GSI Helmholtzzentrum für
Schwerionenforschung GmbH

JOHANNES GUTENBERG UNIVERSITÄT MAINZ

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CHEP 2024
Conference on Computing in High Energy and Nuclear Physics

Novel Fitting Approach Based on a Neural Network for JUNO

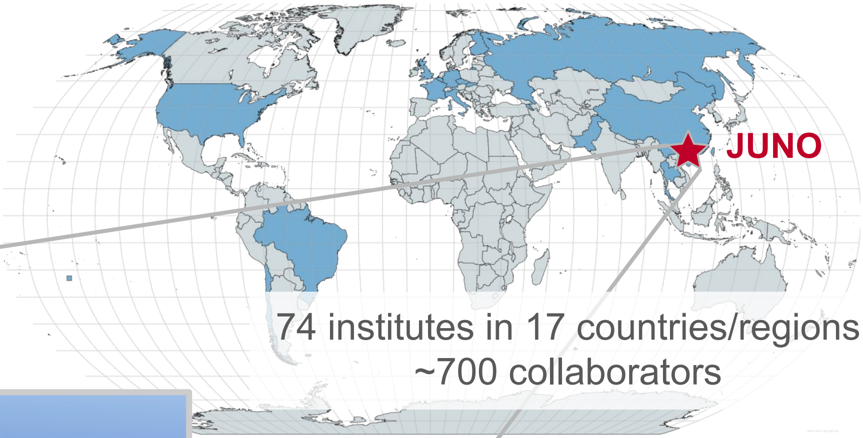
Yury Malyshkin

on behalf of the JUNO collaboration

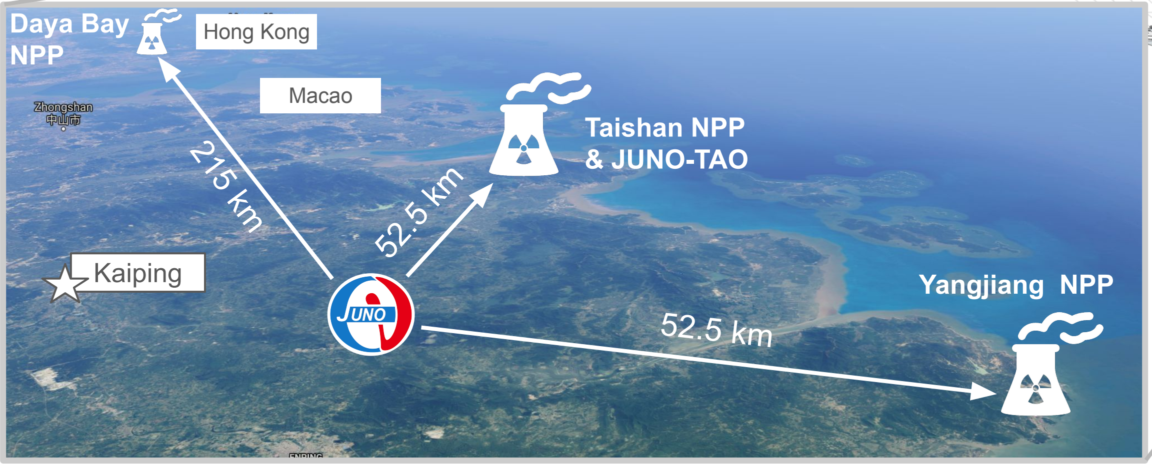
Jiangmen Underground Neutrino Observatory

– a high-resolution neutrino detector

- Anti-ν_e from nuclear reactors
- Solar neutrinos
- Geoneutrinos
- Atmospheric neutrinos
- Supernova neutrinos



74 institutes in 17 countries/regions
~700 collaborators



See also talk by Xiaomei Zhang

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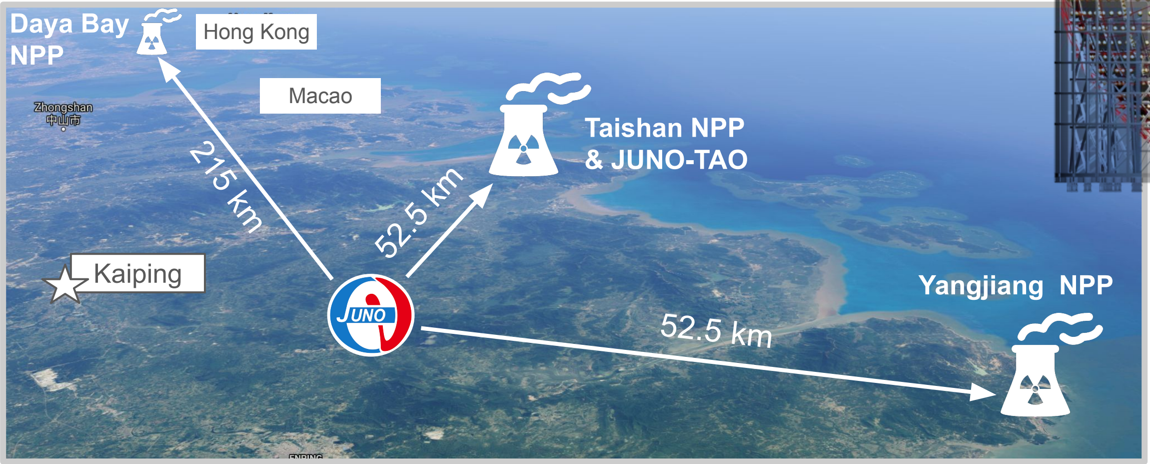
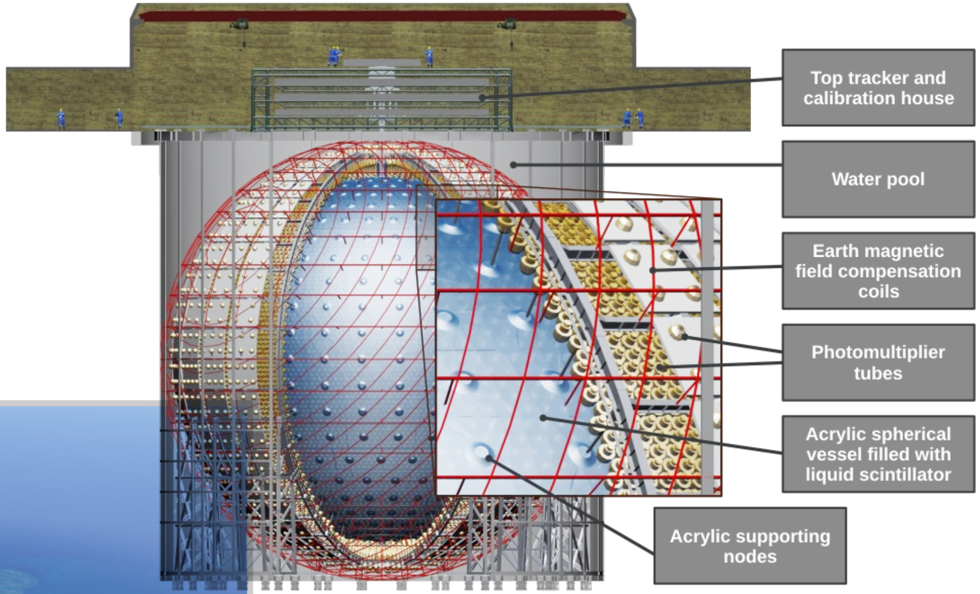




78% photo-coverage:

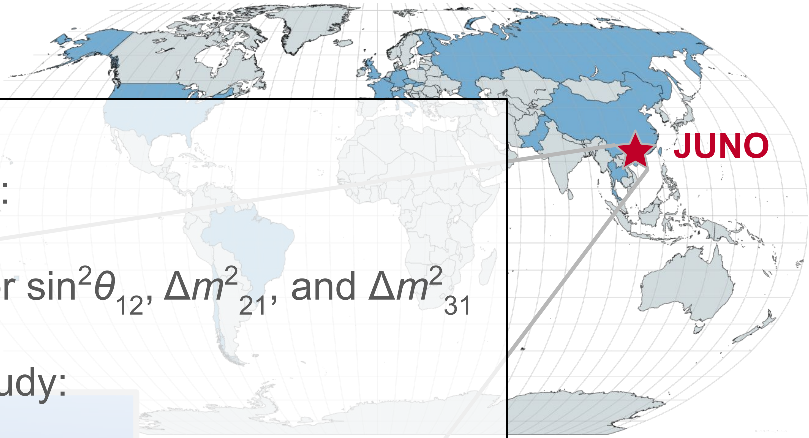
~17,612k large (20-inch) PMTs

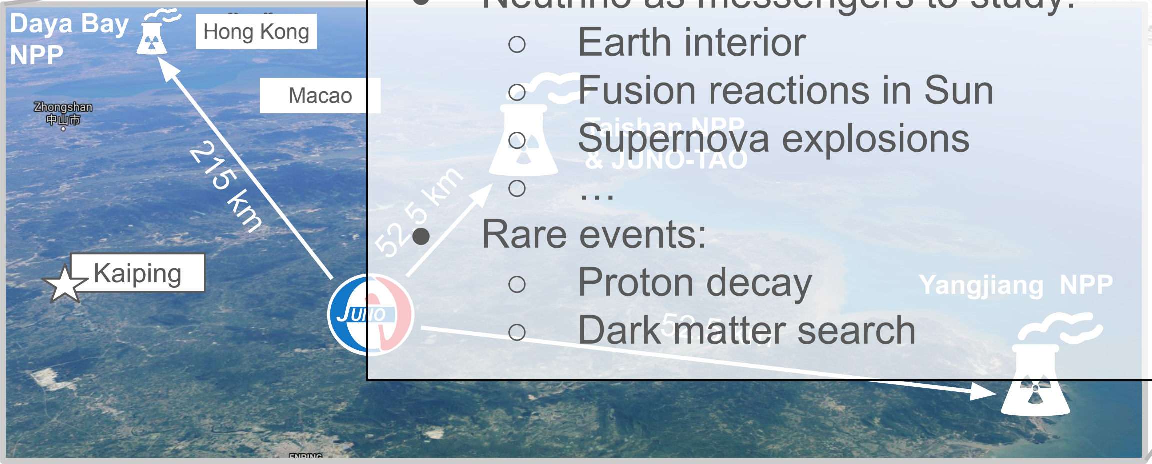
~25,600k small (3-inch) PMTs

Jiangmen Underground Neutrino Observatory

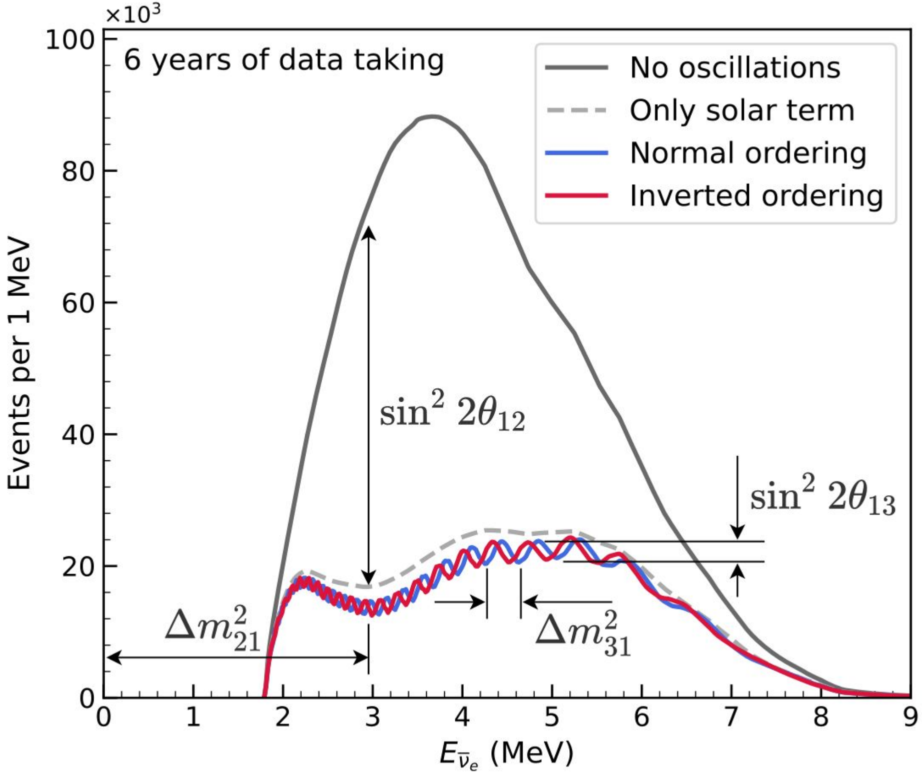
Physics potential:

- Neutrino oscillation properties:
  - Neutrino mass ordering
  - Sub-percent precision for $\sin^2\theta_{12}$, Δm^2_{21}, and Δm^2_{31}
- Sterile neutrinos
- Neutrino as messengers to study:
  - Earth interior
  - Fusion reactions in Sun
  - Supernova explosions
  - …
- Rare events:
  - Proton decay
  - Dark matter search





Reactor Anti-ν_e Spectrum at JUNO



Unoscillated spectrum is also monitored with a satellite detector (Taishan Antineutrino Observatory) at 44 m from one of the reactors

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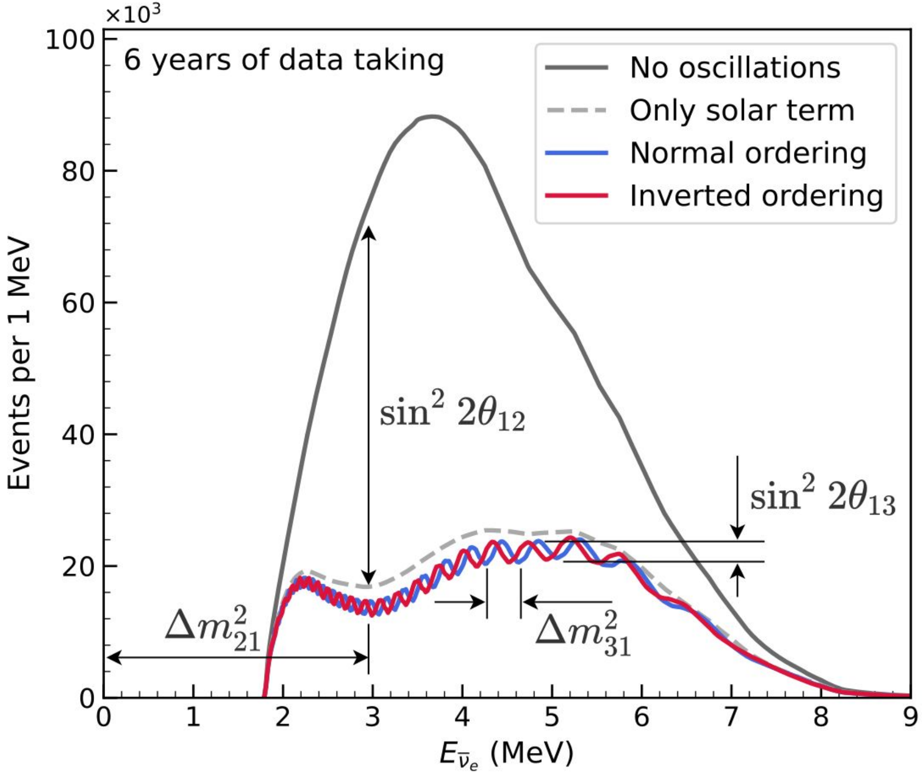

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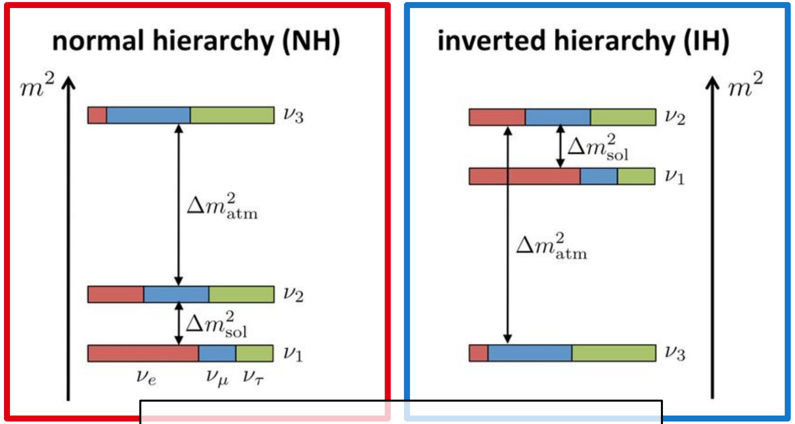
Positions of small wiggles: **neutrino mass ordering**



~3σ in 6 years

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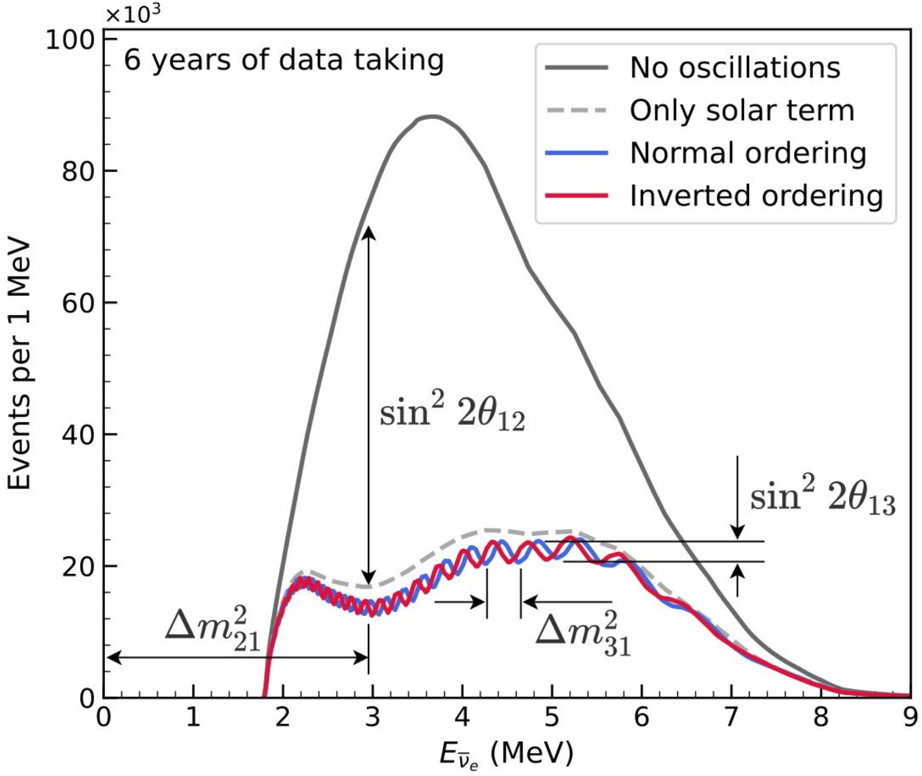

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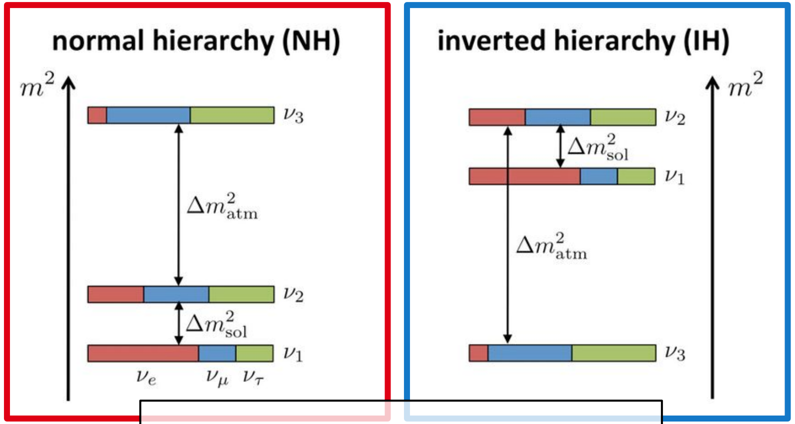


~3σ in 6 years

Frequency and amplitudes:

- slow mode: **"solar"** terms $\sin^2\theta_{12}$, Δm^2_{21}
- fast mode: "**atmospheric**" Δm^2_{31}

<1% precision in 6 years

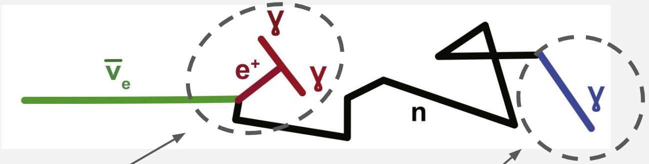
Oscillation Analysis in JUNO

1. Predict reactor spectrum at JUNO site :

$$S(E) = f_\nu(E) \times R^{-2} \times \sigma_{\mathrm{IBD}}(E) \times P_{ee}(E, L, \text{oscillation parameters})$$

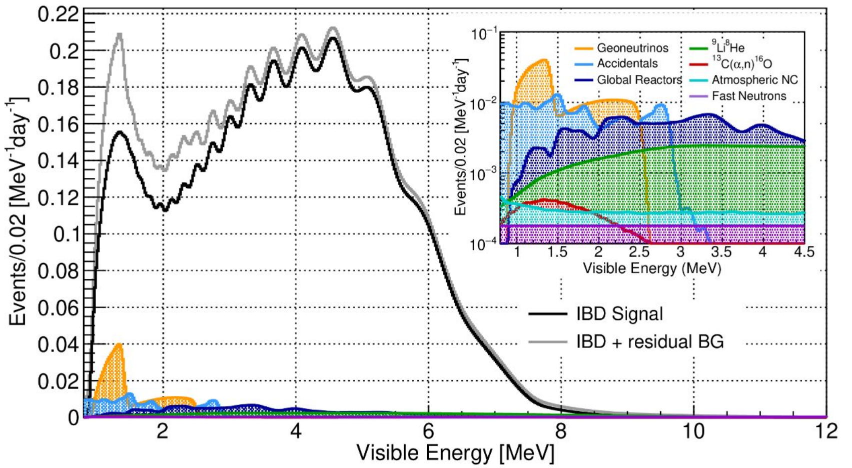
2. Predict backgrounds
3. Apply detector effects to get **reconstructed spectrum** (in terms of visible energy of prompt signal)
4. Fit oscillation parameters under NO and IO assumptions

Detection channel:
Inverse Beta-Decay (IBD) $\bar{\nu}_e + p \rightarrow e^+ + n$



Prompt signal
handle for neutrino energy:
$E_\nu \simeq E_{e^+} + \Delta m_{n-p} + T_n$

Delayed signal
neutron capture: 2.2 MeV (H) or 4.9 MeV (^{12}C) within ~200 μs



Two approaches to predict reconstructed spectrum

Standard Approach

– analytical transformations using a parameterized model for detector response [1]. The model parameters are based on MC or data*.

- Fast
- More flexible
  (easier to add new parameters)
- May lack some features
  (e.g. non-Gaussian energy resolution and its position dependence)

[1] arXiv:2405.18008 (2024), accepted by Chin.Phys.C

* from Daya Bay and calibration data from JUNO, once available

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Full MC Simulation Driven Approach

– use E_ν -> $E_{rec.}$ mapping directly from simulation.

- Slow
- Relies on accuracy of MC
- Extra flexibility is possible
  (introducing extra parameters on top of MC outcome)
- More complete picture

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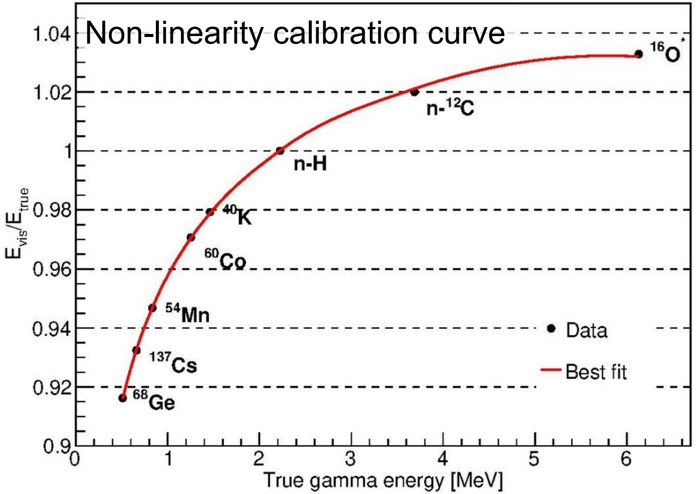
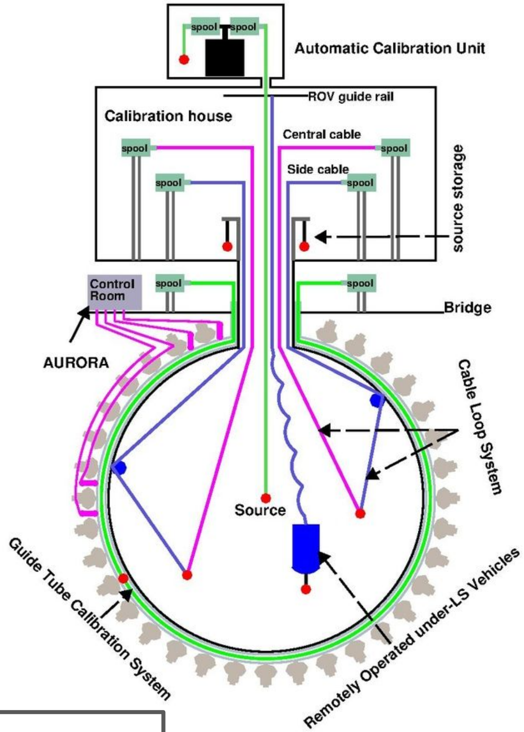
Can we afford this as well?

Calibration

JUNO will have multiple calibration systems:

- to cover the whole detector
- to cover the whole energy range
- to monitor detector stability





Expected calibration performance:

< 1% energy scale uncertainty

[JHEP 2021, 4 (2021)]

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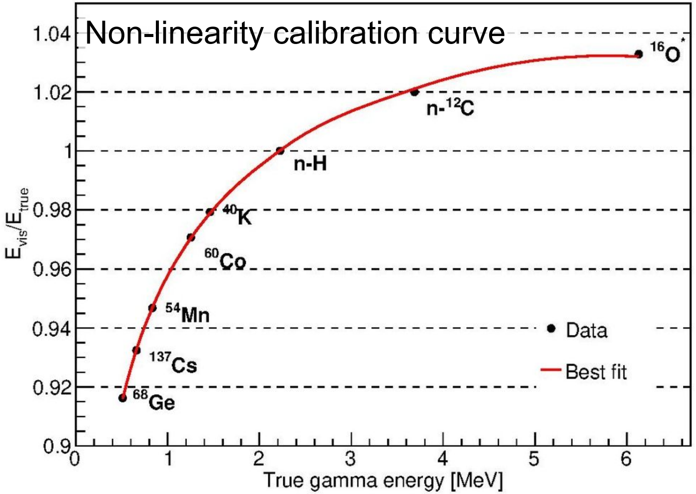

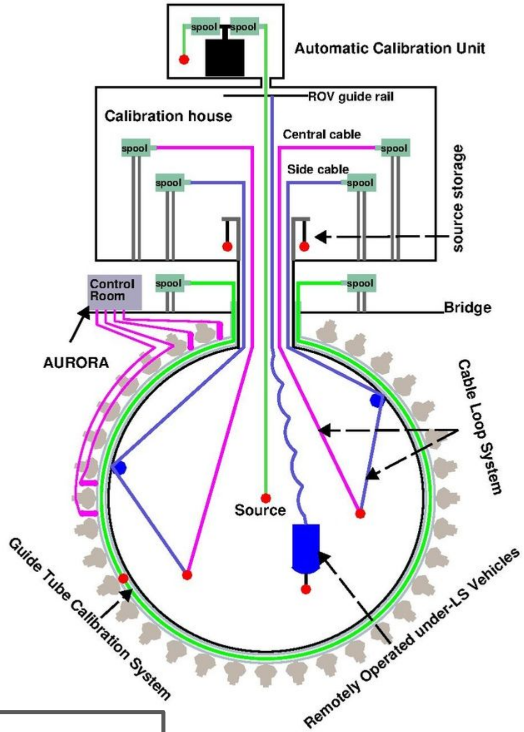

[JHEP 2021, 4 (2021)]

Expected calibration performance:

< 1% energy scale uncertainty

- Official MC will be tuned with the data from calibration **-> more precise training data for NN**
- NN-based approaches may help to tune MC *See talk by Arsenii Gavrikov*

MC-based Detector Response

One has to:

1. Get E_ν and E_{rec} from simulation (no oscillations)
2. Put events in energy bins according to E_{rec}
3. Weight them according to $P_{ee}(E_\nu)$

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One has to calculate P_{ee} for each **event** for each **set of parameters** (θ_{12}, θ_{13}, Δm^2_{21}, Δm^2_{31})

$$\mathcal{P}(\overline{\nu}_e \to \overline{\nu}_e) = 1 - \sin^2 2\theta_{12}\, c_{13}^4 \sin^2 \Delta_{21} - \sin^2 2\theta_{13} \left(c_{12}^2 \sin^2 \Delta_{31} + s_{12}^2 \sin^2 \Delta_{32}\right)$$

$$c_{ij} \equiv \cos\theta_{ij}$$
$$s_{ij} \equiv \sin\theta_{ij}$$

$$\Delta_{ij} = \frac{c^3}{\hbar} \cdot \frac{\Delta m_{ij}^2 L}{4E}$$

Computationally expensive operations!

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Computationally expensive operations!

10^7 events/spectrum

$\times$

10^3 predictions/fit

⇩

10^{10} invocations/fit

Possible Technical Realizations

1. Calculate $P_{ee}(E_\nu)$ analytically and fill histograms on the fly:
   - **SLOW:** ~0.1 sec per spectrum

Example configuration:
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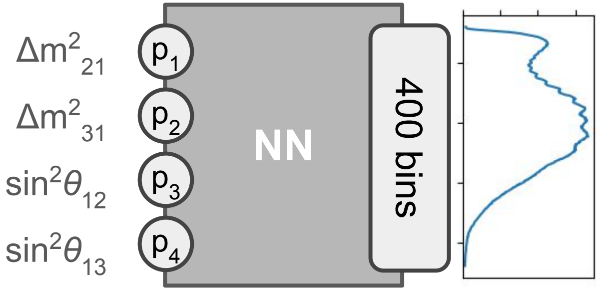

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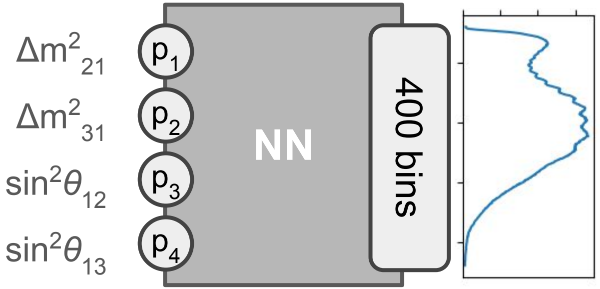
Note: KATRIN already uses this approach [Eur. Phys. J. C 82, 439 (2022)]



Reactor Spectrum Prediction Performance

Dataset:

Pre-calculated spectra for 5M combinations of
Δm^2_{21}, Δm^2_{31}, $\sin^2\theta_{12}$ within 3σ [PDG2022]
$\sin^2\theta_{13}$ within 5σ [PDG2022]
70% for training, 30% for validation

NN architecture (dense layers):

- input layer: 4 input nodes
- 2 layers with 400 nodes and RELU activation function
- output layer: 400 nodes, no activation function

Loss function: **MSE**
Optimizer: **RMSprop(learning_rate=0.02)**

Model size: **322800 parameters / 1.23MB**

Prediction speed: **~1 msec / spectrum**
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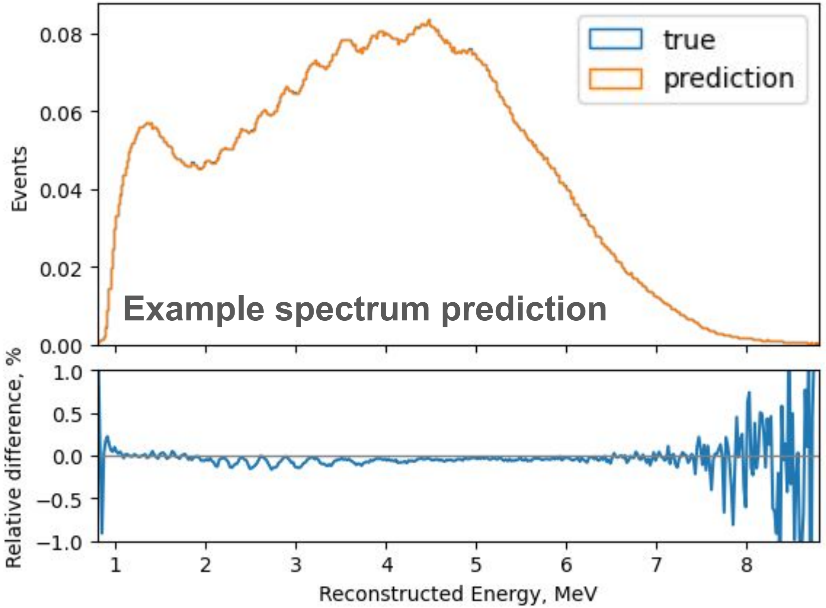

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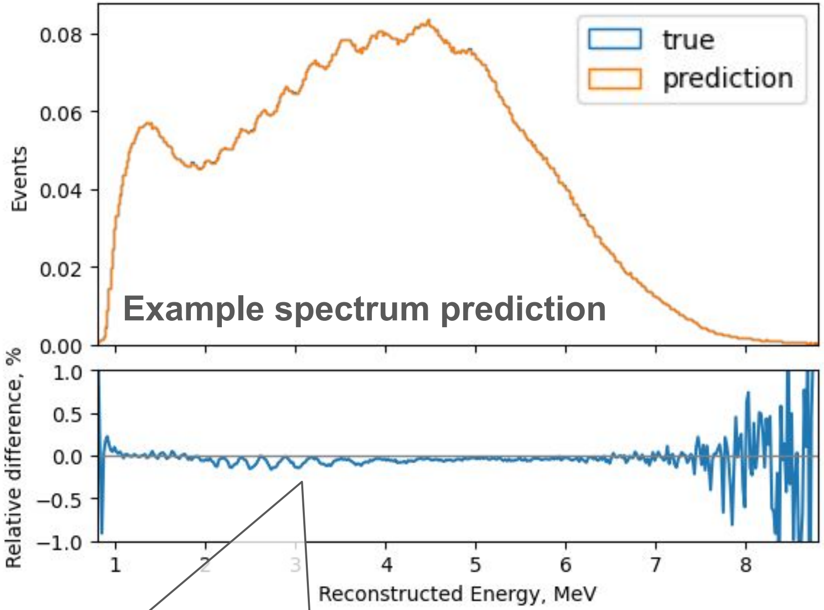
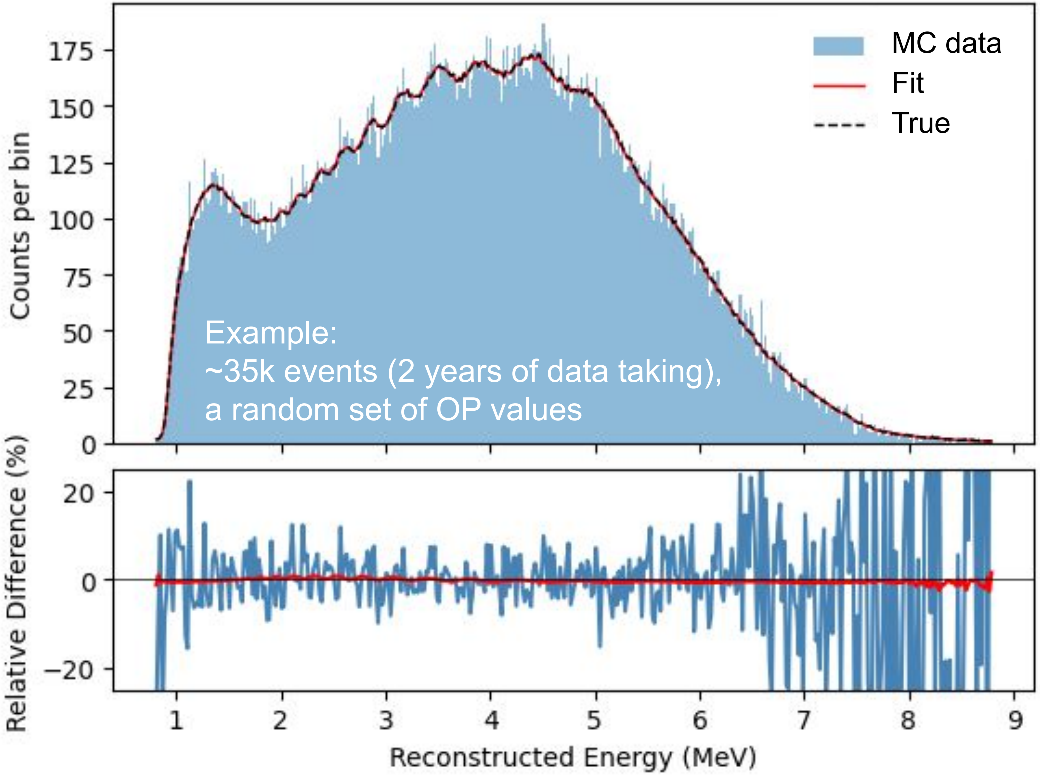


Small oscillatory artifacts

- could not suppress so far
- no significant effect on analysis observed

Using NN as Part of Fitting Software

NODA (Neutrino Oscillation Data Analysis) Python framework – one of the fitter codes in JUNO



Migrad

FCN = 178.7	Nfcn = 332
EDM = 0.0135 (Goal: 0.2)	
Valid Minimum	Below EDM threshold (goal x 10)
No parameters at limit	Below call limit
Hesse ok	Covariance accurate

	Name	Value	Hesse Error	Minos Error-	Minos Error+	Limit-	Limit+	Fixed
0	dm2_21	7.410	0.022			7.35	7.71	
1	dm2_31	2.502	0.013			2.49	2.56	
2	sin2_th12	0.2974	0.0021			0.294	0.32	
3	sin2_th13	2.19	0.06			2.11	2.25	
4	norm	0.995	0.010			0	10	

	dm2_21	dm2_31	sin2_th12	sin2_th13	norm
dm2_21	0.000492	0.01e-3 **(0.023)**	21e-6 **(0.454)**	-0.1e-3 **(-0.097)**	0.12e-3 **(0.564)**
dm2_31	0.01e-3 **(0.023)**	0.00019	1e-6 **(0.023)**	0.01e-3 **(0.014)**	0 **(0.015)**
sin2_th12	21e-6 **(0.454)**	1e-6 **(0.023)**	4.55e-06	15e-6 **(0.099)**	17e-6 **(0.813)**
sin2_th13	-0.1e-3 **(-0.097)**	0.01e-3 **(0.014)**	15e-6 **(0.099)**	0.00473	-0.05e-3 **(-0.080)**
norm	0.12e-3 **(0.564)**	0 **(0.015)**	17e-6 **(0.813)**	-0.05e-3 **(-0.080)**	9.84e-05

Successfully coupled with iMinuit
– demonstrates that it can be used for real fitting!

Summary

- JUNO requires powerful tools for sensitivity and real data analyses of reactor anti-ν_e.
- Other analyses, e.g. geoneutrino, also requires fitting of reactor anti-ν_e.
- Standard "analytical" approach, used by other fitters, may miss some features which are, however, present in the full Monte Carlo simulation.
- Full MC-based approach relies on the accuracy of detector simulation.
- Full MC-based approach is computationally challenging, but using a neural network for spectrum prediction gives a dramatic speed.
- Inclusion of extra parameters, which can be fitted, is being considered.
- First sensitivity results are in agreement with other fitters.