Machine Learning based photon counting for PMT waveforms and its application to the energy reconstruction in JUNO

ID: 201

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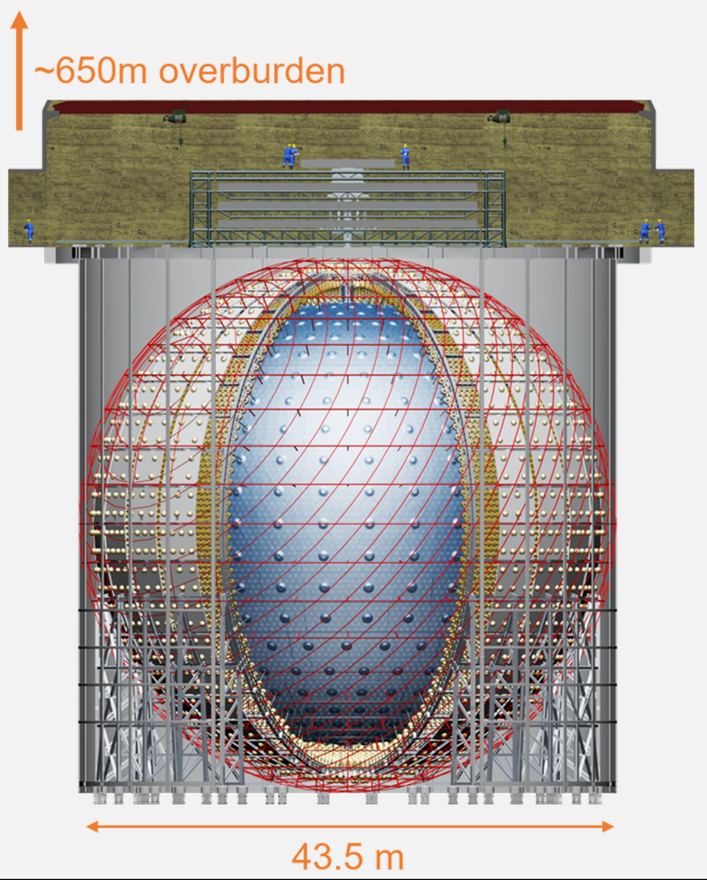
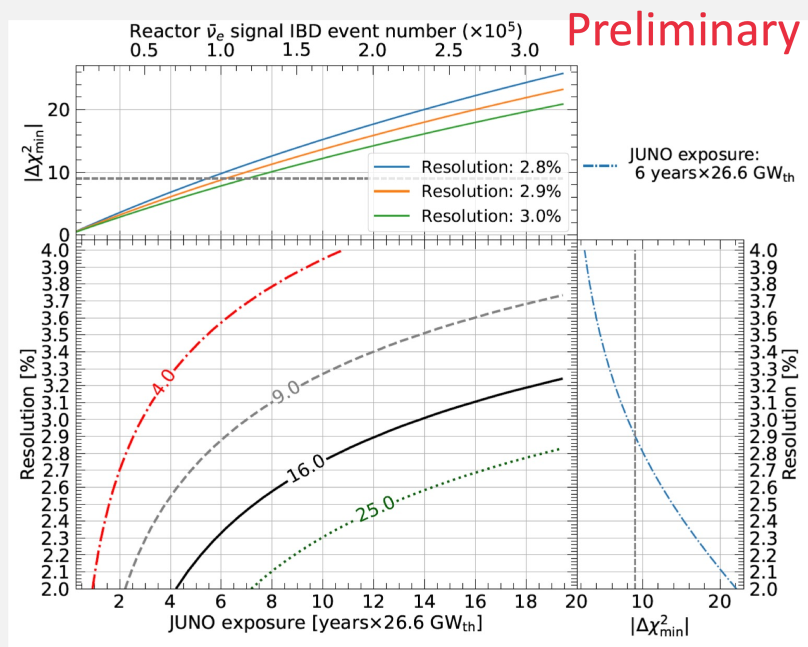
On behalf of JUNO

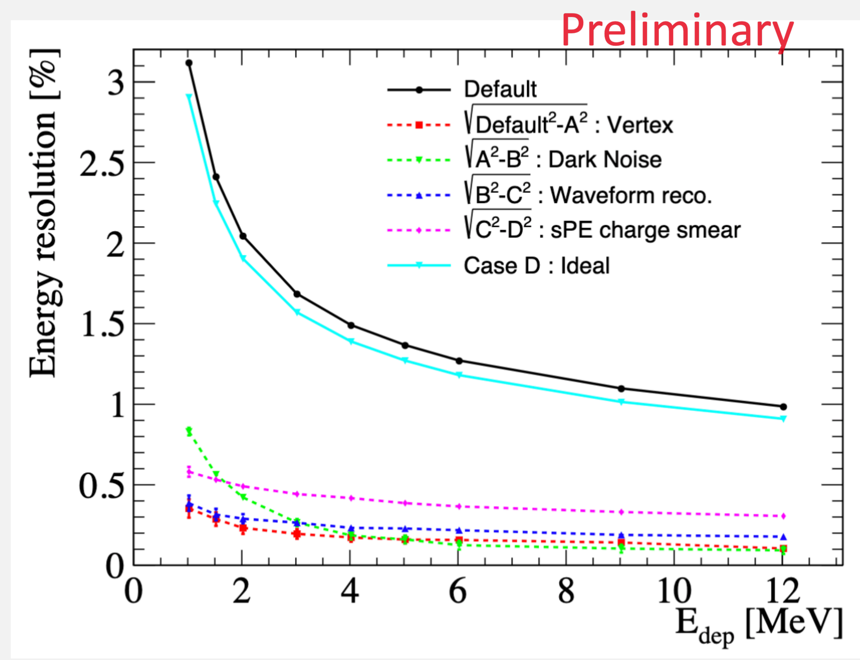
1 JUNO Experiment



- World's largest liquid-scintillator detector
- Central Detector: 20kton LS, 17'612 20" PMTs and 25'600 3" PMTs
- Unprecedented energy resolution 3%@1MeV
- *Main physics goal*: determination of neutrino mass ordering (NMO)

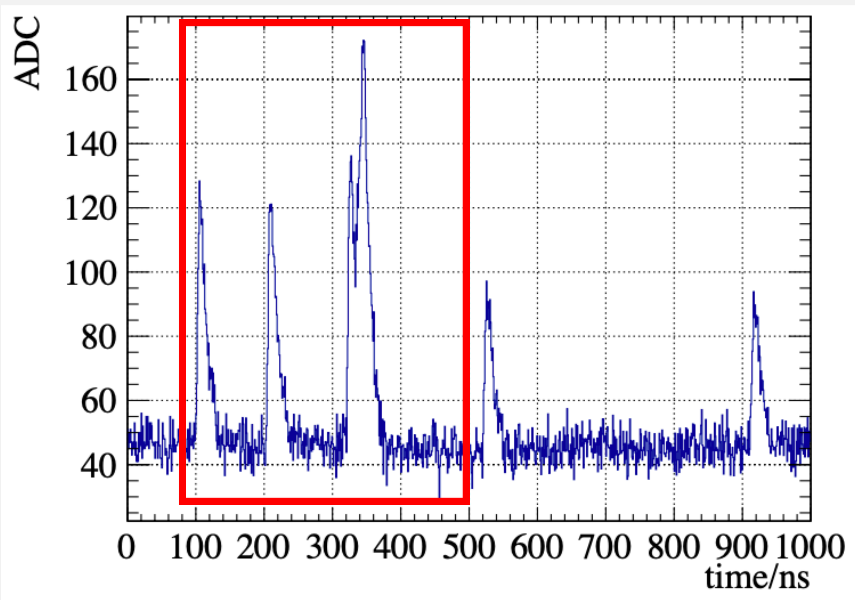
2 Energy Resolution





- Energy resolution is crucial for NMO sensitivity in JUNO
- PMT charge smearing is one of the dominant factors

3 ML based Photon Counting

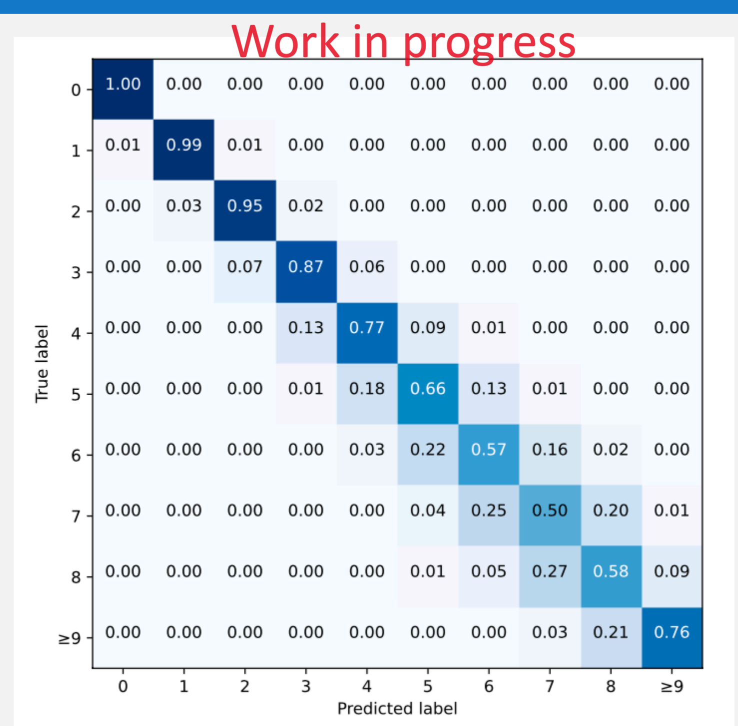


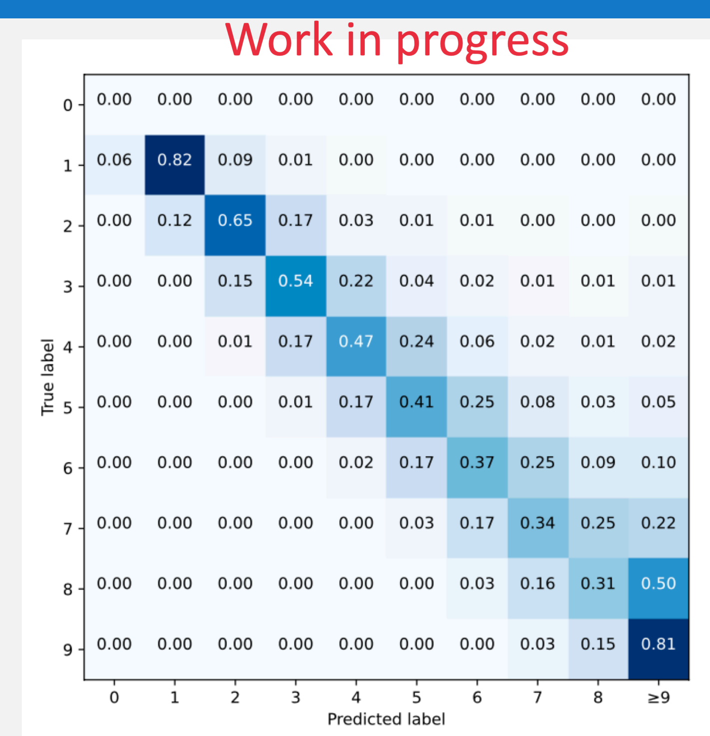
- *Input*: pre-processed PMT waveform within 420ns signal window
- *Model*: Customized RawNet
- *Output*: $\{p_k\}$ the probability for predicting (k=0,1, … ≥9) PEs

Table 2: Modified RawNet architecture. For convolutional layers, numbers inside parentheses refer to filter length, stride size, and number of filters. For gated recurrent unit (GRU) and fully-connected layers, numbers inside the parentheses indicate the number of nodes.

Layer	Input	Output shape
Strided -conv	Conv(3,3,128) BN LeakyReLU	(128, 140)
Res block	{ Conv(3,1,128) BN LeakyReLU Conv(3,1,128) BN LeakyReLU MaxPool(3) } ×2	(128, 46)
Res block	{ Conv(3,1,256) BN LeakyReLU Conv(3,1,256) BN LeakyReLU MaxPool(3) } ×2	(256, 1)
GRU	GRU(1024)	(1024,)
Speaker embedding	FC(128)	(128,)
Output	FC(10)	(10,)

4 Photon Counting Performance





- Left: Confusion matrix of RawNet
  - 99% (95%, 87%) accuracy for 1PE (2PEs, 3PEs)
  - Accuracy decreases rapidly as nPEs increases
- Right: Confusion matrix based on charge classification
  - The accuracy is markedly inferior to that of RawNet

5 Energy Reconstruction

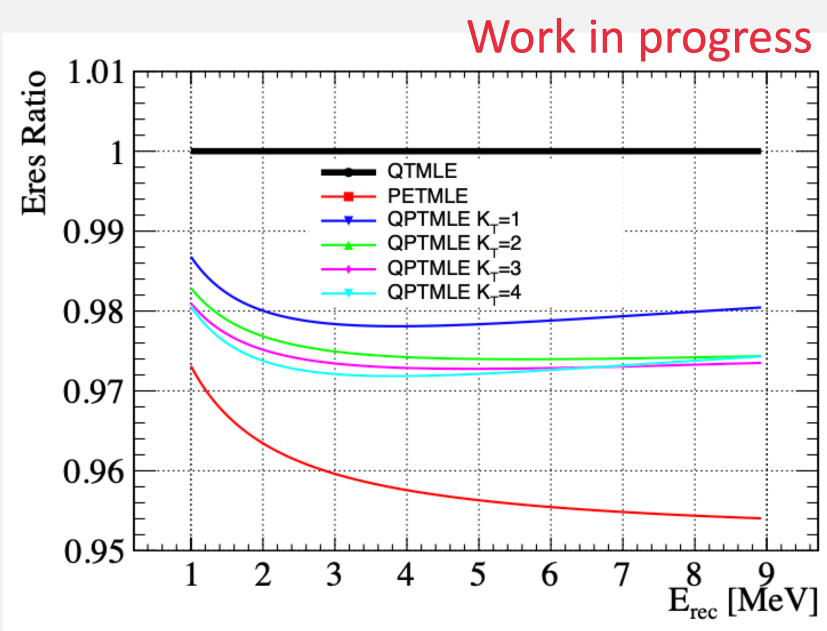
Algo. Name	Observable	Likelihood: $\kappa \le K_T$	Likelihood: $\kappa > K_T$
QTMLE (reference)	q (charge)	$\mathcal{L}(q_i\|\mu_i) = \sum_{k=1}^{+\infty} P_Q(q_i\|k)P(k,\mu_i)$	
PETMLE (ideal)	k (true PEs)	$\mathcal{L}(k_i\|\mu_i) = P(k_i,\mu_i)$	
QPTMLE (realistic)	$\{p_k\}$, q	$\mathcal{L}(\{p_k^i\}\|\mu_i) = \sum_{k=0}^{9} R_{K_T k} p_k^i P(k,\mu_i)$	$\mathcal{L}(q_i\|\mu_i) = \sum_{k=1}^{+\infty} P_Q(q_i\|k)P(k,\mu_i)$
QPETMLE (100% accuracy)	$k(p_k=1)$, q	$\mathcal{L}(k_i\|\mu_i) = P(k_i,\mu_i)$	
QCTMLE	κ (p_κ:max), q	$\mathcal{L}(\kappa_i\|\mu_i) = \sum_{k=0}^{9} C_{k\kappa_i} \times P(k,\mu_i)$	

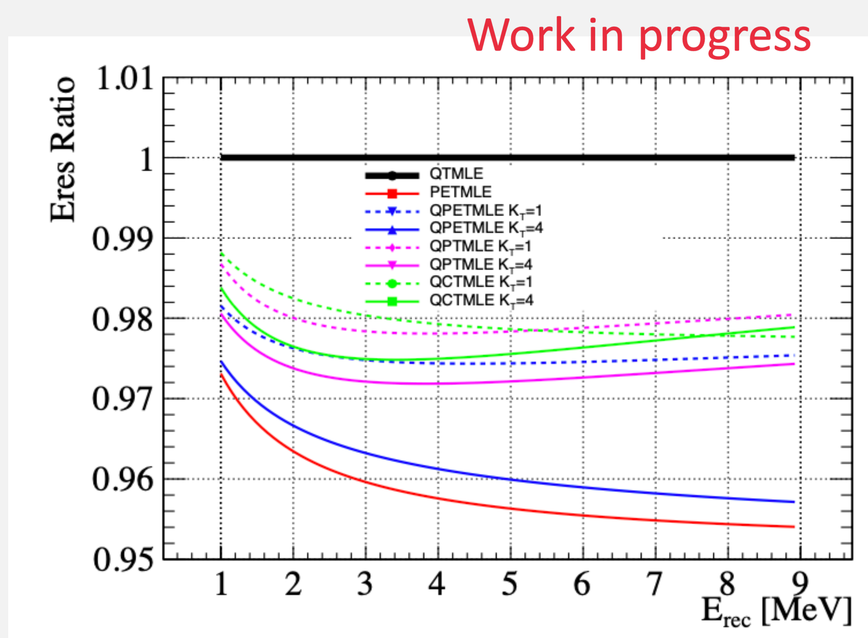
where μ_i is the expected nPEs for the i-th PMT, $P(k,\mu_i)$ is just the Poission probability of observing k p.e. given μ_i and $P_Q(q_i|k)$ is the charge pdf for k p.e..

$$R_{K_T k} = \sum_{\kappa=0}^{K_T} C_{k\kappa}$$

confusion matrix $C_{kk'}$

6 Energy Resolution Performance





- Using the photon counting information for PMTs with ($\kappa \le K_T$) PEs can improve the energy resolution
- The improvement becomes smaller as K_T increases due to the dropping accuracy for high PEs
- Additional checks were done to validate the results

Summary

- Energy resolution is crucial for the NMO sensitivity in JUNO, while PMT charge smear is one of the dominant factors
- A Machine Learning based photon counting method was developed for PMT waveforms, which can achieve high accuracy at low PEs
- Integration of the photon counting information in the energy reconstruction can partially mitigate the impact of PMT charge smearing, leading to 2% to 2.8% relative improvement on the energy resolution

References

1. GuiHong Huang et al, Data-driven simultaneous vertex and energy reconstruction for large liquid scintillator detectors, Nucl.Sci.Tech. 34 (2023) 6, 83
2. JUNO Collaboration, Prediction of Energy Resolution in the JUNO Experiment, arXiv:2405.17860
3. Wei Jiang et al, Machine-Learning based photon counting for PMT waveforms and its application to the improvement of the energy resolution in large liquid scintillator detectors, arXiv:2405.18720