

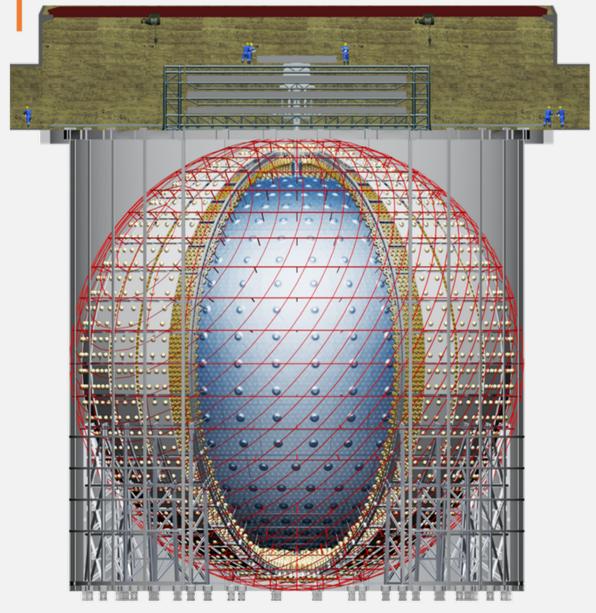
Machine Learning based photon counting for PMT waveforms and its application to the energy reconstruction in JUNO

ID: 201

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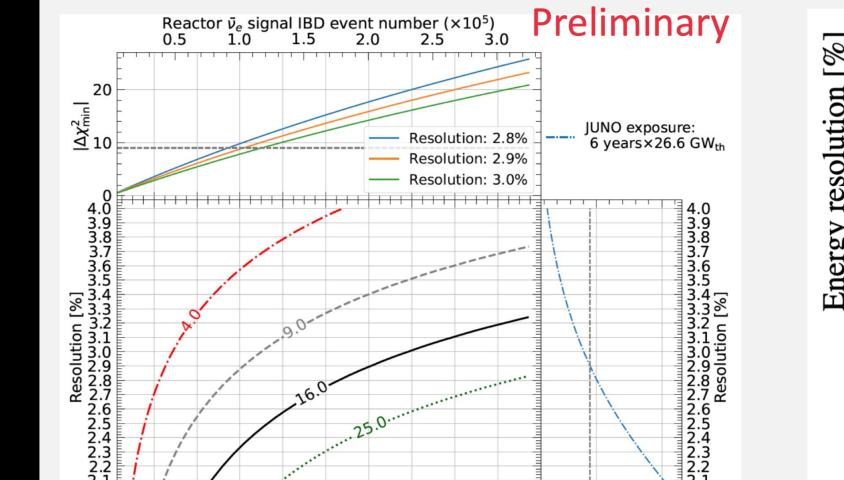
JUNO Experiment

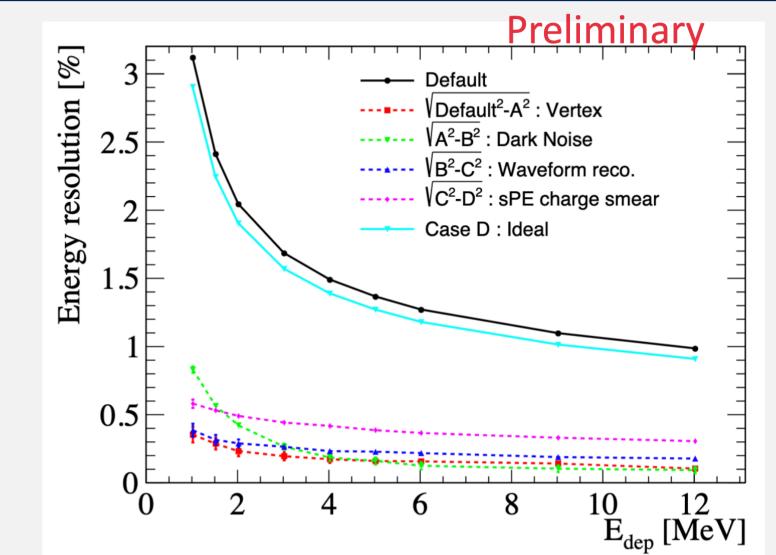
~650m overburden



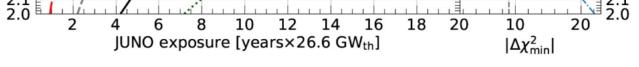
43.5 m

- World's largest liquidscintillator detector
- Central Detector: 20kton LS, 17'612 20" PMTs and 25'600 3" PMTs
- Unprecedented energy resolution 3%@1MeV





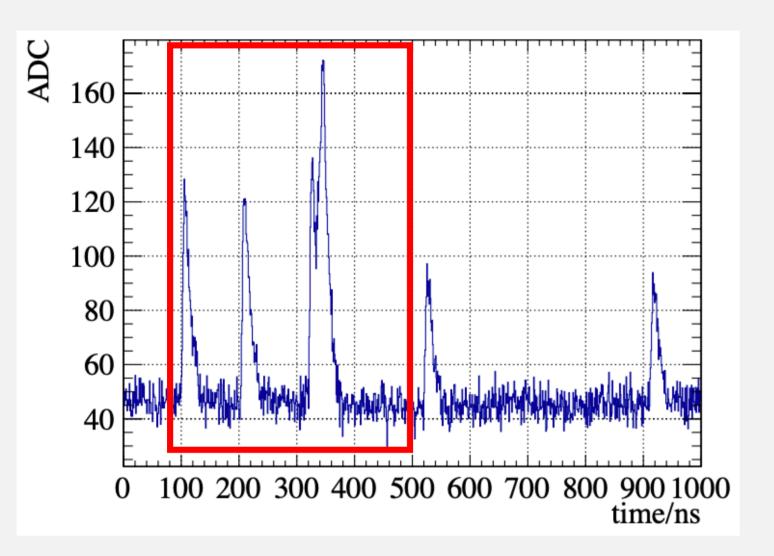
Main physics goal: determination of neutrino mass ordering (NMO)



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

Energy Resolution

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	Output shape		
Stridad	Conv(3,3,128)		
Strided	BN	(128, 140)	
-conv	LeakyReLU		
	(Conv(3,1,128))		
	BN		
	LeakyReLU		
Res block	Conv(3,1,128) > x2	(128, 46)	
	BN		
	(MaxPool(3))		
	(Conv(3,1,256))		
	BN		
	LeakyReLU		
Res block	Conv(3,1,256) > x2	(256, 1)	
	BN		
	LeakyReLU		
	(MaxPool(3))		
GRU	GRU(1024)	(1024,)	
Speaker	FC(128)	(128)	

Photon Counting Performance

Work in progress											
	0 -	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1 -	0.01	0.99	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2 -	0.00	0.03	0.95	0.02	0.00	0.00	0.00	0.00	0.00	0.00
	3 -	0.00	0.00	0.07	0.87	0.06	0.00	0.00	0.00	0.00	0.00
True label	4 -	0.00	0.00	0.00	0.13	0.77	0.09	0.01	0.00	0.00	0.00
True	5 -	0.00	0.00	0.00	0.01	0.18	0.66	0.13	0.01	0.00	0.00
	6 -	0.00	0.00	0.00	0.00	0.03	0.22	0.57	0.16	0.02	0.00
	7 -	0.00	0.00	0.00	0.00	0.00	0.04	0.25	0.50	0.20	0.01
	8 -	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.27	0.58	0.09
1	≥9 -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.21	0.76
0 1 2 3 4 5 6 7 8 ≥9 Predicted label											

Work in progress

0 -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1 -	0.06	0.82	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00
2 -	0.00	0.12	0.65	0.17	0.03	0.01	0.01	0.00	0.00	0.00
3 -	0.00	0.00	0.15	0.54	0.22	0.04	0.02	0.01	0.01	0.01
abel 4	0.00	0.00	0.01	0.17	0.47	0.24	0.06	0.02	0.01	0.02
True label G 5	0.00	0.00	0.00	0.01	0.17	0.41	0.25	0.08	0.03	0.05
6 -	0.00	0.00	0.00	0.00	0.02	0.17	0.37	0.25	0.09	0.10
7 -	0.00	0.00	0.00	0.00	0.00	0.03	0.17	0.34	0.25	0.22
8 -	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.16	0.31	0.50
9 -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.15	0.81
	Ó	i	2	3	4 Predicte	5 ed label	6	7	8	≥9

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

embedding	FC(128)	(120,)
Output	FC(10)	(10,)

Energy Reconstruction

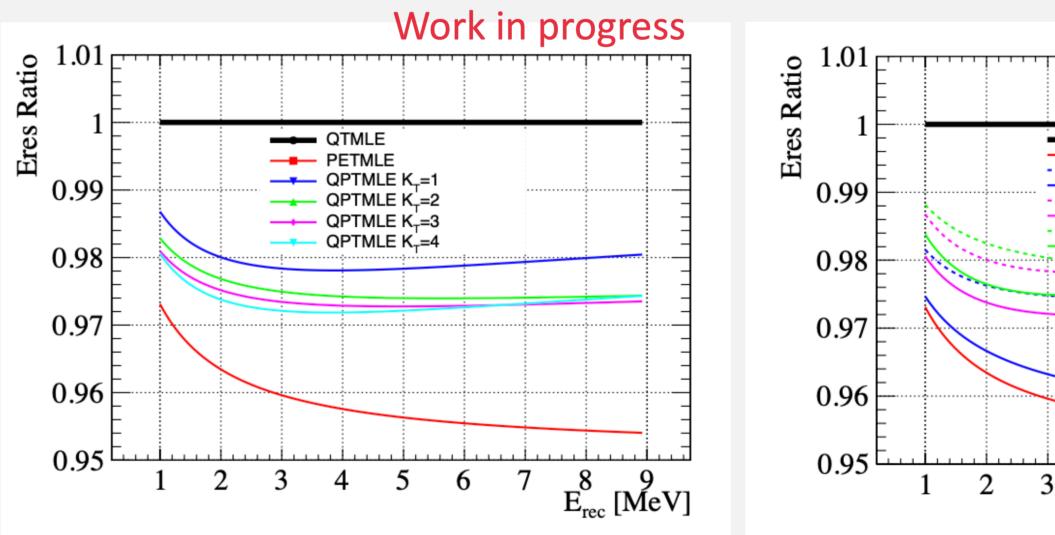
Algo. Name	Observable	Likelihood: $\kappa \leq K_T$	Likelihood: $\kappa > K_T$		
QTMLE (reference)	q (charge)	$\mathcal{L}(q_i \mu_i) = \sum_{k=1}^{+\infty} P_{q_i}$	$Q(q_i k)P(k,\mu_i)$		
PETMLE (ideal)	k (true PEs)	$\mathcal{L}(k_i \mu_i) =$	$P(k_i,\mu_i)$		
QPTMLE (realistic)	{p _k }, q	$\mathcal{L}(\{p_k^i\} \mu_i) = \sum_{k=0}^9 R_{K_T k} p_k^i P(k,\mu_i),$			
QPETMLE (100% accuracy)	k(p _k =1), q	$\mathcal{L}(k_i \mu_i) = P(k_i,\mu_i)$	$\mathcal{L}(q_i \mu_i) = \sum_{k=1}^{+\infty} P_Q(q_i k) P(k,\mu_i)$		
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 just₄ 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 $C_{kk'}$

Energy Resolution Performance



June 21st, 2024

Neutrino2024 @ Milano

Work in progress

- > Using the photon counting information for PMTs with ($\kappa \leq K_T$) 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

- GuiHong Huang et al, Data-driven simultaneous vertex and energy reconstruction for large liquid scintillator detectors, Nucl.Sci.Tech. 34 (2023) 6, 83
 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

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