Decomposition of fissile isotope antineutrino spectra using convolutional neural network: Postprint

Authors: Zeng, Yuda, Wang, Jun, Zhao, Rong, An, Fengpeng, Xiao, Xiang, Hor, Yuenkeung, Wang, Wei, An, Fengpeng, Wang, Wei

Date: 2023-06-01T09:46:33+00:00

Abstract

Recent reactor antineutrino experiments have observed that the neutrino spectrum changes with the reactor core evolution and that the individual fissile isotope antineutrino spectra can be decomposed from the evolving data, providing valuable information for the reactor model and data inconsistent problems. We propose a machine learning method by building a convolutional neural network based on a virtual experiment with a typical short-baseline reactor antineutrino experiment configuration: by utilizing the reactor evolution information, the major fissile isotope spectra are correctly extracted, and the uncertainties are evaluated using the Monte Carlo method. Validation tests show that the method is unbiased and introduces tiny extra uncertainties.

Full Text

Decomposition of Fissile Isotope Antineutrino Spectra Using Convolutional Neural Networks

Yu-Da Zeng (https://orcid.org/0000-0003-2013-9440)[1], **Jun Wang** (https://orcid.org/0000-0003-0376-6071)[2], **Rong Zhao** (https://orcid.org/0000-0003-0177-5468)[1], **Feng-Peng An**[1],*, **Xiang Xiao**[1], **Yuenkeung Hor**[1], and **Wei Wang** (https://orcid.org/0000-0002-4728-6291)[2],[1],†

[1]School of Physics, Sun Yat-sen University, Guangzhou 510275, China
[2]Sino-French Institute of Nuclear Engineering and Technology, Sun Yat-sen University, Zhuhai 519082, China

Recent reactor antineutrino experiments have observed that the neutrino spectrum changes with reactor core evolution, and that individual fissile isotope antineutrino spectra can be decomposed from this evolving data. This provides

valuable information for reactor modeling and helps address data inconsistency problems. We propose a machine learning method based on a convolutional neural network trained on a virtual experiment configured as a typical short-baseline reactor antineutrino experiment. By utilizing reactor evolution information, the major fissile isotope spectra are correctly extracted, and uncertainties are evaluated using the Monte Carlo method. Validation tests show that the method is unbiased and introduces only minimal additional uncertainties.

Keywords: Reactor antineutrino, Isotope antineutrino spectrum decomposition, Convolutional neural network

INTRODUCTION

Significant deviations have been observed between the Huber-Mueller model isotope antineutrino spectra and experimental measurements, causing a ~6% deficit in the reactor antineutrino flux (the so-called Reactor Antineutrino Anomaly, RAA) and an excess of reconstructed positron signal events in the 4–6 MeV region (the so-called 5-MeV bump) [1–6]. Determining the origin of the reactor antineutrino rate and shape anomaly is critical, particularly for understanding nuclear physics and improving nuclear databases for fundamental and applied research. Relevant experimental and theoretical efforts have been undertaken to address this problem, including attempts to determine the individual isotope contributions of reactor $\bar{\nu}_e$, which has prompted further investigations. In 2017, the Daya Bay experiment revealed a 7.8% discrepancy between observed and predicted ^{235}U yields by using the span of effective ^{239}Pu fission fractions, suggesting this may be the primary contributor to the RAA [7]. In 2019, the PROSPECT experiment measured the ^{235}U spectrum from highly enriched uranium at the High Flux Isotope Reactor, finding the ^{235}U spectrum shape deviated from the prediction made by the Daya Bay experiment in the 5–7 MeV energy region [8]. Also in 2019, theoretical results from the summation method were compared with Daya Bay experimental data without renormalization, reducing the flux discrepancy to 1.9% by incorporating corrections for the pandemonium effect [9]. In the same year, the Daya Bay experiment first extracted the ^{235}U and ^{239}Pu neutrino spectra from commercial reactors using reactor evolution information [10].

Determining individual isotope antineutrino spectra also plays an important role in nuclear safeguards. The International Atomic Energy Agency (IAEA) cooperates with neutrino physicists to develop new reactor monitoring approaches by observing $\bar{\nu}_e$ emitted from reactors, where isotope antineutrino spectra serve as key inputs for monitoring applications [11] because reactor antineutrino flux and spectra are sensitive to changes in fuel content and can be observed with suitable detectors. The applied neutrino physics community has also explored reactor antineutrinos as a tool for reactor monitoring, concluding that improved knowledge of reactor antineutrino flux and spectrum is required for safeguards applications [12]. The DOE National Nuclear Security Administration (NNSA) Office of Defense Nuclear Nonproliferation Research and Development (DNN

R&D) convened a group of neutrino physicists and nuclear engineers to identify practical roles for neutrino technology in nuclear energy and security; the final report, called Nu Tools, asserted that it is possible to exploit the neutrino spectrum to determine fissile material content in reactors with high antineutrino rates [13]. Isotope antineutrino spectra decomposed directly from reactor experiments avoid the RAA and spectrum distortion problems while achieving uncertainties comparable to or better than those in the Huber-Mueller model, providing more reliable data inputs for nuclear safeguards.

Only the Daya Bay experiment has published reactor isotope antineutrino spectra using two methods—the minimum χ^2 and Markov Chain Monte Carlo (MCMC) methods—obtaining consistent results. The minimum χ^2 method is a statistical inference approach that minimizes the χ^2 statistic, constructed as a χ^2 function. The χ^2 function $\chi^2(\theta)$ serves as an estimator for parameter θ and is composed of a likelihood function comparing binned observation data $\mathbf{n} = (n_1, ..., n_N)$, expectation $\mu(\theta) = (\mu_1(\theta), ..., \mu_N(\theta))$, and a penalty term for parameter constraints: $\chi^2(\theta) = 2\sum\left[\mu_j(\theta) - n_j + n_j \ln \frac{\mu_j(\theta)}{n_j}\right] + f(\epsilon, \Sigma)$, where n_j follows a Poisson distribution and $f(\epsilon, \Sigma)$ is the penalty term constraining nuisance parameters ϵ with correlation matrix Σ. The minimum χ^2 method naturally incorporates statistical and systematic uncertainties into the estimator, yielding best-fit parameters and uncertainties by minimizing the χ^2 function. This robust, traditional frequentist fitting method is commonly used in high-energy physics. The second method employed in Daya Bay's decomposition research is the MCMC method based on Bayesian inference. In Bayesian theory, all knowledge of parameter θ is summarized in the posterior probability density function (p.d.f.) $p(\theta|D)$: $p(\theta|D) \propto P(D|\theta)\pi(\theta)$, where D is data, θ is the parameter, $P(D|\theta)$ is the likelihood function, and $\pi(\theta)$ is the prior p.d.f. of θ. Calculating the posterior p.d.f. is typically difficult, especially for high-dimensional problems, so the MCMC method samples from the posterior p.d.f. instead, extracting mean values and uncertainties from the samples.

In the Daya Bay experiment, measured data were divided into 20 groups of inverse beta-decay (IBD) spectra corresponding to different burning stages of a reactor cycle. Prediction spectra for these 20 groups were obtained by combining detector and reactor models with reactor information. Data and predictions were used to construct the likelihood function for both the minimum χ^2 and Bayesian inference methods. Uncertainties from detectors and reactors were incorporated into penalty terms for the minimum χ^2 method and prior p.d.f.s for the Bayesian method, respectively. Ultimately, consistent decomposed isotope spectra were obtained using both approaches.

While isotope antineutrino spectrum extraction has been studied in reactor neutrino physics without a conclusive resolution to the RAA, we consider it beneficial to explore new methods. Here, we propose a novel approach using a convolutional neural network (CNN) to decompose primary fissile isotope antineutrino spectra by fitting weekly detected antineutrino spectra as functions of

individual isotope fission fractions. A CNN is a machine learning network model that provides optimal architecture for detecting key features in images and time series data, with broad applications in computer vision and natural language processing [14–17]. CNNs have also been used in physics research to extract information from experimental data and fit model parameters [18]. Notably, established decomposition methods such as minimum χ^2 and MCMC are offline algorithms, requiring complete reanalysis from scratch as new data arrives—an inefficient use of time, particularly for long-term experiments. Second, these methods must load entire datasets into computer memory, demanding substantial memory resources for big data scenarios (e.g., many reactor burning cycles with detailed reactor information), potentially rendering them unusable. They also typically resample original data to reduce dataset size, which may introduce information loss and analysis bias. By contrast, the CNN approach is an online algorithm [19] whose primary advantage is enabling analysis without requiring access to historical data, thus overcoming storage and computational limitations in certain cases.

Furthermore, the proposed method utilizes data fully without causing excessive information loss, providing an additional machine learning technique for decomposing reactor fissile isotope spectra that can be applied to neutrino spectrum analysis in future reactor antineutrino experiments.

II. SETUP OF THE VIRTUAL EXPERIMENT

We describe a virtual reactor antineutrino experiment to generate simulation datasets for training and testing the proposed CNN method.

We consider a virtual experiment with a one-reactor, one-detector layout, where the reactor is a pressurized water reactor (PWR) serving as the sole $\bar{\nu}_e$ flux source. Antineutrinos are produced from thousands of beta-decay branches of fission products from four major fissile isotopes: ^{235}U, ^{238}U, ^{239}Pu, and ^{241}Pu in the reactor core. A virtual 20-ton liquid scintillator antineutrino detector is positioned 50 m from the reactor using parameters listed in [20]. Antineutrinos are detected via IBD reactions in the detector: $\bar{\nu}_e + p \to e^+ + n$. The predicted $\bar{\nu}_e$ spectrum at time t is calculated as:

$$S_d(E_\nu, t) = N_p \cdot \epsilon \cdot \sigma(E_\nu) \cdot P_{\text{sur}}(E_\nu, L) \sum_i \frac{W(t) \cdot f_i(t) \cdot e_i}{\sum_l f_l(t) \cdot e_l} \cdot S_i(E_\nu),$$

where E_ν is the $\bar{\nu}_e$ energy, N_p is the number of target protons, ϵ is detection efficiency, $\sigma(E_\nu)$ is the inverse beta-decay cross section, L is the reactor-detector distance, $P_{\text{sur}}(E_\nu, L)$ is the $\bar{\nu}_e$ survival probability, $W(t)$ is reactor thermal power, e_i is energy released per fission for isotope i, f_i is the fission fraction, and $S_i(E_\nu)$ is the $\bar{\nu}_e$ energy spectrum per fission for isotope i.

presents the experimental parameter values used in Eq. (3), based on Daya Bay experiment configurations. For the virtual experiment, isotope antineutrino

spectra $S_i(E_\nu)$ are assumed identical to those in the Huber-Mueller model, denoted $S_i^{\mathrm{HM}}(E_\nu)$. In addition to , the top panel of [Figure 1: see original paper] shows fission fraction evolution over a fuel cycle, displaying fission fractions for the four major fissile isotopes as functions of burn-up. For PWRs, the reactor core typically consists of three batches of fuel assemblies with different ages, with one-third of old batches replaced by fresh fuel at each refueling cycle end. During reactor operation, fissile isotopes are depleted primarily through fission, decay, and neutron capture processes. Some isotopes, such as plutonium isotopes, are also generated through neutron captures and decays from parent nuclei in reaction chains. This depletion and generation drives fuel evolution.

Burn-up in the top panel of [Figure 1: see original paper] is defined as:

$$\text{burn-up} = \frac{W \cdot D}{M_U},$$

where W is the average power of the fuel element, D is days since the fuel element began burning in the core, and M_U is the initial uranium mass (assumed to be 72 tons in this study). Fission fraction uncertainties for the four major isotopes are assumed to be 5%, as in the Daya Bay experiment, with uncertainty correlation matrices from Ref. [20] extracted from typical PWR simulations. Energy released per fission values are from Ref. [21]. All uncertainties are assumed time-correlated.

Due to evolution of the four major fissile isotopes, $\bar{\nu}_e$ emission from the reactor core varies with time. The bottom panel of [Figure 1: see original paper] shows reactor antineutrino spectrum evolution across nine fuel cycles over 657 weeks. These spectra serve as measurement data from the virtual detector, containing reactor evolution information. Individual fissile isotope antineutrino spectra are decomposed from these observed spectra using reactor information from , which employs typical values similar to those in Daya Bay and would be provided by the nuclear power plant in a real experiment.

Notably, the IBD cross section $\sigma(E_\nu)$ and isotope antineutrino spectrum $S_i(E_\nu)$ are coupled with antineutrino energy in Eq. (3). The IBD yield per fission from individual isotopes can be defined as $\sigma_i(E_\nu) = \sigma(E_\nu) \cdot S_i(E_\nu)$ for $i = (235, 238, 239, 241)$, which represents the isotope spectrum to be decomposed, as done in the Daya Bay experiment [10]. In the Huber-Mueller model case, $\sigma_i(E_\nu)$ is denoted $\sigma_i^{\mathrm{HM}}(E_\nu)$.

Thus, the predicted $\bar{\nu}_e$ spectrum can be expressed as a combination of $\sigma_i(E_\nu)$ and coefficients $k_i(E_\nu, t)$:

$$S_d(E_\nu, t) = \sum_i k_i(E_\nu, t) \cdot \sigma_i(E_\nu),$$

where coefficient $k_i(E_\nu, t)$ combines experimental parameters from Eq. (3):

$$k_i(E_\nu, t) = N_p \cdot \epsilon \cdot P_{\text{sur}}(E_\nu, L) \cdot \frac{W(t) \cdot f_i(t)}{\sum_l f_l(t) \cdot e_l}.$$

Assuming the virtual experiment ran for nine fuel cycles (~4600 days), reactor thermal power and antineutrino spectrum information were collected weekly during operation, producing a time-varying list of coefficients and $\bar{\nu}_e$ observations (see bottom panel of [Figure 1: see original paper]).

III. CONFIGURATIONS OF CONVOLUTIONAL NEURAL NETWORK

Among machine learning methods, CNNs are commonly applied to extract shift-invariant features from data using specialized convolutional layers. In reactor antineutrino spectrum decomposition studies, isotope antineutrino spectra are time-invariant within reactor evolution data, making the CNN approach potentially suitable for extraction. To extract isotope spectra from the simulation dataset, we constructed a one-dimensional CNN. Before introducing the CNN architecture, we first describe the data structures, operations, and key concepts required by the model, summarized in .

The virtual experiment dataset is organized sample-by-sample, tagged with time $(t_1, t_2, ..., t_n)$ for each week. The CNN splits periodic experimental measurements (one week) to create training samples. The "Coefficient" columns in represent the key CNN input, where coefficient k_{ti} is calculated using Eq. (7) from virtual experiment parameters for week t and isotope i, on a weekly basis. The CNN's core component is the convolutional kernel—a small matrix for feature extraction defined as $(\sigma_{235}, \sigma_{238}, \sigma_{239}, \sigma_{241})$, shown in the second row of , representing the respective isotope spectra in Eq. (5). A linear operation called convolution is performed between the kernel and input data to generate output in the "Expectation" column of . This output represents the expected antineutrino spectrum from Eq. (6). The convolution operation is performed sample-by-sample across the entire dataset; the kernel $(\sigma_{235}, \sigma_{238}, \sigma_{239}, \sigma_{241})$ slides along the timeline and combines with each coefficient row to predict $\bar{\nu}_e$ spectrum outcomes. This process returns a list of calculated outputs ("Expectation" column) that are compared with label data—the $\bar{\nu}_e$ spectra observed by the detector ("Observation" column). Notably, entries in focus on the same energy bin. In this study, neutrino energy bins range from 2 to 8 MeV, each covering 0.25 MeV, yielding 24 energy bins.

The CNN learns from reactor antineutrino experimental data to fit isotope spectra by updating its convolutional kernel. Since the energy range is divided into 24 bins from 2 to 8 MeV, a corresponding number of convolutional kernels are employed.

The constructed CNN model architecture is shown in [Figure 2: see original paper]. This CNN comprises three layers: a convolutional layer, a flatten layer,

and a fully connected layer. The convolutional layer performs most computations, requiring input data (rectangles on the left side of [Figure 2: see original paper]) and convolutional kernels (shaded patch at bottom left). Input data come from simulation coefficients as shown in . For each energy bin, the coefficient table and respective kernels perform convolution, conveying outcomes (representing expected $\bar{\nu}_e$) to the second layer (bars in middle, marked as feature maps). Next, flattening transforms multidimensional data into one dimension, commonly used when transitioning from convolutional to fully connected layers. The final layer (bars on right side), the fully connected layer, outputs flattened results as $\bar{\nu}_e$ expectations. The CNN then compares outputs with corresponding $\bar{\nu}_e$ label data and begins training via back-propagation, aiming to make outputs as close as possible to label values. During training, the CNN repeats back-propagation many times, adjusting convolutional kernel parameters $(\sigma_{235}, \sigma_{238}, \sigma_{239}, \sigma_{241})$ to optimal values through iteration. Unlike conventional "black box" neural networks, this CNN model is interpretable: convolutional kernel components carry isotope spectrum information, inputs corresponding to kernel components represent fission rates of the four isotopes, and outputs simulate predicted $\bar{\nu}_e$ spectra.

After building the CNN architecture, we tune hyperparameters controlling the training process—objective function, optimizer, and learning rate. Hyperparameters are typically set before training, so appropriate configurations must be identified beforehand. This tuning process is called pre-training to distinguish it from subsequent real decomposition training. However, hyperparameters cannot be estimated directly from data and must be specified manually, usually through trial and error without golden rules.

During pre-training, the simulation dataset fed into the CNN is noiseless, with systematic uncertainties of parameters in assumed zero—virtual experimental parameter measurements are considered sufficiently precise to suppress noise effects. This enables the CNN model to determine optimal hyperparameters.

Our computation uses a server cluster of 16-core CPU computers supporting up to 500 multi-core jobs, allowing simultaneous decomposition from 500 Monte Carlo datasets [22]. CNN pre-training is implemented in Keras 2.3, a user-friendly framework providing a Python frontend with TensorFlow backend. These tools offer sufficient standard modules for building and training neural networks, though we developed a new objective function prototype for this study. This setup requires ~300 MB memory and ~5 hours per decomposition task.

For decomposing individual isotope spectra, the CNN requires an objective function to optimize network parameters σ_i by minimizing differences between outputs and label data. For general CNN regression problems, mean squared error (MSE) is conventional but ignores uncertainties. In this study, we construct an objective function in χ^2 form that considers statistical uncertainties and uncertainties from ^{238}U and ^{241}Pu, as commonly done in high-energy physics:

$$J(E_\nu,\sigma)=\sum_j \frac{(S^j_{\rm obs}(E_\nu)-S^j_{\rm exp}(E_\nu))^2}{\sigma^2_{\rm stat}}+\frac{(\sigma_{238}(E_\nu)-\sigma^{\rm HM}_{238}(E_\nu))^2}{(\sigma^{\rm HM}_{238}(E_\nu)\times 15\%)^2}+\frac{(\sigma_{241}(E_\nu)-\sigma^{\rm HM}_{241}(E_\nu))^2}{(\sigma^{\rm HM}_{241}(E_\nu)\times 10\%)^2},$$

where j is the sample index, $S^j_{\rm obs}(E_\nu)$ is the observed $\bar{\nu}_e$ spectrum of the j-th sample (assumed Gaussian-distributed), and $S^j_{\rm exp}(E_\nu)$ is the expected $\bar{\nu}_e$ spectrum calculated by the CNN via convolution:

$$S^j_{\rm exp}(E_\nu)=\sum_i k_i(E_\nu,t_j)\cdot\sigma_i(E_\nu).$$

The first term in Eq. (8) is a likelihood function measuring distance between predicted and observed $\bar{\nu}_e$ values, which the CNN minimizes by iteratively updating network parameters. The remaining terms are penalty terms allowing the CNN to apply prior constraints on σ_{238} and σ_{241} with their uncertainties. Because ^{238}U and ^{241}Pu fission fractions are small and fuel evolution is insensitive to these isotopes, they are treated as penalty terms. Using the Huber-Mueller model as priors, shape uncertainties of 15% and 10% are assigned to ^{238}U and ^{241}Pu, respectively.

During training, the neural network uses an iterative algorithm (optimizer) to minimize the objective function and adjust internal parameters. This CNN implements adaptive moment estimation (Adam) as its optimizer, which computes learning rates using first and second moments of gradients [23, 24].

Initially, CNN parameters σ_i are set as:

$$\sigma_i(E_\nu)=\sigma^{\rm HM}_i(E_\nu),\quad (i=235,238,239,241).$$

The starting point can be crucial because neural network optimizers may find local optima and become stuck. To examine sensitivity to initial values, we assigned 50% uncertainty to σ_i in Eq. (10) for initialization testing, finding nearly identical results—demonstrating the CNN model is not sensitive to parameter initialization schemes in this study.

Based on the objective function and optimizer, the neural network iteratively updates parameters. Controlling parameter update speed (learning rate) is important: rates that are too large may cause premature convergence to local optima, while rates that are too small may stall the process. In this study, CNN parameter learning rates follow the schedule shown in the top panel of [Figure 3: see original paper], appearing as functions of epoch. High-energy parameters use smaller learning rates than low-energy parameters because isotope spectra have smaller values at high energies, requiring greater precision.

An epoch trains the neural network on all training data for one cycle, consisting of one or more batches using dataset subsets. Batch size is set to four samples, meaning four weeks of data pass into the CNN between parameter iterations.

When preparing to train, the number of training cycles (epochs) must be set beforehand. Determining the optimal epoch number is challenging; it depends on network model and dataset characteristics, requiring identification of parameter convergence and appropriate stopping points. In machine learning, excessive training cycles cause overfitting (perfect training data fit but poor generalization), while insufficient cycles cause underfitting (inadequate data learning). Common practice examines training result variation with epochs—too few epochs terminate training before convergence, while too many likely cause overfitting.

To evaluate and visualize CNN decomposition effectiveness, we define a verification factor:

$$\mathrm{ratio}_i(E_\nu) = \frac{\sigma_i(E_\nu)}{\sigma_i^{\mathrm{true}}(E_\nu)} \times 100\%,$$

representing the ratio between predicted and true isotope spectra.

We assess epoch configuration influence by conducting thousands of training processes and superposing results, shown in the bottom panel of [Figure 3: see original paper]. The X-axis shows training cycle number, Y-axis shows verification factor, and data color represents result frequency. When epochs reach ~1500, the verification factor stably converges to nearly 100%. Conservatively, we set epochs to 2000 cycles.

After determining hyperparameters and completing pre-training, we establish the full CNN model and test decomposition performance using experimental data (simulation data in this study).

IV. RESULTS OF DECOMPOSITION

Using the aforementioned hyperparameter configurations, the CNN decomposes individual isotope spectra from both noiseless and noisy simulation datasets. We primarily examine decomposition unbiasedness and uncertainties.

Using noiseless datasets (ignoring systematic and statistical uncertainties), we perform decomposition 1000 times and compare extracted spectra samples with true values to evaluate bias and uncertainties. As shown in [Figure 4: see original paper], ratios of extracted spectra sample means to true spectra are presented as data points with deviations below 0.1% (negligible), indicating unbiased decomposed isotope spectra. Tiny error bars represent CNN model-introduced uncertainties, obtained by calculating standard deviations of ratios between extracted samples and true spectra.

When considering noise effects, we assign statistical errors (Poisson fluctuations) and systematic uncertainties from to experimental measurements. One thousand different noisy datasets are generated with these uncertainties, from which individual isotope spectra are extracted. Decomposition results vary under noise disturbance; mean values and standard deviations are shown in [Figure 5: see original paper].

Because ^{238}U and ^{241}Pu spectra are treated as prior knowledge, we present decomposition results for ^{235}U and ^{239}Pu, whose fitting is primarily driven by experimental data. As shown in the bottom panel of [Figure 5: see original paper], both isotope decomposition results deviate from true spectra by less than 0.3%, demonstrating practical unbiasedness. The decomposed ^{235}U spectrum has smaller uncertainty than ^{239}Pu because ^{235}U is the primary reactor $\bar{\nu}_e$ contributor, providing the largest antineutrino event sample.

V. CONCLUSION AND DISCUSSION

We propose a machine learning approach to decompose ^{235}U and ^{239}Pu isotope antineutrino spectra from simulated reactor antineutrino experiment evolution data. The CNN decomposition method is applied to noiseless and noisy datasets incorporating main reactor antineutrino experiment uncertainties. Validation tests show decomposed spectrum deviations below 0.1% and 0.3%, respectively, demonstrating unbiased performance. Uncertainty introduced by the CNN method is below 0.1%, with statistical and systematic uncertainties evaluable via Monte Carlo methods.

The CNN decomposition method is applicable to realistic commercial reactor antineutrino experiments because $\bar{\nu}_e$ emission and detection physical principles are essentially identical to those in our virtual experiment. Unlike the virtual experiment, realistic experiments commonly employ multiple reactors and detectors, requiring replacement of coefficient $k_i(E_\nu, t)$ from Eq. (7) with effective coefficients for different reactors. The effective coefficient is calculated as:

$$k_i^d(E_\nu, t) = N_d \cdot \epsilon_d \sum_r \frac{W_r(t) \cdot f_{ir}(t) \cdot P_{\text{sur}}(E_\nu, L_{rd})}{\sum_l f_{lr}(t) \cdot e_l},$$

where subscript d is detector index, r is reactor index, E_ν is $\bar{\nu}_e$ energy, N_d is target proton number, ϵ_d is detection efficiency, L_{rd} is distance from reactor r to detector d, $P_{\text{sur}}(E_\nu, L_{rd})$ is $\bar{\nu}_e$ survival probability, $W_r(t)$ is reactor r thermal power, e_l is energy released per fission for isotope l, and f_{lr} is reactor r fission fraction for isotope l. This simply sums coefficient contributions from individual reactors.

Due to varying experimental operation times and baselines ranging from ~10 m to ~1000 m, observed $\bar{\nu}_e$ rates can differ significantly across periods and experiments. We can merge periodic measurement data and rearrange them into new groups to ensure sample antineutrino event rates scale similarly to this

study, guaranteeing χ^2 objective function validity. Such efforts make the CNN method applicable to realistic experimental cases.

Additionally, this study's decomposition is applied directly to the antineutrino spectrum. However, realistic experiments detect $\bar{\nu}_e$ energy spectra converted via visible prompt energy, related as $E_p \approx E_{\bar{\nu}e} - 0.78$ MeV. Before CNN decomposition, measured prompt spectra must be transferred to $\bar{\nu}_e$ spectra (commonly called unfolding), which could be integrated into CNN layers. We plan to append additional neural network layers to our established CNN model in future studies to accomplish unfolding analysis.

In the near future, very short-baseline reactor antineutrino experiments are expected to measure reactor antineutrino spectra with higher precision and energy resolution. The promising decomposition approach introduced and demonstrated in this paper could be applied in these experiments to provide the most up-to-date individual isotope antineutrino spectra.

AUTHOR CONTRIBUTIONS

All authors contributed to study conception and design. Material preparation, data collection, and analysis were performed by Yu-Da Zeng, guided by Feng-Peng An and Wei Wang. The first draft was written by Yu-Da Zeng, Feng-Peng An, and Wei Wang, with all authors commenting on previous versions. All authors read and approved the final manuscript.

DATA AVAILABILITY STATEMENT

The data supporting this study's findings are openly available in Science Data Bank at https://doi.org/10.57760/sciencedb.j00186.00075 and https://cstr.cn/31253.11.sciencedb.j00186.00075.

REFERENCES

[1] Th. A. Mueller, D. Lhuillier, M. Fallot et al., Improved predictions of reactor antineutrino spectra. Phys. Rev. C 83, 054615 (2011). doi: 10.1103/PhysRevC.83.054615
[2] P. Huber, Determination of antineutrino spectra from nuclear reactors. Phys. Rev. C 84, 024617 (2011). doi: 10.1103/PhysRevC.84.024617
[3] G. Mention, M. Fechner, Th. Lasserre et al., Reactor antineutrino anomaly. Phys. Rev. D 83, 073006 (2011). doi: 10.1103/PhysRevD.83.073006
[4] Y. Abe, J.C. dos Anjos, J. C. Barriere et al., Improved measurements of the neutrino mixing angle θ_{13} with the Double Chooz detector. J. High Energy Phys. 2014, 86 (2014). doi: 10.1007/JHEP10(2014)086
[5] S. H. Seo et al., (RENO Collaboration), New results from RENO and the 5 MeV excess. AIP Conf. Proc. 1666, 080002 (2015). doi: 10.1063/1.4915563
[6] F.P. An, A.B. Balantekin, H.R. Band et al., (Daya Bay Collaboration), Measurement of the Reactor Antineutrino Flux and Spectrum at Daya Bay.

Phys. Rev. Lett. 116, 061801 (2016). doi: 10.1103/PhysRevLett.116.061801
[7] F.P. An, A.B. Balantekin, H.R. Band et al., (Daya Bay Collaboration), Evolution of the Reactor Antineutrino Flux and Spectrum at Daya Bay. Phys. Rev. Lett. 118, 251801 (2017). doi: 10.1103/PhysRevLett.118.251801
[8] J. Ashenfelter, A.B. Balantekin, H.R. Band et al., (PROSPECT Collaboration), Measurement of the Antineutrino Spectrum from ^{235}U Fission at HFIR with PROSPECT. Phys. Rev. Lett. 122, 251801 (2019). doi: 10.1103/PhysRevLett.122.251801
[9] M. Estienne, M. Fallot, A. Algora et al., Updated summation model: An improved agreement with the Daya Bay antineutrino fluxes. Phys. Rev. Lett. 123, 022502 (2019). doi: 10.1103/PhysRevLett.123.022502
[10] D. Adey, F.P. An, A.B. Balantekin et al., (Daya Bay Collaboration), Extraction of the ^{235}U and ^{239}Pu Antineutrino Spectra at Daya Bay. Phys. Rev. Lett. 123, 111801 (2019). doi: 10.1103/PhysRevLett.123.111801
[11] Technical Meeting on Nuclear Data for Antineutrino Spectra and their Applications, 23-26 Apr 2019, Vienna, Austria. https://www.iaea.org/events/evt1703666
[12] N.S. Bowden, J.M. Link, W. Wang, Report of the Topical Group on Neutrino Applications for Snowmass 2021. doi: 10.48550/arXiv.2209.07483
[13] O. Akindele, N. Bowden, R. Carr et al., Nu tools: Exploring practical roles for neutrinos in nuclear energy and security. doi: 10.48550/arXiv.2112.12593
[14] D. Bhatt, C. Patel, H. Talsania et al., CNN variants for computer vision: History, architecture, application, challenges and future scope. Electronics. 10, 2470 (2021). doi: 10.3390/electronics10202470
[15] Y. T. Luo, H. Du, and Y. M. Yan, MeshCNN-based BREP to CSG conversion algorithm for 3D CAD models and its application. Nucl. Sci. Tech. 33, 74 (2022). doi: 10.1007/s41365-
[16] X.Y. Guo, L. Zhang, Y.X. Xing, Study on analytical noise propagation in convolutional neural network methods used in computed tomography imaging. Nucl. Sci. Tech. 33, 77 (2022). doi: 10.1007/s41365-022-01057-3
[17] L.Y. Zhou, H. Zha, J.R. Shi et al., A non-invasive diagnostic method of cavity detuning based on a convolutional neural network. Nucl. Sci. Tech. 33, 94 (2022) doi: 10.1007/s41365-022-01069-z
[18] D. Ribli, B. Á. Pataki, J.M. Zorrilla Matilla et al., Weak lensing cosmology with convolutional neural networks on noisy data. Mon. Not. R. Astron. Soc. 490, 1843 (2019). doi: 10.1093/mnras/stz2610
[19] C.M. Bishop, N.M. Nasser, Pattern recognition and machine learning, Vol. 4. No. 4. (New York: springer, 2006).
[20] F.P. An, A.B. Balantekin, H.R. Band et al., (Daya Bay Collaboration), Improved measurement of the reactor antineutrino flux and spectrum at Daya Bay. Chin. Phys. C 41, 013002. doi: 10.1088/1674-1137/41/1/013002
[21] X.B. Ma, W.L. Zhong, L.Z. Wang et al., Improved calculation of the energy release in neutron-induced fission. Phys. Rev. C 88, 014605. doi: 10.1103/PhysRevC.88.014605
[22] J.Y. Shi, Q.L. Huang, L. Wang et al., Distributed data processing platform of national high energy physics data center. Frontiers of Data and Computing 4, 97 (2022). doi: 10.11871/jfdc.issn.2096-742X.2022.01.008 (in Chinese)

[23] D.P. Kingma, J. Ba, Adam: A method for stochastic optimization. Proceedings of the 3rd International Conference on Learning Representations (ICLR 2015). https://www.iclr.cc/archive/www/2015.html
[24] S. Ruder, An overview of gradient descent optimization algorithms. doi: 10.48550/arXiv.1609.04747

Note: Figure translations are in progress. See original paper for figures.