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論文要約

Fission product yield (FPY) is a crucial component of nuclear data, providing fundamental insights into the fission process while also playing a vital role in numerous nuclear engineering applications. Accurate FPY data is essential for reactor physics, nuclear forensics, and nuclear safeguards, among other fields. However, due to inconsistencies in theoretical predictions and limitations in experimental measurements, achieving a comprehensive and systematic evaluation of FPY as a function of incident neutron energy remains a challenging task. This dissertation addresses these challenges by developing an innovative method that integrates deep learning with nuclear physics knowledge to predict and evaluate FPY data systematically. Specifically, a Bayesian neural network (BNN) model is employed to refine existing nuclear data, enabling more accurate predictions of FPY in energy regions where experimental data is scarce or unavailable.

By comparing the predicted FPY values obtained from the BNN model with available experimental validation data, it is demonstrated that the model can accurately estimate FPY in unmeasured energy domains. The effectiveness of the developed BNN model is further confirmed by evaluating the fission yields of key fissile and fissionable isotopes, including ^{232}Th, $^{233, 235, 238}$U and $^{239, 241}$Pu. The results indicate that the predictive capability of the BNN model is highly promising, suggesting that this approach can serve as a constructive and efficient tool for FPY evaluations.

Chapter 1 provides an introduction to the fission process, highlighting the importance of FPY data in both theoretical and applied nuclear research. Given the well-known limitations in theoretical and experimental FPY evaluations, the necessity of applying deep learning techniques is discussed. This chapter also outlines the research objectives, the novelty of the approach, and the scope of the study.

Chapter 2 presents the theoretical foundation of Bayesian deep learning, which forms the basis of the BNN model. This chapter covers key concepts, including Bayesian inference and its application to neural networks. A critical aspect of this framework is the implementation of Markov Chain Monte Carlo (MCMC) methods, particularly the Hamiltonian Monte Carlo (HMC) algorithm coupled with the No-U-Turn Sampler (NUTS) kernel. These advanced sampling techniques are employed to optimize Bayesian calculations and mitigate computational inefficiencies. The NumPyro library is utilized for implementing these probabilistic models, ensuring robust and efficient computations.

Chapter 3 describes the development of a deep-learning-based approach for evaluating and predicting FPY data across unknown energy ranges. The dissertation introduces three key advancements that significantly enhance FPY prediction accuracy:

1. Augmentation of Training Data: One of the primary challenges in training deep learning models for FPY prediction is the scarcity of high-quality training data. To address this issue, FPY data from the Japanese Evaluated Nuclear Data Library Version 5 (JENDL-5) is partitioned, with 80% of the data used for training and the remaining 20% reserved for validation. JENDL-5 provides FPY data only for limited neutron energies, namely 0.0253 eV (thermal neutron), 500 keV (fast neutron), and 14 MeV (D-T reaction). This limitation makes it difficult to train a deep-learning model effectively. To overcome this, additional FPY data from experimental measurements in the EXFOR database and theoretical calculations from TALYS, H3FD, 4D-Langevin, and five-Gaussian models are incorporated into the training dataset. Notably, experimental FPY data obtained after 2010 are used for training, while older

data (pre-2010) are used for validation.

2. Embedding of Physical Information: A unique feature of this study is the integration of nuclear physics knowledge directly into the BNN model to enhance prediction accuracy. One of the persistent challenges in FPY evaluations is the presence of fine structures in the fission mass distribution, particularly around mass numbers A = 134, 140, and 144. These fine structures arise due to interactions between nuclear shell effects before neutron emission and prompt neutron multiplicities after neutron emission. To account for these effects, a shell factor function is designed to phenomenologically represent these interactions. This shell factor function is embedded into the input layer of the BNN model, improving its ability to capture the intricate behavior of FPY distributions and reproduce fine structural features more accurately.

3. Validation and Predictive Performance Assessment: The predictive performance of the developed BNN model is rigorously evaluated by comparing its predictions with experimental FPY data for various isotopes. The model successfully reconstructs known FPY trends and accurately extrapolates FPY values in energy regions where no direct experimental data exists. The results demonstrate that the BNN model effectively reduces uncertainties in FPY predictions, providing reliable evaluations for nuclear data applications.

In Chapter 4, the prediction results from the BNN model are primarily validated, either directly or indirectly, and the predictive accuracy of the BNN model is evaluated both qualitatively and quantitatively. The direct validation methods include comparing measured values from EXFOR before 2010 with predicted values, as well as comparing the remaining 20% of the JENDL-5 data. Moreover, the indirect validation methods include comparisons of charge distribution and delayed neutron distribution.

This dissertation presents a novel approach to FPY prediction and evaluation using Bayesian deep learning techniques. By combining nuclear physics knowledge with probabilistic deep learning models, this research successfully improves the accuracy and reliability of FPY data across a wide range of neutron incident energies. The findings of this study have significant implications for nuclear engineering, particularly in reactor physics, nuclear waste management, and nuclear forensics. The developed BNN model can be further extended to other areas of nuclear data evaluation, including cross-section predictions and decay heat calculations.