

## Reconstruction of atmospheric neutrino events at JUNO

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The Jiangmen Underground Neutrino Observatory (JUNO) is a 20 kt liquid scintillation detector, which will be completed in 2023 as the largest of its kind. JUNO aims to determine the neutrino mass ordering by observing the energy dependent oscillation probabilities of reactor anti-neutrinos. JUNO's large volume provides the opportunity to detect atmospheric neutrino events with lower energies than today's large Cherenkov experiments. As atmospheric neutrinos reach the detector from all directions, partially experiencing the matter effect, they are especially interesting for observing the neutrino mass ordering via the matter effects on their oscillation probabilities. This article presents the preliminary performance of direction and energy reconstruction methods for atmospheric neutrino events at JUNO. The former uses a traditional approach, based on the reconstruction of the photon emission topology in the JUNO detector. For the energy reconstruction, a traditional approach as well as a machine learning based using Graph Convolutional Networks, are shown.

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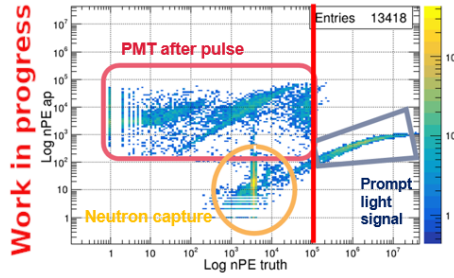
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## 1. Introduction

The Jiangmen Underground Neutrino Observatory (JUNO), a large liquid scintillation detector, will be able to detect atmospheric neutrinos, among other sources. JUNO's main goal is to determine the neutrino mass ordering (NMO), by observing reactor neutrinos from two nuclear plants at  $\sim 53$  km distance. The JUNO detector design and physics goals are discussed in details in [1]. The atmospheric neutrino oscillation pattern is sensitive to the matter effects, which depend on neutrino mass ordering, and could therefore improve JUNO's NMO sensitivity. This work shows the first steps towards the reconstruction of the direction and the energy of atmospheric neutrino events in JUNO, aiming to make this channel accessible for JUNO NMO analysis.

## 2. Data

For this work, Monte Carlo data, produced with the official JUNO software [2], has been used. Only the 17612 large PMTs (lpmts) of JUNO are considered for now. As the readout window (duration of a triggered event) was optimized for the reactor anti-electron neutrinos, on the one hand one needs to consider that high-energy atmospheric neutrino events: i) might deposit part of the energy into a second readout ii) leak into several readout windows, triggered by secondary interactions and afterpulses. The nPe summed over all trigger windows with  $\geq 10^5$  p.e. improves the nPe to deposited energy relation, while afterpulse dominated readout windows are cut off, as shown in figure 1.



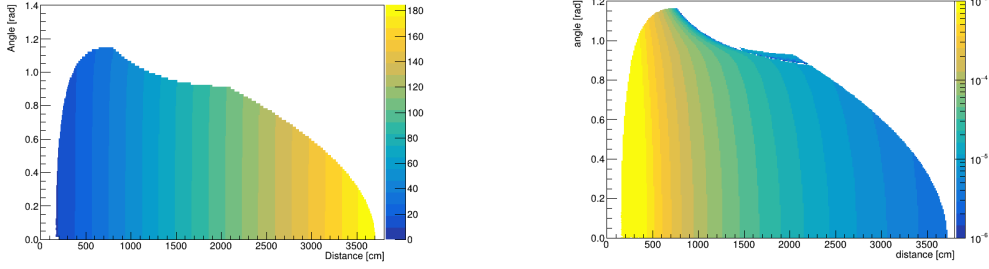
**Figure 1:** Number of readout events (z-axis) as a function of after pulse nPE (y-axis) and of true signal nPE (x-axis). The red line indicates the chosen cut at  $10^5$  p.e..

## 3. Topological Track Reconstruction

The descriptive name reflects the fact that the result represents a spatial probability distribution for the origin of the photon emission. All the technical details can be found in [3–5]. The topological track reconstruction method, was initially tested with the LENA detector, but designed as a flexible framework so that it can easily be adapted to other experiments. In order to use this method for JUNO, different steps were followed. The most relevant ones are described in [4, 5]. In addition, we updated the JUNO PMT data file and scintillation profile to the latest one used in the JUNO offline software. Then, the first step was to modify the inputs: i) updating the photon probability distribution functions (PDFs), or look-up tables (LUTs), and ii) converting the output of the JUNO offline simulation to the input of the reconstruction algorithm.

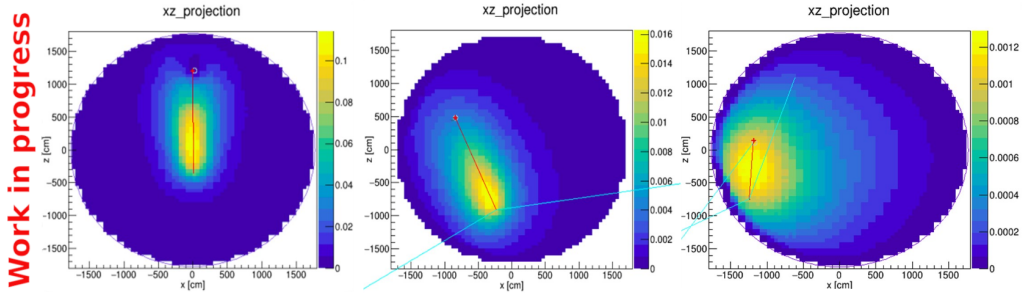
The reconstruction algorithm makes use of two different PDFs: the first one provides the mean propagation time of photons in JUNO as a function of the distance from the emission point to the

PMT where it is detected, and the angle between the source and the PMT. The second one gives the probability of a certain amount of charge being detected by a PMT as a function of the same two parameters. With this, the algorithm will be able to infer the photon emission probability map from the information on the hit time, charge and PMT. Both of them, displayed in figure 2, are analytically calculated by using the knowledge on the JUNO detector geometry and composition.



**Figure 2:** Time (left) and charge (right) PDFs, and a function of the distance and angle (X and Y-Axis). The Z-axis shows mean time of photon flight from the emission point to the PMT observing the light for the time PDF, and the fraction of the total charge deposited observed by each PMT for the charge PDF.

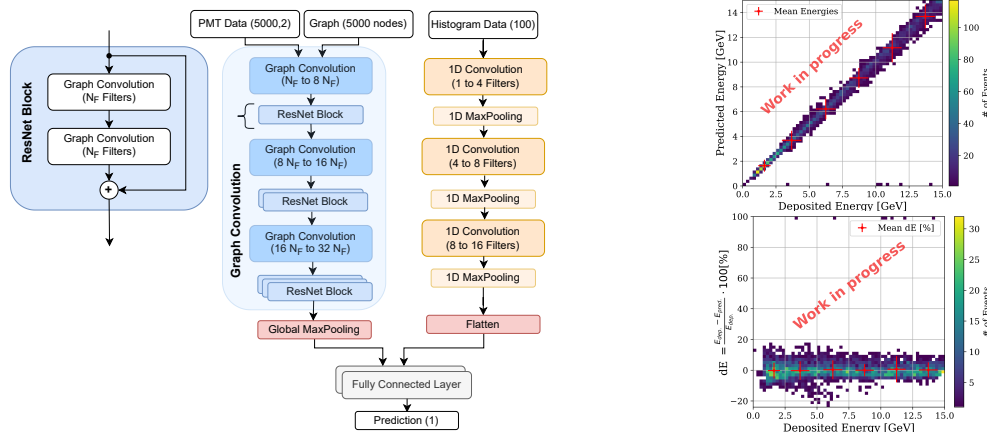
Figure 3 shows the XZ projections of current results of the Topological Reconstruction adapted for atmospheric neutrinos at JUNO, for three different events. All three reconstruction show the results after the 6th iteration using different mesh sizes. All three reconstructed events have an energy of 3 GeV and the atmospheric events are charged current muon neutrino events.



**Figure 3:** The left plot shows the reconstruction of a muon event, the central and right ones the reconstruction of an atmospheric neutrino with negligible (center) and non negligible (right) hadron contribution. The red and blue tracks show the primary track from and the outgoing neutrinos from the MC.

#### 4. Energy Reconstruction

As a first step the deposited energy was reconstructed using a linear fit. The summed nPe using the readout window selection are fitted against the deposited energy. The fit parameter are then reapplied to the detected nPe to obtain a reconstructed energy. This results in a mean difference between deposited and reconstructed energy of  $dE = \frac{E_{\text{label}} - E_{\text{reco}}}{E_{\text{label}}} \cdot 100 \sim 20\%$ , which was used as a first benchmark. Afterwards, we focused on the more advanced machine learning technique, using Graph Convolution with a geometric representation of the detector setup. The graph's nodes represent the LPMTs of JUNO central detector. As input features, the first hit time and nPe per PMT, and the total charge over time distribution are used. The network architecture is displayed on



**Figure 4:** Schematics of used neural network architecture,  $N_F$  is short for number of features on the left. Results on the right, showing the predicted energy (top) and resolution (bottom) against the deposited energy.

the left plot in figure 4 and consists of three parts: i) a Graph Convolution (see [6]) with increasing node features is followed by one or more ResNet blocks [7], ii) a 1D Convolution alternating with 1D MaxPooling and iii) previous outputs are further processed in the fully connected layer. The Mean-square-error is used as loss function, and all layers but the last one use the ReLU activation function. The results of the reconstruction of deposited energy for atmospheric neutrinos with energy range  $\in [1, 15]$  GeV are shown on the right plot in figure 4 the. The bias are corrected by factors evaluated bin-by-bin on the Monte Carlo data, and applied to the reconstruction results. The mean divergence in percent, defined as  $dE = \frac{E_{\text{label}} - E_{\text{reco}}}{E_{\text{label}}} \cdot 100$ , is below 6%. This is a large improvement compared to the linear fit.

## 5. Conclusion

JUNO will be a multi-purpose experiment that will study neutrino oscillations using reactor and atmospheric neutrinos. The chosen directional and energy reconstruction algorithms show promising results to reconstruct GeV-scale atmospheric neutrinos at JUNO. Further improvements will come from additional optimizations. Next up the reconstruction of visible energy will be investigated, as it is closely related to nPE. Additionally, the particle identification needs to be tackled to make the atmospheric neutrino channel accessible for the NMO analysis.

## References

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