begindocument/before

Optimization of Coefficients of Semi-Empirical Mass Formula Using Physics Informed Neural Networks

Ayushi Awasthi [1], Sanyam Walia [1], Swapna Gora [1], and O.S.K.S. Sastri[1]
[1] *Central University of Himachal Pradesh, Dharamshala, 176215, India (Bharat)*

Introduction

Nuclear binding energy is a key factor in understanding the stability of atomic nuclei, the processes of nucleosynthesis, and the release of energy in both astrophysical and nuclear phenomena. The Semi-Empirical Mass Formula (SEMF), or Bethe-Weizsäcker mass formula, has long been used as a practical method to estimate nuclear binding energies by combining macroscopic liquid-drop contributions with symmetry and pairing corrections [1]. Traditionally, the coefficients of the SEMF are determined using regression-based fitting approaches [2]. However, with the rapid advancement of machine learning, data-driven methods offer an alternative way to enhance nuclear models while maintaining their physical foundation. Physics-Informed Neural Networks (PINNs) incorporate domain-specific equations into the training process, ensuring that the results remain physically consistent while optimizing model parameters [3]. In this study, we present a PINN-based SEMF framework in which the five coefficients: volume, surface, Coulomb, asymmetry, and pairing, are treated as trainable parameters. Using experimental nuclear mass data, the model iteratively reduces the difference between predicted and observed binding energies.

Methodology

The binding energy in the semi-empirical mass formula (SEMF) is given by

$$B(A,Z) = a_v A - a_s A^{2/3} - a_c \frac{Z(Z-1)}{A^{1/3}} - a_{sym} \frac{(A-2Z)^2}{A} + \frac{a_p\, \delta}{\sqrt{A}},$$

where A is the mass number and Z is the proton number and δ is the pairing term: $\delta = +1$ for even-even nuclei, $\delta = -1$ for odd-odd nuclei, and $\delta = 0$ otherwise.

Neural Network Implementation

The SEMF-PINN model is implemented in PyTorch [4]. The coefficients $(a_v, a_s, a_c, a_{sym}, a_p)$ are initialized as trainable parameters. The input data (A, Z) and the experimental binding energies are taken from the Atomic Mass Evaluation 2020 [5]. The training loop involves: **Forward pass:** computing predicted binding energy. **Loss calculation:** mean squared error between predicted and experimental binding energies, with chi-square error as an additional metric. **Backpropagation:** updating coefficients using the Adam optimizer. The training was performed for 50,000 epochs with a learning rate of 10^{-3}.

Results and Discussion

The complete workflow has been shown in Fig. 1, beginning with data import and tensor conversion, followed by PINN initialization, iterative training, and final evaluation. The model successfully converged to physically meaningful coefficients. The learned values obtained after training are presented in Table I. The chi-square error between pre-

TABLE I: Optimized parameters of SEMF using PINNs

Coefficients	Value (MeV)
a_v	15.2258
a_s	16.1331
a_c	0.6871
a_{sym}	22.1403
a_p	11.0913

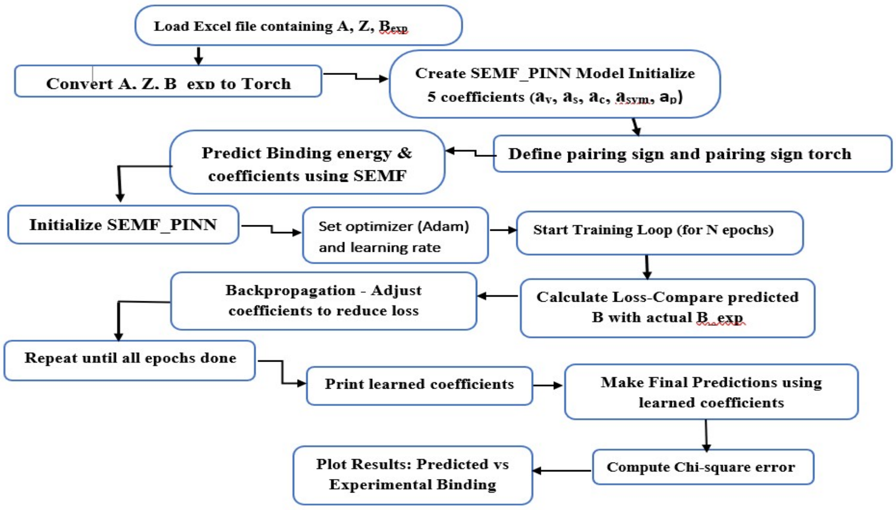

FIG. 1: Workflow of the SEMF-PINN framework.

dicted and experimental binding energies was found to be $\chi^2 = 0.1031$.This low error demonstrates the effectiveness of the PINN approach in capturing nuclear binding energy trends. Fig. 2 shows the correlation between experimental and predicted binding energies, confirming the strong agreement.

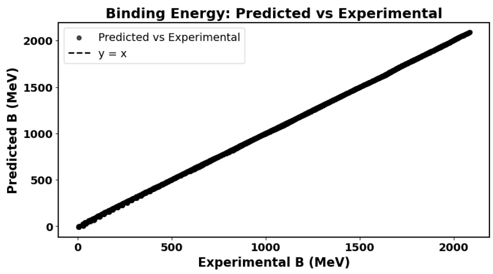

FIG. 2: Predicted vs experimental binding energies using SEMF-PINN.

Conclusion

We have developed a Physics-Informed Neural Network for optimizing the Semi-Empirical Mass Formula parameters. The learned coefficients closely reproduce standard values while achieving a low chi-square error in fitting nuclear binding energies. This approach demonstrates the potential of PINNs as a robust framework for refining traditional nuclear models. Future work will extend this methodology to include shell corrections and explore its application to exotic nuclei.

Acknowledgments

A. Awasthi acknowledges the financial support provided by the DST, Govt. of India, through Grant No. DST/INSPIRE Fellowship/2020/IF200538.

References

[1] D. Benzaid, et.al, *Nucl. Sci. Tech.* **31**, 9 (2020).

[2] S. Gora, et.al., *Eur. J. Phys.* **43**, 035802 (2022).

[3] M. Raissi, P. Perdikaris, G. E. Karniadakis, J. Comput. Phys. 378, 686 (2019).

[4] S. Cuomo, et.al., *J. Sci. Comput.* **92**, 88 (2022).

[5] M. Wang et.al., *Chin. Phys. C* **45**, 030003 (2021).