

PMT waveform analysis is essential for high precision measurement of position and energy of incident particles in liquid scintillator (LS) detectors. JUNO is a next generation high precision neutrino experiment with a designed energy resolution of 3%@1MeV. The accuracy of the reconstruction of number of photo-electron (nPE) is one important key of achieving the best energy resolution. This poster introduces the machine learning-based nPE estimation methods. The calibration parameters of LS responses and PMT responses are used to generate training waveforms for supervised learning. Weakly supervised learning is applied to handle simulation errors. The photon counting performances of different methods will be presented.

The JUNO experiment

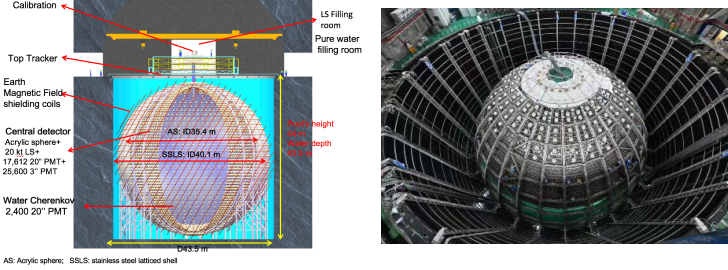


Fig. 1 JUNO detector.

- A multi-purpose observatory for determining the neutrino mass ordering, precisely measuring $\sin^2 2\theta_{12}$, Δm_{21}^2 , Δm_{31}^2 , studying the solar neutrinos, supernova neutrinos, diffuse supernova neutrino background, etc. [1]
- 3% @ 1 MeV unprecedented energy resolution.
- More than 6000 LPMT and 6000 SPMT were installed and commissioning was began.

Motivation

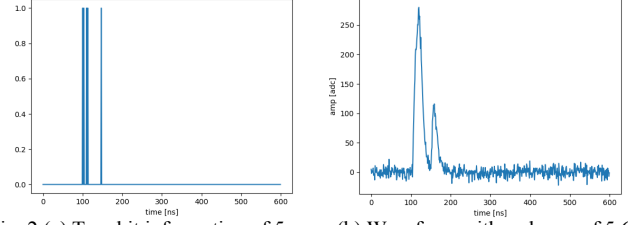


Fig. 2 (a) True hit information of 5. p.e.. (b) Waveform with a charge of 5.6 p.e..

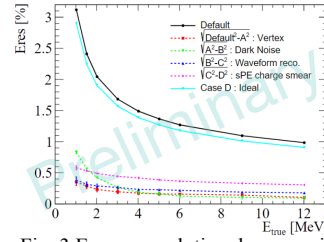


Fig. 3 Energy resolution decomposition.

- This study aims to optimize the accuracy of nPE estimation using machine learning (ML), which can improve the charge-based energy reconstruction [2].

Supervised method

- PMT waveforms are modeled by the waveform shape, noise spectrum, hit time distribution and charge pdf. These detector responses can be extracted from calibration data.
- Supervised method uses simulation waveforms with known nPE to train neural network by minimizing the categorical crossing-entropy between predicted nPE and true nPE.
- The classes are chosen as $\{0, 1, 2, \dots, K\}$ p.e., where $K=9$ in this study. Training waveforms are labeled with n_m p.e.: 0, 1, ..., 9 p.e.. The statistic of each set I_m is ~ 1000000 .
- For I_m calibration waveforms of n_m p.e., the output of neural network is a $I_m \times (K+1)$ matrix y_{ik}^m , the CCE is given by

$CCE_m = - \sum_{i=1}^{I_m} \log(y_{im}^m)$. The loss function of training data is defined as

$$L_{CCE} = \sum_{m=0}^M CCE_m.$$

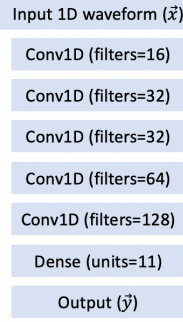


Fig. 4 Neural network architecture shared by two methods.

Weakly supervised method

- The nPE of waveform is unknown, but the mean light intensity μ of calibration data is known. This study uses μ label data to conduct weakly supervised training by minimizing the KL divergence between predicted nPE distribution and true nPE distribution (Poisson distribution).
- The classes are chosen as $\{1, 2, \dots, K+1\}$ p.e., where $K=10$ in this study. Waveforms with nPE $> K$ p.e. are categorized as $K+1$ p.e.. Training waveforms are labeled with μ_m p.e.: 0.5, 1, ..., 9.5 p.e.. The statistic of each set I_m is ~ 1000000 . Noise waveforms are excluded.
- For I_m calibration waveforms with known " μ_m ", the output of neural network is a $I_m \times (K+1)$ matrix y_{ik}^m . The probability of reconstructed k

p.e. is calculated by $Q_m(k) = \frac{1}{I_m} \sum_{i=1}^{I_m} y_{ik}^m$. The probability of detected k

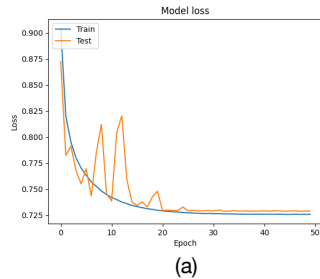
p.e. is $P_m(k) = \frac{e^{-\mu_m} \mu_m^k}{k!(1 - e^{-\mu_m})} (k \leq K), P_m(K+1) = 1 - \sum_{k=1}^K P_m(k)$.

The loss function of training data is defined as

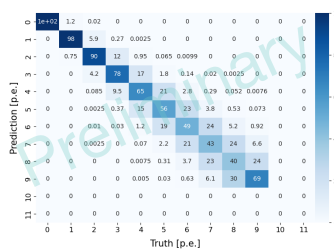
$$L_{KL} = \sum_{m=0}^M \sum_{k=1}^{K+1} P_m(k) \log \frac{P_m(k)}{Q_m(k)}$$

Reconstruction performances

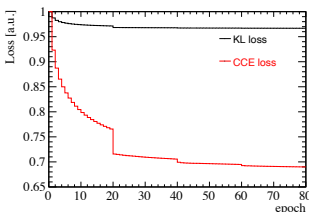
The testing data are labeled with n_m p.e.: 0, 1, ..., 9 p.e.. The statistic of each set N_m is ~ 200000 . The 0 p.e. waveforms are excluded for weakly supervised method.



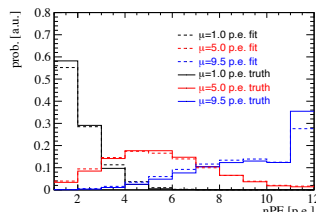
(a)



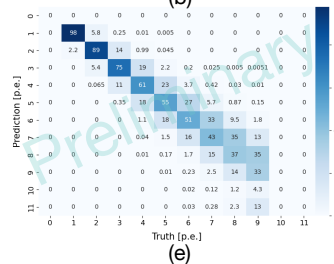
(b)



(c)



(d)



(e)

Fig. 4 (a) CCE loss vs. epoch of supervised method. (b) Confusion matrix of supervised method. (c) KL loss and CCE loss vs. epoch of weakly supervised method. (d) Poisson-fitting results. (e) Confusion matrix of weakly supervised method.

Conclusion

The nPE information is essential for the energy reconstruction. Machine learning has potential to extract accurate nPE information. Supervised method depends on electronic simulation. Weakly supervised method is data-driven. Weakly supervised method achieves 100%, 99%, 96%, 94%, 98% efficiency of the supervised method in the case of 1, 2, 3, 4, 5 p.e., respectively. Optimizations are on going.

References

- [1] JUNO Collaboration, J. Phys. G 43 (2016) 030401.
- [2] G. Huang et al. Nucl. Sci. Tech. 34 (2023) no.6, 83.

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