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Novel Fitting Approach Based on a Neural Network for JUNO

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Abstract. JUNO (Jiangmen Underground Neutrino Observatory) is a neutrino experiment in South China. Its primary goals are to resolve the order of the neutrino mass eigenstates and to precisely measure the oscillation parameters $\sin^2\theta_{12}$, Δm^2_{21}, and $\Delta m^2_{31(32)}$ by observing the oscillation pattern of electron antineutrinos produced in eight reactor cores of two commercial nuclear power plants at a distance of 52.5 km. A crucial stage in the data analysis is to fit the observed spectrum to the expected one under different oscillation scenarios taking into account realistic detector response, backgrounds, and all relevant uncertainties. This task becomes computationally challenging when a full Monte Carlo simulation of the detector is directly used to predict the detector response instead of otherwise used analytical empirical models. It is proposed to use a neural network to precisely predict the detector spectrum as a function of oscillation parameters and a set of detector response parameters. This approach drastically reduces computation time and makes it possible to fit a spectrum within a few seconds. This contribution presents the details, performance, and limitations of the method.

1 Introduction

Neutrino oscillation experiments provide a unique window into the fundamental properties of neutrinos, such as mass ordering and mixing parameters. Precise measurements of these properties are vital for understanding the underlying mechanisms of particle physics and for testing the completeness of the Standard Model. The Jiangmen Underground Neutrino Observatory (JUNO) [1], with its unprecedented energy resolution of 3% at 1 MeV [2], aims to contribute significantly to this field. By detecting antineutrinos produced in reactor cores of nearby nuclear power plants at a distance of 52.5 km, JUNO is expected to resolve the neutrino mass ordering with better than 3σ significance level [3] and refine our knowledge of oscillation parameters such as $\sin^2\theta_{12}$, Δm^2_{21}, and $\Delta m^2_{31(32)}$ at sub-percent precision [4].

Beyond oscillation analyses, the JUNO detector will enable studies of geoneutrinos [5], solar [6, 7] and atmospheric neutrinos [8], neutrinos from supernova bursts [9], and rare events such as proton decay [10] or search for dark matter [11]. Importantly, reactor antineutrinos serve as a critical background in some of these analyses, emphasizing the necessity of precise spectrum prediction.

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JUNO's measurement will be supported by the complementary Taishan Antineutrino Observatory (TAO) [12], which will monitor the unoscillated reactor spectrum at a distance of 44 m from one of the reactors, providing a benchmark for theoretical models and improving the reliability of JUNO analyses. This setup ensures that the unexplored fine structures in the reactor spectrum will not harm JUNO sensitivity to neutrino mass ordering.

Traditional methods for oscillation analyses rely on a parametrized model for detector response tuned based on Monte Carlo (MC) simulations and calibration measurements [3, 4]. While these methods have been successfully employed, they may miss certain effects not present in the underlying model. For instance, analytical approaches may oversimplify the complex detector response. A possible solution would be a direct utilization of MC simulations for the detector response, tuned with calibrations, ensuring better accuracy. However, this approach demands immense computational resources, especially during iterative fitting. Neural networks (NNs) have emerged as a promising alternative, offering a balance of speed and accuracy. Motivated by their success in the KATRIN experiment [13], we explore the integration of NNs for reactor spectrum fitting and their broader applicability in neutrino experiments. The key innovation lies in using pre-trained NNs to predict reconstructed spectra directly from oscillation parameters, bypassing the need for computationally expensive intermediate steps.

2 JUNO detector

The JUNO detector, illustrated in Figure 1, consists of:

- **Central Detector (CD)** [14] — 20 kt of LAB-based liquid scintillator (LS) contained in a transparent acrylic sphere with 17.7 m inner diameter and surrounded by an array of photomultiplier tubes (PMTs) providing 78% coverage. The array includes 17,612 large (20-inch) PMTs and 25,600 small (3-inch) PMTs. JUNO CD, thanks to the high light yield and transparency of LS and to high photon-detection efficiency and dense arrangement of PMTs, provides unprecedented energy resolution of 3% at 1 MeV [2].
- **Water Pool (WP)** — cylindrical water reservoir equipped with additional 2,400 PMTs, providing cosmic muon veto and shielding against radioactivity originating from surrounding rock.
- **Top Tracker (TT)** [15] — plastic scintillator strips monitored by PMTs and placed above WP for additional muon veto and, importantly, to provide a sample of muons to calibrate WP and CD.

The detector's spherical geometry and optical properties are optimized to minimize systematic uncertainties. The liquid scintillator provides high light yield and transparency, while the dual-PMT system enhances timing, spatial resolution, mitigates uncertainties related to the electronics non-linearities [16], and extends the dynamic range of JUNO to higher energies. The WP Cherenkov veto reduces cosmic muon background, and the muon tracker provides additional redundancy in background suppression.

JUNO is sensitive to neutrinos of different flavors in a wide range across the energy. Electron antineutrinos emitted in reactor cores are detected via Inverse Beta-Decay (IBD) reaction:

$$\bar{\nu}_e + p \to e^+ + n.$$

Fast energy release of the emitted positron forms the so-called "prompt" signal, carrying the momentum of the original neutrino and providing information about its energy. The correlated signal detected after the capture of the thermalized neutron forms the "delayed"

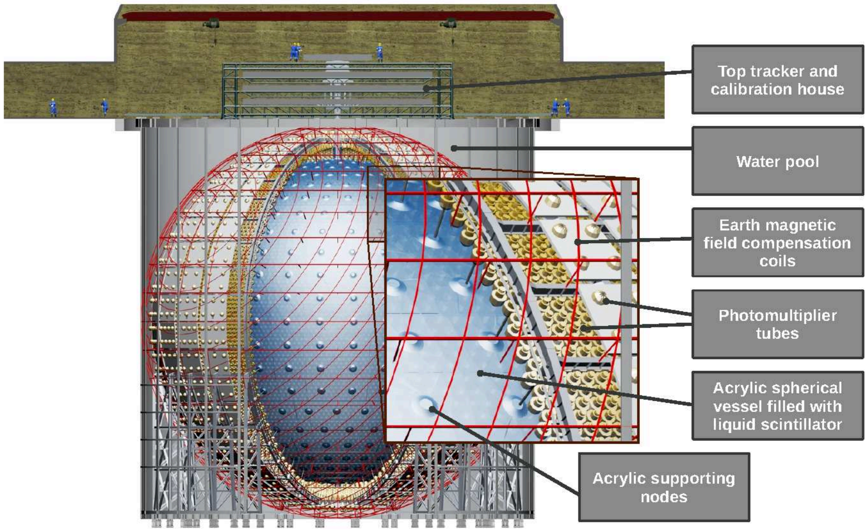

Figure 1. Schematic view of the JUNO detector [4].

signal. The time and space coincidence of these two signals serves as a powerful discriminator against the majority of backgrounds.

Reactor antineutrinos observed by JUNO are mainly produced in Taishan (at 52.5 km) and Yangjiang (at 52.5 km) nuclear power plants. The other nuclear power plants, including Daya Bay (at 215 km) and the rest world reactors located at larger distances, contribute to about 8% of the signal. Traveling from the reactor cores to the detector, neutrinos oscillate to other flavors, non-visible for JUNO in the IBD channel. The oscillation probability depends on the energy and the baseline, resulting in the spectrum with an oscillatory pattern (see Figure 2):

$$\begin{aligned} P(\nu_e \to \nu_e) = 1 &- \cos^4\theta_{13}\sin^2(2\theta_{12})\sin^2\left(\frac{\Delta m^2_{21}L}{4E}\right) \\ &- \sin^2(2\theta_{13})\cos^2\theta_{12}\sin^2\left(\frac{\Delta m^2_{31}L}{4E}\right) \\ &- \sin^2(2\theta_{13})\sin^2\theta_{12}\sin^2\left(\frac{\Delta m^2_{32}L}{4E}\right), \end{aligned} \tag{1}$$

where θ_{12} and θ_{13} are mixing angles, $\Delta m^2_{ij} = m^2_i - m^2_j$ are mass splittings, L is the distance from the source to the detector, and E is neutrino energy. The matter effects are omitted for simplicity here, they introduce only a small correction. JUNO is sensitive to neutrino mass ordering via the slight relative displacement of the small wiggles of the oscillation pattern for the normal and inverted ordering (compare red and blue curves in Figure 2).

Energy scale calibration plays a pivotal role for JUNO measurements. Multiple calibration systems [17] — spanning the detector's volume and energy range — will ensure subpercent energy scale uncertainty. Calibration measurements will be used both directly as an input for energy reconstruction and for validation and tuning of Monte Carlo simulation to make it more realistic.

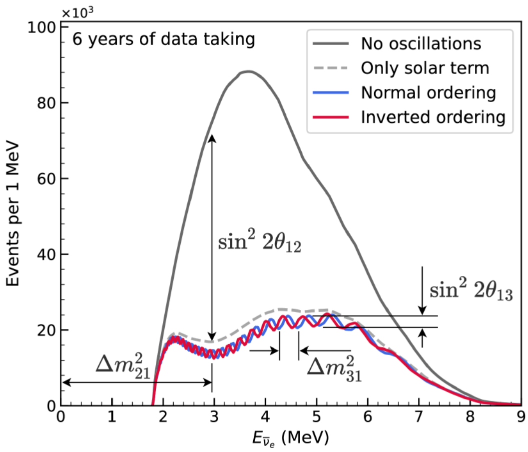

Figure 2. Reactor electron antineutrino spectrum expected at the JUNO site, assuming ideal detection efficiency. The lower frequency mode is driven by "solar" oscillation parameters $\sin^2\theta_{12}$ and Δm^2_{21}, while the faster oscillation mode is driven by "atmospheric" oscillation parameters $\sin^2\theta_{13}$ and $\Delta m^2_{31(32)}$ [4].

3 Methodology

3.1 Standard and Monte Carlo-Based Approaches

Traditional methods for spectrum prediction can be divided into two main categories: analytical approaches and MC simulations. Analytical models use parameterized representations of the detector response to transform input spectra into reconstructed spectra. While computationally efficient, these models may oversimplify complex detector effects, such as non-Gaussian energy resolution and position-dependent variations.

In contrast, MC simulations provide a detailed mapping of the neutrino energy (E_ν) to the reconstructed energy (E_{rec}) by simulating particle interactions and detector responses, including stochastic effects. These simulations incorporate detailed modeling of physics processes and detector geometries, offering a comprehensive representation of the experimental setup. However, MC simulations are computationally expensive, particularly for iterative fitting tasks that require spectrum recalculations for various oscillation parameter sets. For instance, predicting the spectrum for a single fit may involve over 10^{10} computations ($E_{\text{rec}} = f(E_\nu)$), making MC-based methods challenging for large-scale analyses. In JUNO, MC-based fitting was used only for solar neutrino analyses with spectral templates for the signal and backgrounds [6], that is the fitting parameters were weighting factors for fixed components constituting the total spectrum. The MC-based approach was never used for oscillation analysis when the spectral shape depends also on the oscillation parameters.

3.2 Neural Network Approach

The NN approach addresses the limitations of traditional methods (both analytical and MC-based). The core idea is to map oscillation parameters (i.e., Δm^2_{21}, Δm^2_{31}, $\sin^2\theta_{12}$, $\sin^2\theta_{13}$) directly to the reconstructed spectrum's bin contents (see Figures 3). This approach requires an initial computational effort to generate training data, which involves pre-calculated spectra for millions of parameter combinations within a wide range, safely covering known uncertainties. Once trained, the NN provides rapid predictions with minimal storage requirements. Its prediction accuracy, however, should be carefully checked.

The NN architecture, used here, comprises two hidden dense layers with 400 nodes each and with rectified linear unit (ReLU) activation functions. Note that even more compact NNs with fewer nodes were producing comparable accuracy. The input layer accepts four

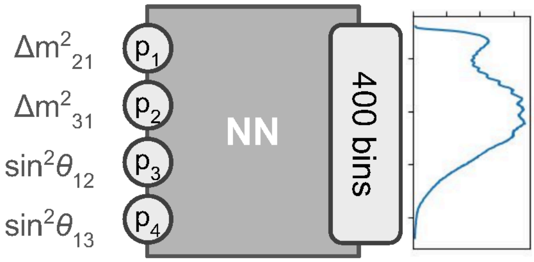

Figure 3. Schematic illustration of the NN model: a feed-forward neural network with 4 input nodes accepting values of oscillation parameters and 400 output bins yielding bin contents of the corresponding reactor neutrino spectrum.

oscillation parameters, while the output layer produces the bin contents for the reconstructed spectrum. Training is performed using mean squared error (MSE) loss and the RMSprop optimizer with a learning rate of 0.02. The resulting model, containing approximately 322,800 parameters, occupies only 1.23 MB and achieves prediction speeds of ~1 ms per spectrum. This is a dramatic improvement in speed enabling real-time fitting and facilitating large-scale studies that were previously infeasible.

The data for training was prepared using the official JUNO simulation software [18] and included 10 millions (E_ν, E_{rec})-pairs. The simulation did not include neutrino oscillations. The (E_ν, E_{rec})-pairs were then used to produce 5 million of oscillated spectra: E_ν was used to calculate the survival probability and weight each event, and E_{rec} was used for bin determination. The training dataset consisted of 5 million sets of oscillation parameters and corresponding spectra (in terms of E_{rec}). The values of oscillation parameters $\sin^2\theta_{12}$, Δm^2_{21}, and Δm^2_{31} were sampled from the range of $\pm 3\sigma$, and $\pm 5\sigma$ for $\sin^2\theta_{13}$ (where σ is PDG2022 uncertainty [19]).

4 Results

The NN-based method achieves remarkable improvement in computational efficiency. Single predictions are completed within milliseconds, enabling fitting, requiring hundreds of iterative invocations, to be completed within a few seconds. Running NN-model on batches of oscillation parameter sets allows to predict an order of a million of spectra within one second, which is useful for a grid scan.

Despite its advantages, the NN approach faces challenges such as oscillatory artifacts, see Figure 4, which are although relatively small, less than 0.1% in the major part of the energy range. These artifacts likely arise from insufficient training data coverage or architectural constraints, highlighting areas for future optimization. Their impact on analyses requires further investigation.

The NN described above has been successfully integration with iMinuit [20] within one of the analysis frameworks used in JUNO — NODA (Neutrino Oscillation Data Analysis). It enables the NN to perform real-time parameter fitting, demonstrating its applicability in practical analyses.

5 Conclusions and Prospects

This study highlights a potential of NN-based spectrum prediction for neutrino oscillation analyses in JUNO. By combining computational efficiency with detailed predictability of the full Monte Carlo simulation, this method addresses key limitations of existing techniques. The ability to integrate seamlessly with existing frameworks, such as NODA, underscores its practicality for real-world applications.

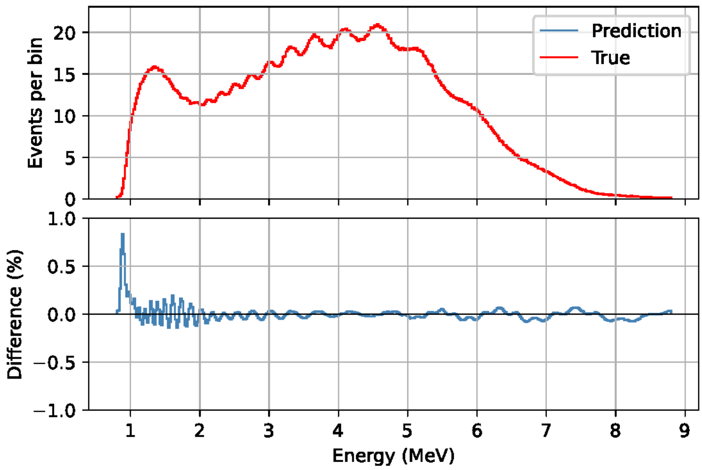

Figure 4. Prediction of the NN model (blue) compared to the true energy (red) for an arbitrary set of oscillation parameters not present in the training dataset. The lower panel shows the relative difference.

One notable limitation is the presence of small oscillatory artifacts in the predicted spectra. While these artifacts do not significantly affect the overall analysis, ongoing efforts aim to refine the training process and architecture to mitigate their occurrence. Future work includes expanding the training dataset to cover a broader parameter space and introducing regularization techniques to enhance model generalization.

Future work will also focus on enhancing the NN framework to incorporate additional parameters, such as detector non-linearities, background variations, and systematic uncertainties. The calibration measurements may be used not only to tune the Monte Carlo simulation software but also for direct validation of models predicting the detector response to particles emitted by calibration sources.

The NN's adaptability makes it a candidate for application in various JUNO analyses, including neutrino mass ordering test, precise measurement of oscillation parameters $\sin^2\theta_{12}$, Δm^2_{21}, and $\Delta m^2_{31(32)}$, geoneutrino studies, and sterile neutrino searches. Beyond JUNO, this approach holds promise for other experiments requiring rapid and precise spectrum predictions.

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