

The CTA pipeline prototype

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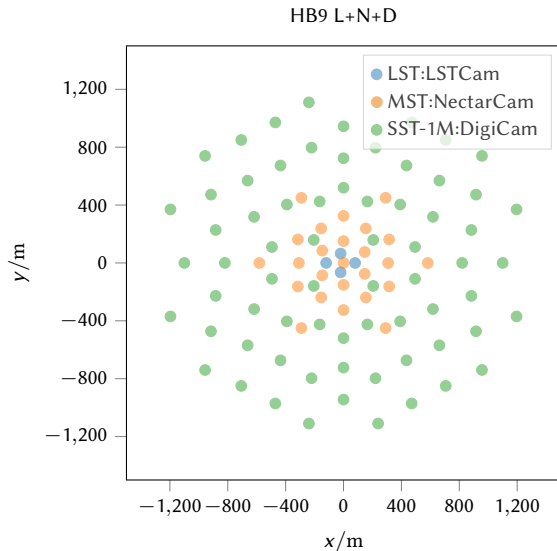
video conference

CEA, 2018-01-15



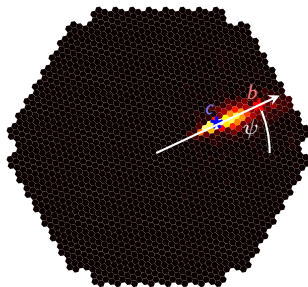
the whole pipeline is up and running; cover here:

- image cleaning (tailcuts vs. wavelets)
 - shower direction and impact reconstruction (purely geometric approach)
 - $h_{\max}$ estimate (numerical minimisation in 3D)
 - energy reconstruction (machine learning)
 - event discrimination (machine learning)
 - point-source sensitivity
-
- my github: https://github.com/tino-michael/tino_cta
 - still needs external libraries for wavelet cleaning



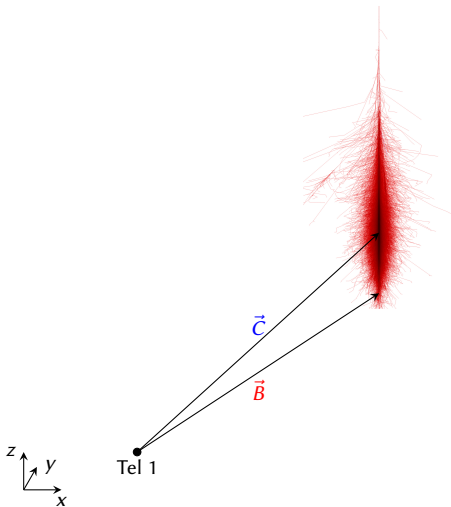
- until recently, only running on ASTRI mini-array
- now on full Paranal array:
- HB9 layout (LST + Nectar + DigiCam)
- pointing north at 20°
- on-axis gammas, diffuse protons and electrons

- Hillas parametrisation provides several parameters:
 - position of image core c
 - tilt of ellipsis ψ
- $\rightarrow$ "arbitrary" point b on shower image axis
- note that every pixel position on the camera can be associated to a direction vector in the horizontal frame (e.g. $c \rightarrow \vec{C}$ and $b \rightarrow \vec{B}$)
- $\vec{B}$ and $\vec{C}$ form a plane in which the shower lies



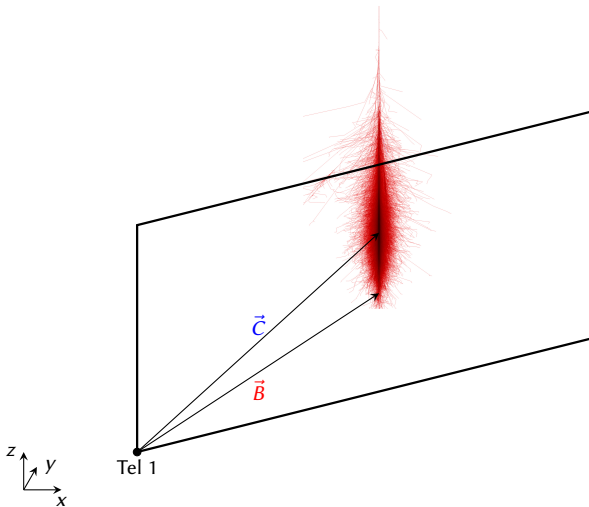
simple shower-reco – direction

horizontal frame



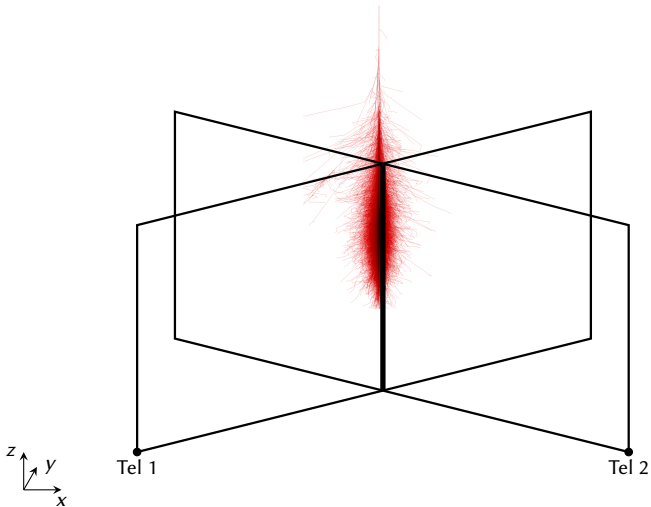
simple shower-reco – direction

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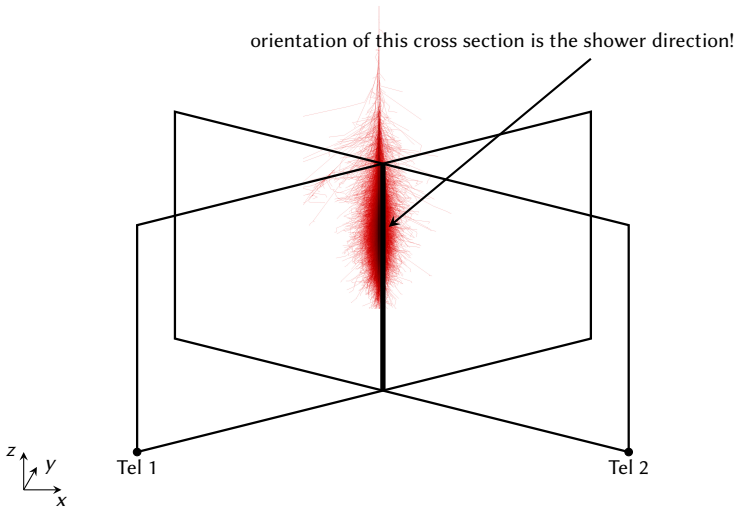
simple shower-reco – direction

horizontal frame



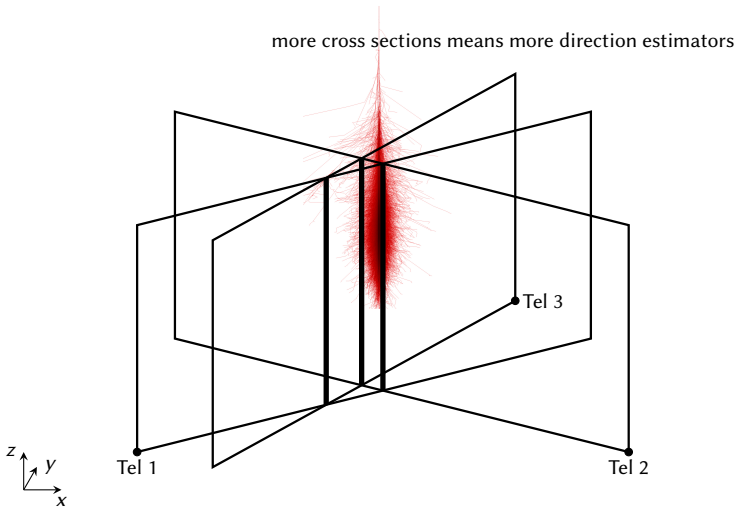
simple shower-reco – direction

horizontal frame



simple shower-reco – direction

horizontal frame



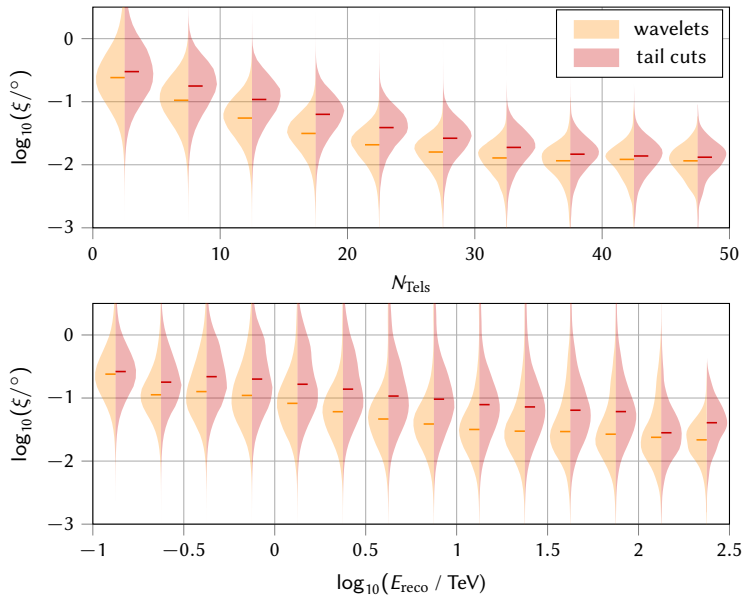
- this cross section is perpendicular to the normal direction of both intersecting planes ($\vec{n} = \vec{b} \times \vec{c}$)
- $\rightarrow$ shower direction is $\vec{n}_1 \times \vec{n}_2$
- add up all cross products for weighted mean direction:

$$\vec{d}_\gamma = \sum_{i=1}^{N_{\text{Tels}}} \sum_{j=i+1}^{N_{\text{Tels}}} w_{ij} \cdot \vec{n}_i \times \vec{n}_j$$

- w_{ij} : weight containing the total image intensity and eccentricity of the Hillas ellipsis
- note: $|\vec{n}_i \times \vec{n}_j| = |\vec{n}_i| \cdot |\vec{n}_j| \cdot \sin[\angle(\vec{n}_i, \vec{n}_j)]$
 - $\rightarrow$ automatically weights contributions according to the angle between intersecting planes
 - $\rightarrow$ planes pairs crossing with more acute angle are weighted less

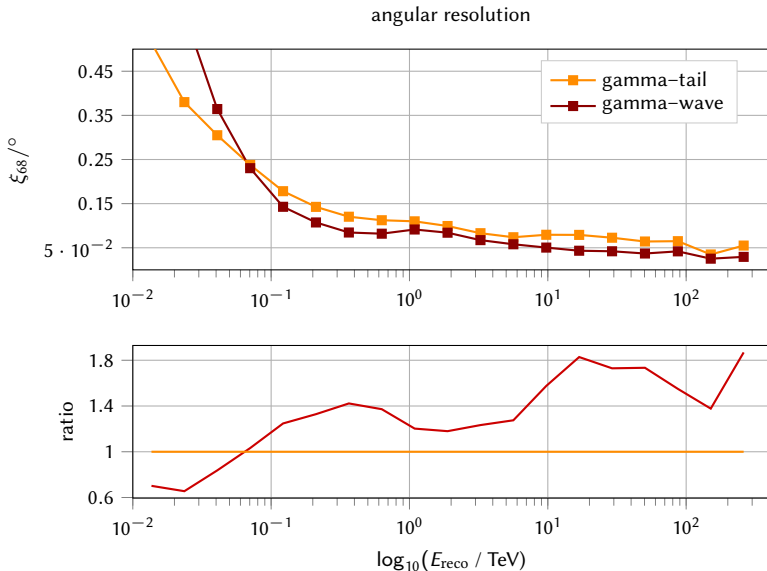
Shower Reconstruction – Direction

Angle between reconstructed and simulated direction



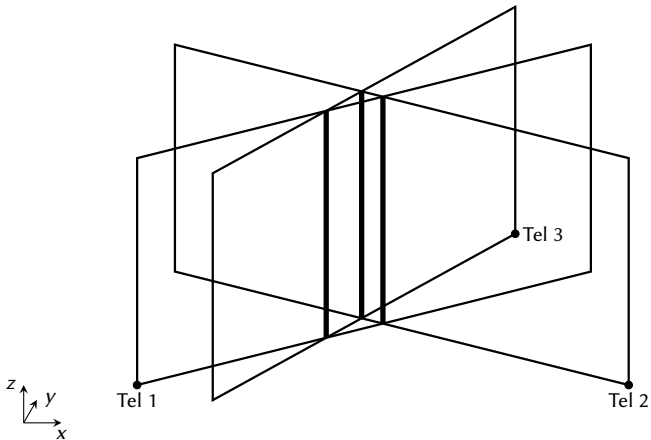
Shower Reconstruction – Direction

Angle between reconstructed and simulated direction



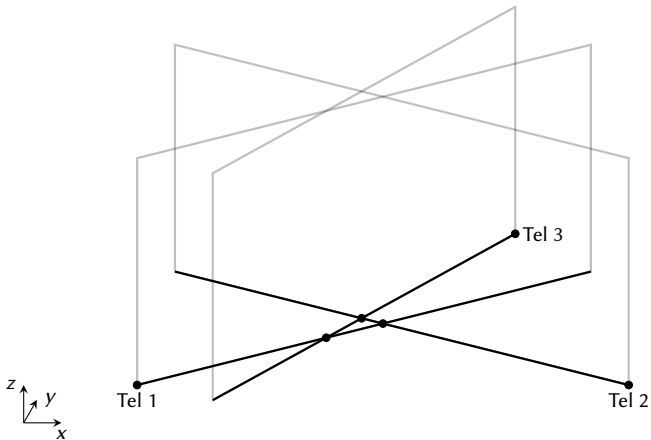
simple shower-reco – impact position

horizontal frame



simple shower-reco – impact position

horizontal frame



For any point $\vec{r}$ on a line i holds

$$\vec{n}_i \cdot \vec{r} = \vec{n}_i \cdot \vec{p}_i = d_i$$

with n_i , the lines normal vector and $\vec{p}_i$, a fixed point on the line (e.g. the telescope position)

If $\vec{r}$ lies on several lines simultaneously, we can write:

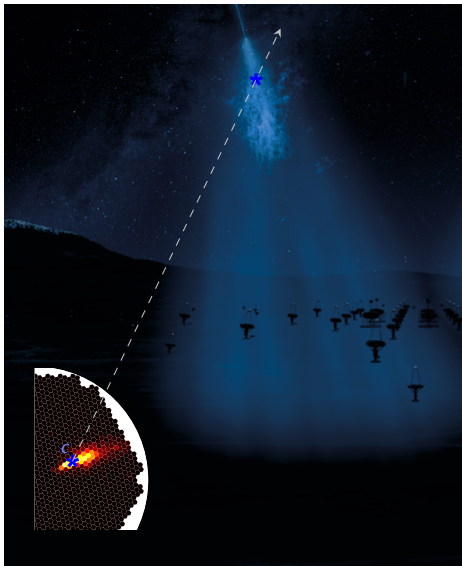
$$\begin{pmatrix} n_1^x & n_1^y \\ \vdots & \vdots \\ n_m^x & n_m^y \end{pmatrix} \cdot \vec{r} = \begin{pmatrix} \vec{n}_1 \cdot \vec{p}_1 \\ \vdots \\ \vec{n}_m \cdot \vec{p}_m \end{pmatrix} = \begin{pmatrix} d_1 \\ \vdots \\ d_m \end{pmatrix}$$

or $\mathbf{A} \cdot \vec{r} = \vec{d}$.

If all lines i do not cross in one single point $\vec{r}$, there won't be a solution for this equation system.

The “optimal” solution can still be found with least linear squares:

$$\vec{r}_{\chi^2} = (\mathbf{A}^T \cdot \mathbf{A})^{-1} \cdot \mathbf{A}^T \cdot \vec{d}$$



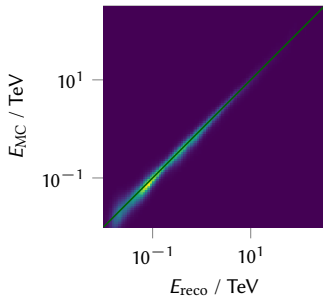
- project the core position of the Hillas ellipsis (vector $\vec{c}$ from direction reco) as a line into the sky
- find the point that minimises the average distance to lines from all telescopes
- no unambiguous normal parametrisation of a line in $\mathbb{R}^3$ ☹
- need to use numeric minimiser after all

Shower Reconstruction – Shower Energy

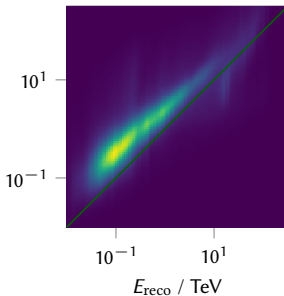
Machine learning

- train 1 Random Decision Forest for each telescope type
- follow a telescope-by-telescope approach
- training features include: Hillas length/width/higher moments, number of telescopes (per size), signal on telescope, summed signal on all triggered telescopes, distance between telescope, shower impact, error estimators, ...
- then, for a given shower event, let the Forest estimate the energy from every telescope separately and combine them into a single energy estimator

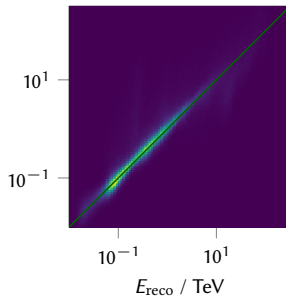
gamma



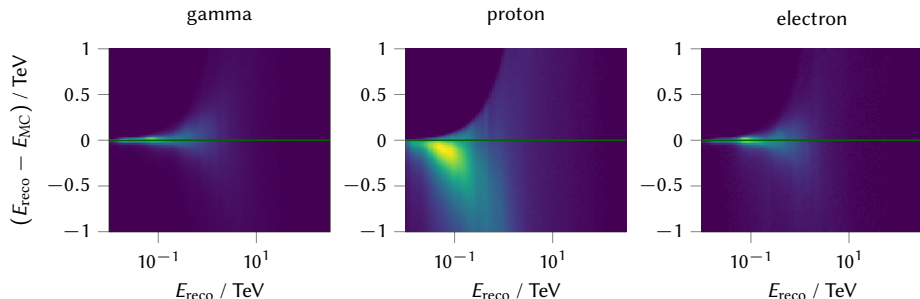
proton



electron

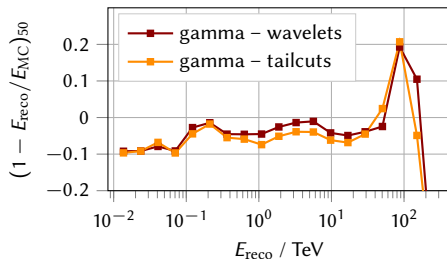
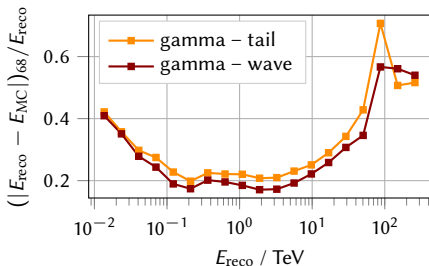


Shower Reconstruction – Shower Energy



Energy Resolution

Energy Bias

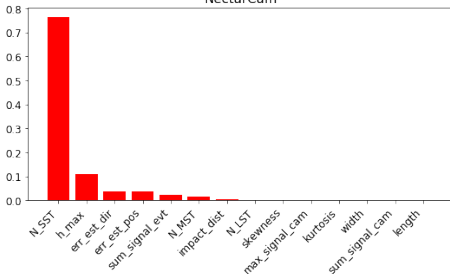


Shower Reconstruction – Shower Energy

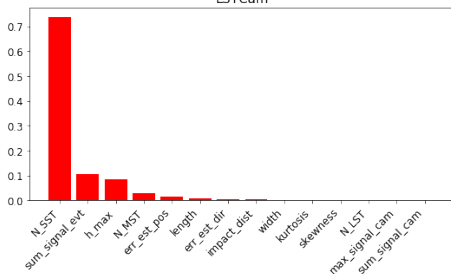
Feature Importance

Feature Importances

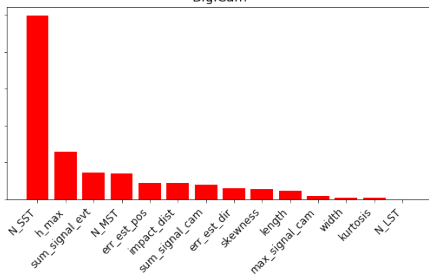
NectarCam



LSTCam

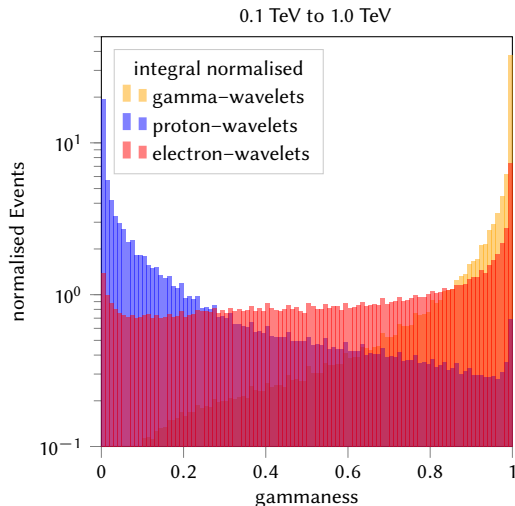


DigiCam

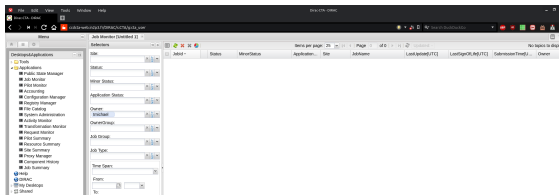


Next Stop: Event Classification

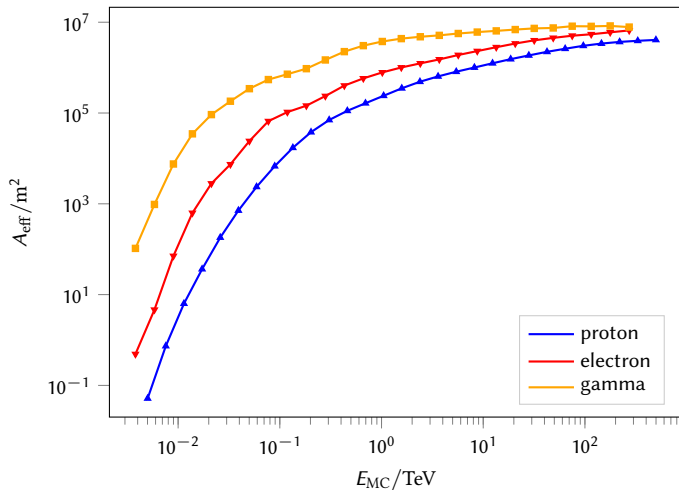
- Protons pose major background
- Event rate about 10^5 times above Photons
- Training Random Forest Classifier
- (virtually identical to energy estimation)



- all this runs with DIRAC on the GRID (including wavelet cleaning)
- lots of sweat, blood and tears to get it going
- Big thanks to Johan and Luisa to take care of the many tickets that I open all the time!
- processing a single setup (5k gamma and electron files, 40k proton files) takes about a week per cleaning mode
- take a look at my **dirac_submit.py** submit-script (handles also some book keeping)



Effective Areas – wavelets



- data pipeline from reading of the MC files to IRFs and differential sensitivity fully implemented
- (almost) completely written in python
- many things unmentioned (pyhessio, camera calibration, ImPACT, muon reconstruction, ...)

Backup

Full List of Features for RandomForest

- impact_dist - distance between telescope and reconstructed impact position
- sum_signal_evt - total signal on all selected telescopes in the event
- sum_signal_cam - total signal on the current camera
- max_signal_cam - signal of the highest intensity pixel in the camera
- N_LST - number of selected LSTs in the event
- N_MST - number of selected MSTs in the event
- N_SST - number of selected SSTs in the event
- Hillas width
- Hillas length
- Hillas skewness
- Hillas kurtosis
- h_max - reconstructed height of shower maximum
- err_est_pos - error estimator of the reconstructed impact position
- err_est_dir - error estimator of the reconstructed shower direction

- reweighting of MC events to correspond to expected physical flux (e.g. Crab nebula for gammas, CR for protons)
- event-by-event weight that considers the generator spectrum:
- $w(E) = A_{\text{gen}} \times I_{\Theta} \times E^{\gamma} \times I_E \times T_{\text{obs}}/N_{\text{gen}}$
with:
 - A_{gen} : MC generator Area
 - $I_{\Theta} = 2\pi(1 - \cos \vartheta)$: angular phase space factor for diffuse flux
 - E^{γ} : considers that MC events have been drawn with an E^{-2} spectrum
 - γ : spectral index of the MC generator (here equal 2)
 - $I_E = (E_{\text{max}}^{(1-\gamma)} - E_{\text{min}}^{(1-\gamma)})/(1 - \gamma)$: energy phase space factor
 - T_{obs} : assumed observation time
 - N_{gen} : number of generated MC events
- $w(E) \times \Phi(E)$ gives weight for every MC event so that their energy distribution looks like the selected events from the assumed flux Φ