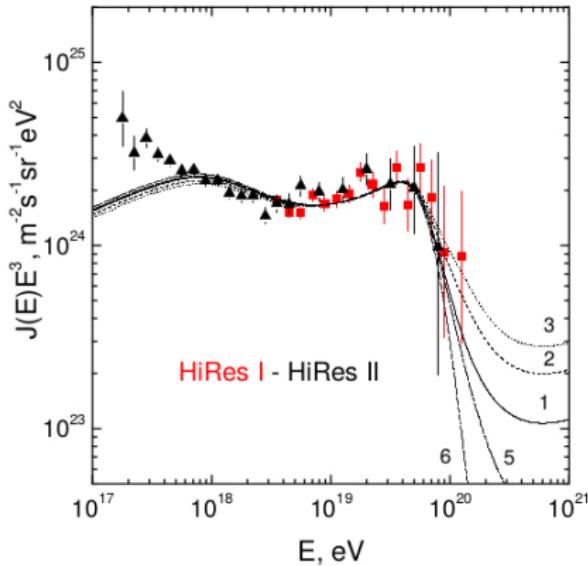


proton MC

iron MC

data

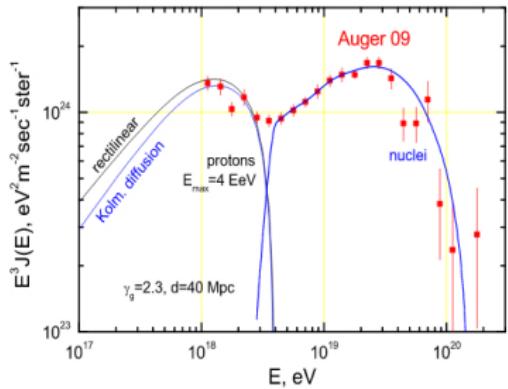
Dip model



- ▶ Power-law injection spectrum.
- ▶ Proton primary composition.
- ▶ Uniformly-distributed sources.
- ▶ Describes the observed spectrum.
- ▶ Predicts cosmogenic photon and neutrino fluxes.

V. Berezinsky, A. Z. Gazizov and S. I. Grigorieva. Phys. Rev. D, 2006.

Disappointing model



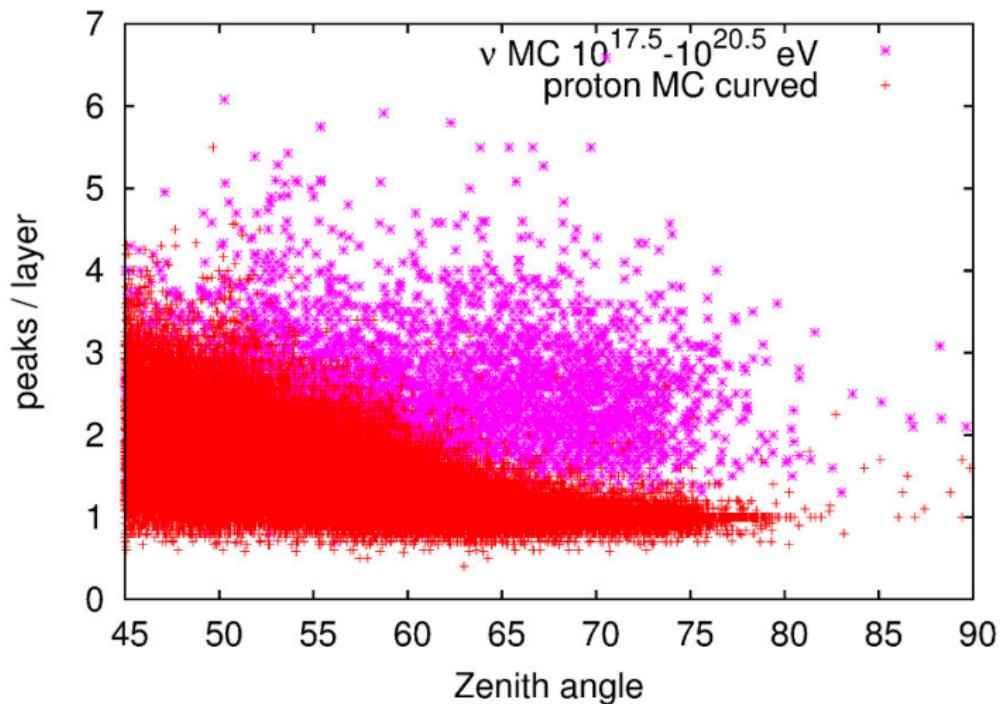
- ▶ Power-law injection spectrum.
- ▶ Proton composition up to (1 – 3) eV.
- ▶ CR energy depends on charge: $E_{max}^{acc} = Z E_0$.
- ▶ Predicts Auger mass composition.
- ▶ Doesn't predict cosmogenic neutrinos.
- ▶ No correlation with sources due to large deflection in magnetic fields.

Askaryan effect

- ▶ EAS propagation in matter cause overabundance of electrons in it: positrons annihilate, electrons are pulled into the shower from the medium.
- ▶ Electron overabundance $1 / (Z E)$, doesn't depend on the medium density, up to 10 %.
- ▶ Electron overabundance creates extra radiation (Cherenkov, bremsstrahlung, transition).

G. A. Askar'yan, JETP, 1961

Number of peaks distribution



neutrino MC proton MC

ν exposure

Particle flux $J(E)$ as a function of energy:

$$J(E) = \frac{d^4N}{dEdAd\Omega dt} \simeq \frac{\Delta N_{\text{sel}}(E)}{\Delta E} \frac{1}{\mathcal{E}(E)}$$

Экспозиция:

$$\mathcal{E}(E) = \int_T \int_\Omega \int_S \varepsilon(E, t, \theta, \phi, x, y) \cos \theta \, dS \, d\Omega \, dt = \int_T \mathcal{A}(E, t) \, dt;$$

where ε – particle registration efficiency,
 $\mathcal{A}(E, t)$ – instantaneous detector aperture.

Cut optimization

- ▶ Initial values of ξ_0 , ξ_1 и ξ_2 correspond to some numbers of proton and neutrino events which pass the cut n_p and n_ν .
- ▶ Surface detector exposure is proportional to n_ν .
- ▶ Number of false neutrino candidates is derived from n_p . It is a random value with Poission statistics. Since it is always a small number, one may use the Feldman-Cousins statistics.
- ▶ Number of background events is set to zero.