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Review

A Unified 6-Terms Formula for Nuclear Binding Energy with a Single Set of Energy Coefficients for Z = 1–140

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Abstract

A newly proposed six-terms semi-empirical binding energy formula demonstrates enhanced accuracy and unified applicability across the entire periodic table, from Z=1 to 140. While retaining the foundational structure of the classical semi-empirical mass formula (SEMF), this model introduces refined corrections for surface, Coulomb, and asymmetry effects. Validated against experimental data, it predicts nuclear binding energies with typical deviations below 1.5%, significantly outperforming the traditional SEMF, particularly for light nuclei, odd-A systems, and superheavy elements. The model exhibits smooth numerical behaviour, physical consistency, and structural simplicity, making it a valuable tool for nuclear structure modelling, astrophysical applications, and future studies of exotic and superheavy isotopes. In a macroscopic framework, integration of machine learning and artificial intelligence techniques—combined with forthcoming experimental binding energy data—may enable the refinement of the six energy coefficients for improved accuracy and predictive power. From a microscopic perspective, further enhancements can be pursued to address shell effects, pairing interactions, and nuclear deformation in greater detail.

Keywords: 6 terms semi empirical mass formula; single set of energy coefficients; Z= (1 to 140); accuracy; predictability; ML and AI techniques; micro-macro refinement

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1. Introduction

The semi-empirical mass formula (SEMF), introduced by Weizsäcker, has long served as a cornerstone for estimating nuclear binding energies. It accounts for general features such as volume, surface tension, Coulomb repulsion, and pairing effects, and has shaped our understanding of nuclear structure for nearly a century [1–10].

Yet despite its utility, SEMF suffers from limitations. Its predictive power declines significantly for light nuclei, odd-A nuclides, and isotopes far from the valley of stability. Moreover, as modern research pushes toward neutron-rich isotopes and superheavy elements ($Z > 100$), a more unified and accurate model becomes essential.

This review presents a concise summary of a recently published six-terms unified semi-empirical binding energy model [11], covering nuclei from Z = (1 to 140). The model demonstrates strong agreement with both experimental data and known theoretical benchmarks, offering a robust alternative to traditional formulations [11–14]. We have developed this formula based on the advanced SEMF proposed in reference [7].

2. Structure of the Unified Model

At the heart of this formulation is a set of six carefully chosen terms, each grounded in well-established nuclear physics principles. These terms are structured to retain the conceptual framework

of SEMF while introducing refined corrections that improve accuracy across a broader range of nuclides. The model addresses:
(1) Volume energy represents the net attraction among nucleons in the nuclear interior.
(2) Surface energy corrects for under bound nucleons at the surface.
(3) Coulomb repulsion penalizes increasing proton content.
(4) Asymmetry energy balances neutron-proton distributions.
(5) Pairing effects account for nuclear pairing preferences.
(6) Congruent effects sensitive to equality of proton and neutron numbers [15].

The functional form maintains analytical simplicity, ensuring computational efficiency, yet is rich enough to capture the nuanced behaviour of binding energy trends across isotopic chains.

This approach allows the model to smoothly interpolate between neighbouring nuclei, avoiding the discontinuities and large local errors often seen in SEMF-based approximations. For light, intermediate, and heavy elements — including both even-even and odd-A nuclei — the model remains numerically stable and physically consistent.

Thus, 6 terms semi empirical mass formula can be expressed as,

$$\left.\begin{aligned} BE \cong & \left[16.0\times A\right]-\left[\gamma\times 19.4\times A^{2/3}\right] \\ & -\left[\frac{0.71\times Z^2}{\gamma^x A^{1/3}}\right]-\left\{\left(1-\frac{1}{A}\right)\frac{(A-2Z)^2}{A}\right\}24.5 \\ & \pm\left[\frac{10.0}{\sqrt{A}}\right]+\left[10.0\times\exp\left(-4.2\frac{|N-Z|}{A}\right)\right] \end{aligned}\right\}\ \text{MeV} \quad (1)$$

where, $\gamma \cong 1-\left(\frac{N-Z}{A}\right)^2$ and $x \cong 0.75-\left(\frac{Z}{2A}\right)$

To evaluate the global accuracy of the proposed six-term binding energy formula, we compared its predictions with those of the machine-learned nuclear mass model developed by Gao et al. [7]. While Gao's model is well-regarded for large-scale nuclear mass predictions, it exhibits noticeable inconsistencies for light nuclei ($Z<11$), especially when compared to experimentally established trends. In contrast, our model achieves very good agreement from $Z=11$ onwards with deviations typically below 1.5%, even across neutron-rich and superheavy regions. This performance extends uniformly across both even and odd mass numbers. Despite the local differences in the light region, the overall standard deviation between the two models, across the whole range of the periodic table, for Z = (1 to 140) with an upper mass limit of approximately $A = 3.5Z$ is about is about 3.4 MeV, affirming the reliability and consistency of the present unified formula. A detailed supplementary data table is available at 'https://www.preprints.org/manuscript/202507.2397/v1'.

Although Gao's machine learning nuclear mass model [7] was developed and validated primarily for nuclei with proton number $Z \geq 8$, we have deliberately applied it to the region Z = (1 to 8) to examine its extrapolative reliability. This exercise exposes notable inaccuracies and inconsistencies for these very light nuclei, including significant deviations from experimental binding energies. These findings highlight the intrinsic limitations of purely data-driven approaches when used outside their intended training domain. By explicitly demonstrating this boundary, we underscore the broader applicability and robustness of our unified six-term semi-empirical formula, which maintains reliable predictive accuracy even in the lightest nuclear region.

3. Model Performance Across the Periodic Table

The applicability of the present formula across the nuclear chart is not only rooted in its physical design but also in its numerical stability and predictive consistency. Unlike traditional SEMF-based models that often require region-specific parameter adjustments [1–8], the current formulation maintains a uniform structure with smooth behaviour across all isotopes. This quality allows the model to be validated directly over a wide range of nuclides, without discontinuities or local tuning. The following subsection presents a detailed comparison of the model's predictions against a well-established benchmark mass model.

3.1. Comparison with Experimental Data

Validation of the model has been carried out by comparing predicted binding energies with experimental values from AME2020 and other nuclear data sources. Table 1 provides the binding energy of benchmark isotopes. (Removed the remarks column)

Table 1. Estimated and experimental binding energy of benchmark isotopes.

Proton number	Mass number	Neutron number	Estimated Binding Energy (MeV)	Experimental Binding Energy (MeV)	Difference in Binding Energy (MeV)	%Error
1	**2**	**1**	**3.57**	**2.225**	**-1.35**	**-60.5**
1	3	2	8.62	8.482	-0.14	-1.63
2	4	2	28.33	28.30	0.03	-0.11
6	12	6	92.04	92.16	0.12	0.13
7	14	7	104.2	104.66	0.46	0.44
8	16	8	127.28	127.62	0.34	0.27
26	56	30	489.57	492.26	3.09	0.55
28	62	34	543.54	545.28	1.74	0.32
50	116	66	988.57	988.68	0.11	0.011
82	208	126	1628.89	1636.43	7.54	0.46
114	286	172	2052.94	2047.6	-5.34	-0.26
118	294	176	2085.66	2081.33	-4.33	-0.21

With reference to experimental binding energy, our model currently faces a notable challenge in fitting the nuclear binding energy of the very lightest nuclide, Hydrogen-2. Our estimated value is 3.57 MeV, while the experimental value is 2.225 MeV. This results in an absolute error of -1.35 MeV and a substantial percentage error of -60.5%. This phenomenon underscores that when total binding energy is on the lower side, minor absolute differences can result in disproportionately high percentage errors.

For each of these representative nuclei, the model performs within ±1.5% of the experimental data often better. Even in odd-A and neutron-rich systems where SEMF typically falters, the current formulation retains good agreement.

3.2. Behaviour in Superheavy Region

In regions beyond Z = 100, where experimental data are sparse, the model continues to produce physically plausible trends. Binding energy per nucleon gradually decreases in accordance with expected Coulomb dominance, but without spurious discontinuities or sharp anomalies.

This makes the model valuable not only for known nuclides, but also for predicting properties of hypothetical or as-yet-unmeasured isotopes including those of interest in r-process nucleosynthesis and heavy element synthesis experiments.

4. Coulomb Term and Effective Radius Behaviour

An important physical insight emerging from the present formulation lies in its treatment of nuclear size effects in neutron-rich systems. While classical models assume that the nuclear radius scales uniformly as $R \propto A^{1/3}$. However, both experimental observations and modern theoretical

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studies indicate that this scaling weakens as the neutron number increases. In such cases, the addition of neutrons does not proportionally expand the nuclear volume; instead, the nucleus tends to remain more compact, or the extra neutrons redistribute non-uniformly without contributing significantly to the effective Coulomb radius [16–18]. This nuanced behaviour is effectively captured in the Coulomb term through the inclusion of a smooth damping factor γ^x where $\gamma \cong 1-\left(\frac{N-Z}{A}\right)^2$ and $x \cong 0.75-\left(\frac{Z}{2A}\right)$.

As neutron excess increases, γ decreases and x remains well within a narrow range of 0.5 at A=2Z and 0.6 at A=3.5Z. This gentle modulation ensures the Coulomb energy, given by

$$E_{Cou} \cong \frac{0.71\times Z^2}{\gamma^x A^{1/3}} \text{ MeV} \quad (2)$$

is enhanced appropriately, reflecting the fact that the effective nuclear radius is smaller than expected from the simple $R \propto A^{1/3}$ scaling. This behaviour is consistent with the interpretation that proton–proton repulsion becomes stronger when additional neutrons fail to sufficiently increase the nuclear radius, leading to a more compact charge distribution. In this way, the modified Coulomb term not only preserves analytic simplicity but also incorporates essential corrections for the reduced radial expansion seen in neutron-rich nuclei.

5. Modified Asymmetry Term and Finite-Size Correction

The asymmetry energy [19] accounts for the reduction in binding energy due to the imbalance between neutrons and protons. In traditional mass formulas, this contribution is modelled as:

$$E_{Asy} \cong \frac{(A-2Z)^2}{A}(23 \text{ to } 25) \text{ MeV} \quad (3)$$

While effective for medium to heavy nuclei, this form tends to overestimate the asymmetry penalty in light nuclei, where surface and shell effects play a larger role. To improve this, our model introduces a finite-size correction factor as,

$$E_{Asy} \cong \left\{\left(1-\frac{1}{A}\right)\frac{(A-2Z)^2}{A}\right\} 24.5 \text{ MeV} \quad (4)$$

This modified term naturally suppresses the asymmetry energy for light nuclei, where A is small, and asymmetry effects are often mitigated by shell structure or local pairing. As A→∞, the proposed factor [1−(1/A)] →1, and the term smoothly approaches the standard form, ensuring consistency in the heavy mass region. This gentle suppression avoids the need for ad hoc mass-region corrections and helps reduce deviations in the light mass region (A<30), where traditional formulas show poor agreement with experimental data. The correction is purely analytic and does not introduce discontinuities or fitting instability. Overall, this modified asymmetry term maintains physical interpretability while delivering better accuracy across the full nuclear chart, especially for isotopes far from the valley of stability.

6. Isospin Surface Energy Term Free from Minor Arbitrary Energy Coefficients

Similar to the advanced SEMF [7] and independent of arbitrary energy coefficients, the surface energy term in this model is given by,

$$E_{Sur} \cong \gamma \times 19.4 \times A^{2/3} \cong \left[1 - \left(\frac{N-Z}{A}\right)^2\right] \times 19.4 \times A^{2/3} \text{ MeV} \quad (5)$$

It accounts for the reduced binding of nucleons on the nuclear surface. The inclusion of γ makes the surface energy sensitive to neutron–proton imbalance, reducing its contribution in highly asymmetric nuclei. This improves accuracy for both light nuclei and neutron-rich isotopes, where surface effects are significant. The form remains smooth, analytical, and applicable across the full mass range.

7. Congruent Energy Term and Its Role as the 6th term

The term "congruent energy" in the nuclear binding energy scheme refers to an additional correction or contribution to nuclear masses and binding energies beyond typical shell- and pairing-corrected models. This congruence energy accounts for finer details in nuclear structure related to the similarity or "congruence" in the nodal structures of neutron and proton wave functions. It essentially represents an extra binding effect that emerges when neutron and proton wave functions have matched quantum properties, yielding more stable nuclear configurations [15].

This concept was discussed in research where the differences between measured binding energies and theoretical binding energies predicted by models like the Thomas-Fermi approach with shell and pairing corrections were explained by adding this congruence energy term [20]. The congruence energy can be modelled approximately by an exponentially decaying function in terms of the neutron-proton imbalance and has effects in nuclear masses and deformation energies, even influencing nuclear fission barrier heights.

8. Broader Scientific Implications and General Discussion

The potential applications of this unified model span a broad spectrum of modern nuclear science:

(1) **Astrophysical modelling**: Accurate BE predictions are vital for simulating r-process nucleosynthesis, supernova dynamics, and neutron star crust evolution.

(2) **Nuclear energy and fusion research**: Better estimates of reaction Q-values, decay paths, and fission barriers improve reactor models and fuel cycle analysis.

(3) **Element discovery and stability mapping**: As experimental facilities push into uncharted nuclear territories, reliable theoretical benchmarks help guide target selection and interpretation.

(4) **Teaching and simulation**: The model offers a simplified, accurate tool for educators and students to understand binding energy trends without the full complexity of ab initio calculations.

Its minimal input parameters, broad accuracy, and clean behaviour make it particularly suitable for use in large-scale nuclear databases and physical modelling platforms like our 4G model of unification [11–14,21–27]. It demonstrates a compact, semi-empirical approach grounded in physical principles but enhanced by refined correction terms can effectively reproduce nuclear binding energies across a wide span of the periodic table. Each term carries clear physical interpretation: the volume and surface terms represent collective nuclear cohesion; the gamma-modulated Coulomb term realistically captures charge repulsion under neutron imbalance; the smoothed asymmetry term improves accuracy for odd-A and neutron-rich nuclei; the reduced pairing term avoids discontinuities; and the exponential congruent term reflects the enhanced stability of nearly symmetric nuclei.

Compared to classical SEMF models, the current formulation avoids abrupt discontinuities, performs better in neutron-rich and heavy regions, and remains applicable up to Z = 140 without separate tuning. Its ability to yield binding energy errors typically below 1.5% (from Z = 11 upward) using a single parameter set reflects both its robustness and generality. Moreover, the use of a

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consistent mathematical form across all nuclear regions without mass region switching or multiple datasets make this model particularly attractive for future integration into nuclear databases, r-process simulations [28,29], and educational software. Potential future refinements may involve the inclusion of deformation or shell corrections, but even in its current form, the model offers a simple and unified perspective on nuclear binding energy. The estimated and reference binding energy curves are given in Figures 1–16 pertaining to the isotopes of magic proton numbers 2,8,20,28,50,82 and 114 [30,31] and their next odd proton numbers. For understanding purpose, we consider two heavy proton numbers 140 and 141. In figure, the red and green curves represent our and Gao estimation, respectively. From the figures, for light atomic nuclides, one can see 'significant increase in binding energy' with reference to other SEMF and 'good approximation' with experimental values. For medium and heavy atomic nuclides, binding energy is in line with advanced SEMF.

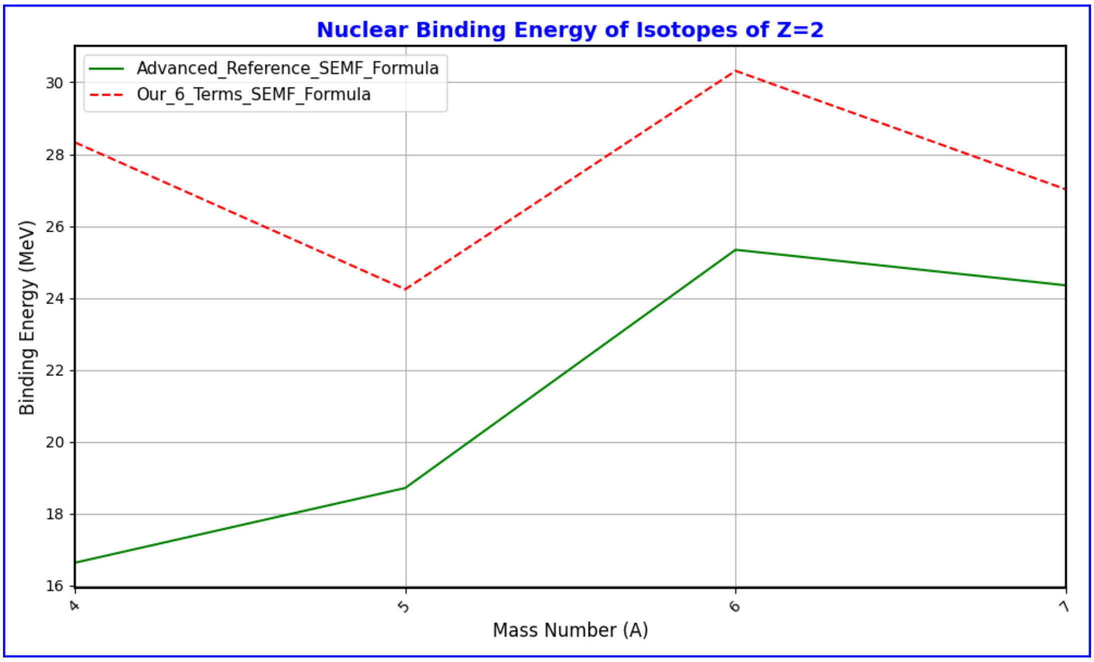

Figure 1. Nuclear binding energy of isotopes of Z=2 estimated with 6 terms SEMF.

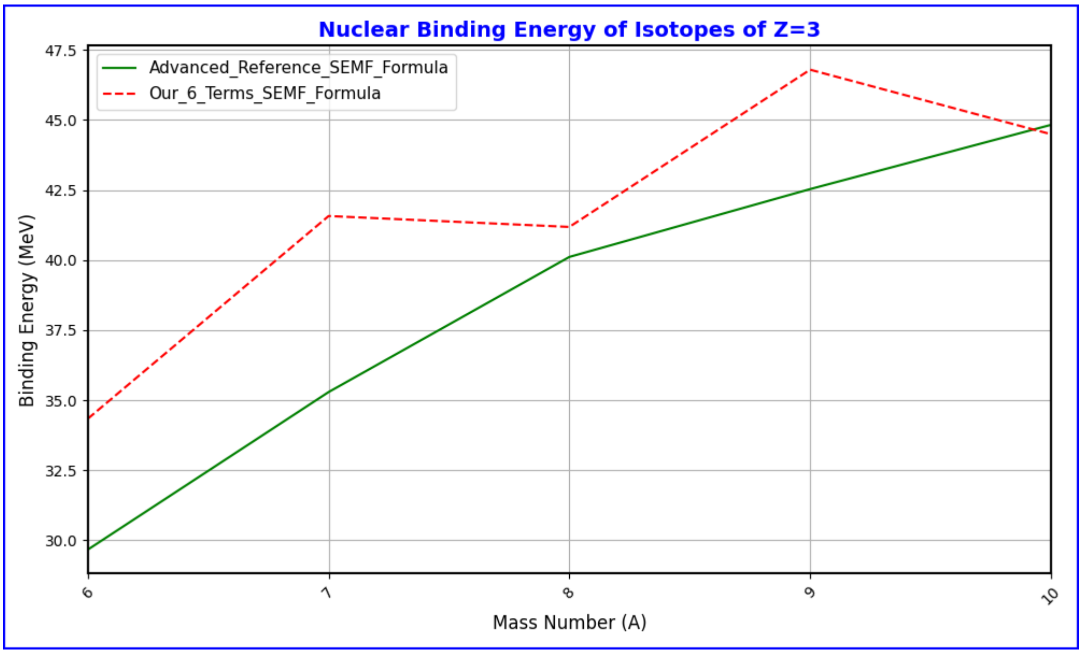

Figure 2. Nuclear binding energy of isotopes of Z=3 estimated with 6 terms SEMF.

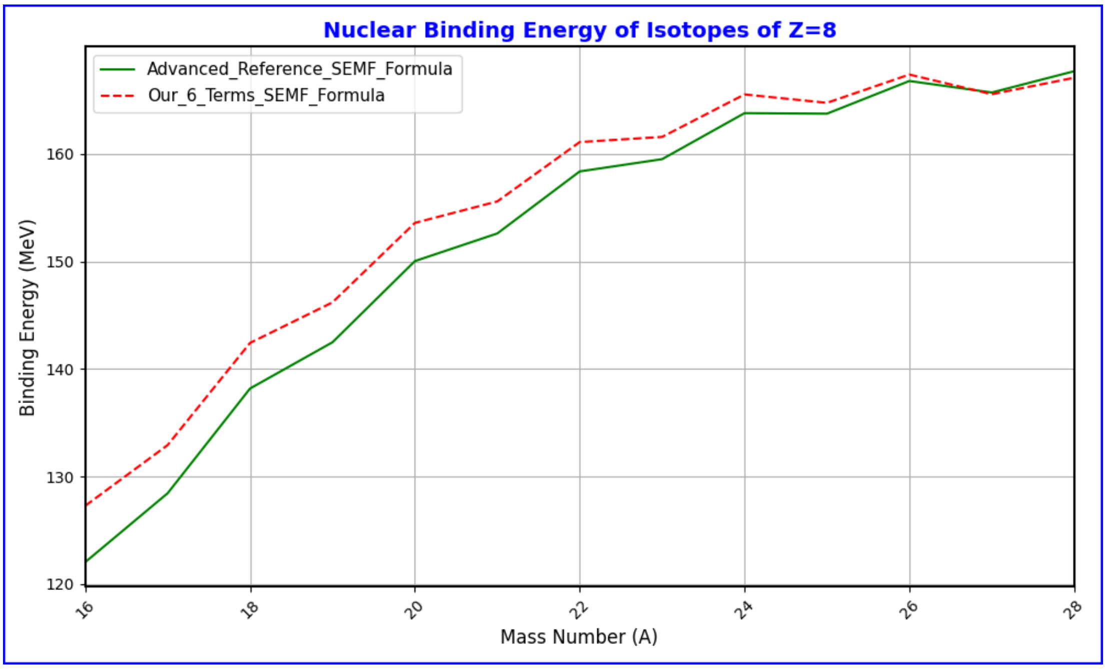

Figure 3. Nuclear binding energy of isotopes of Z=8 estimated with 6 terms SEMF.

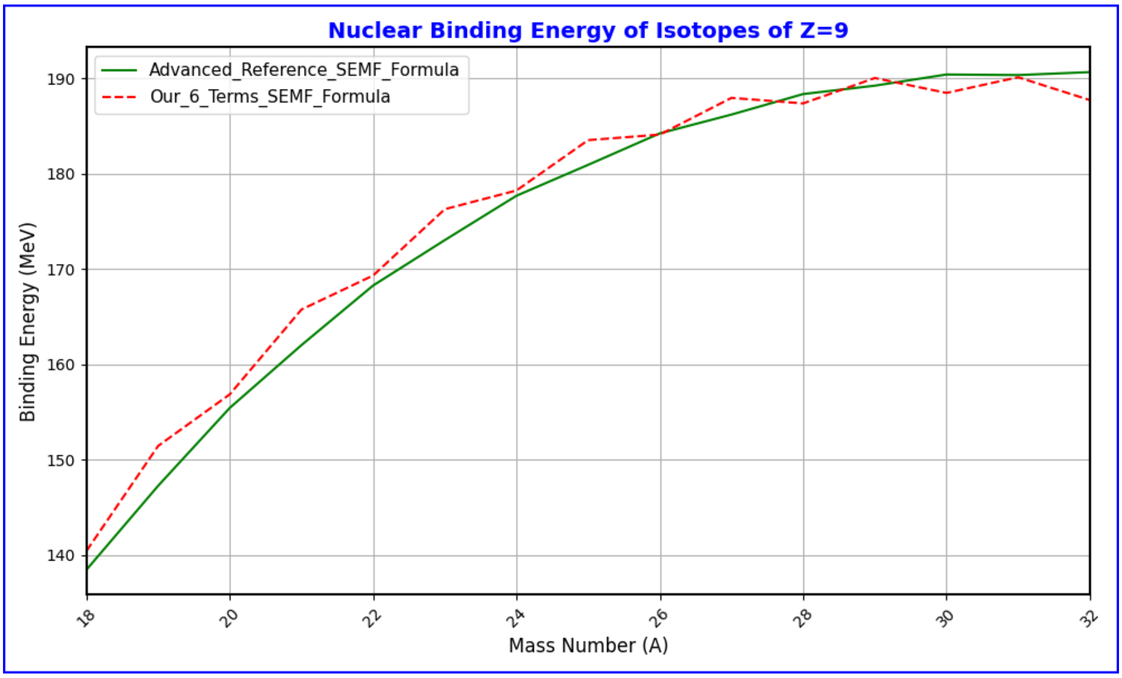

Figure 4. Nuclear binding energy of isotopes of Z=9 estimated with 6 terms SEMF.

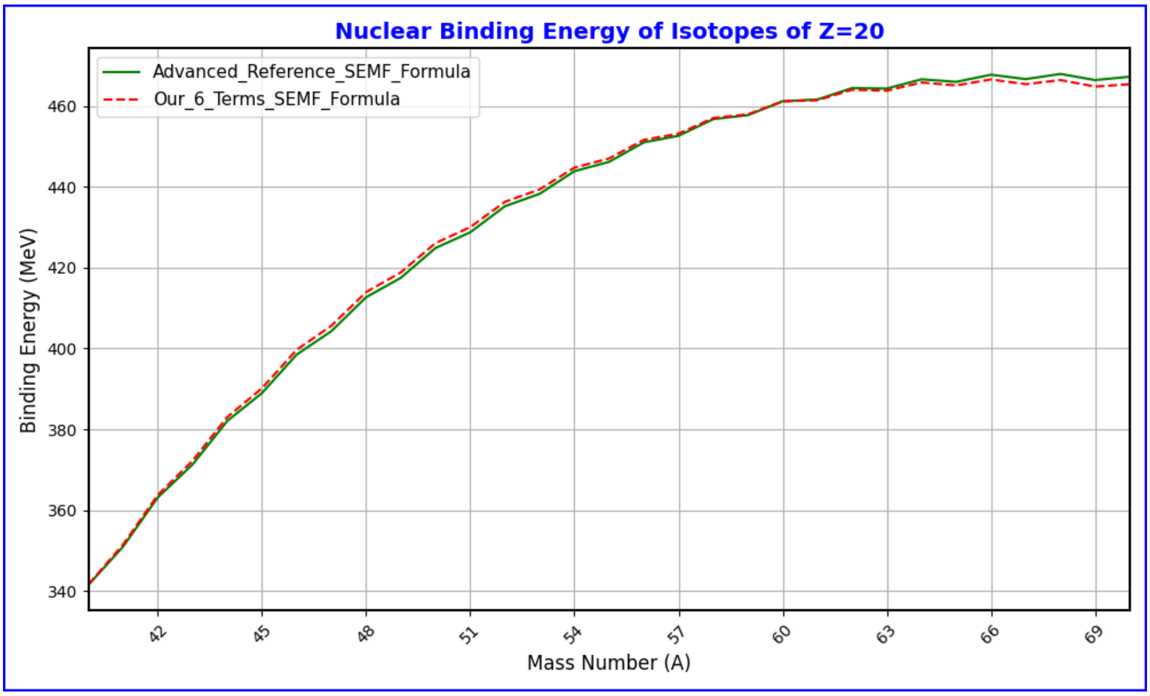

Figure 5. Nuclear binding energy of isotopes of Z=20 estimated with 6 terms SEMF.

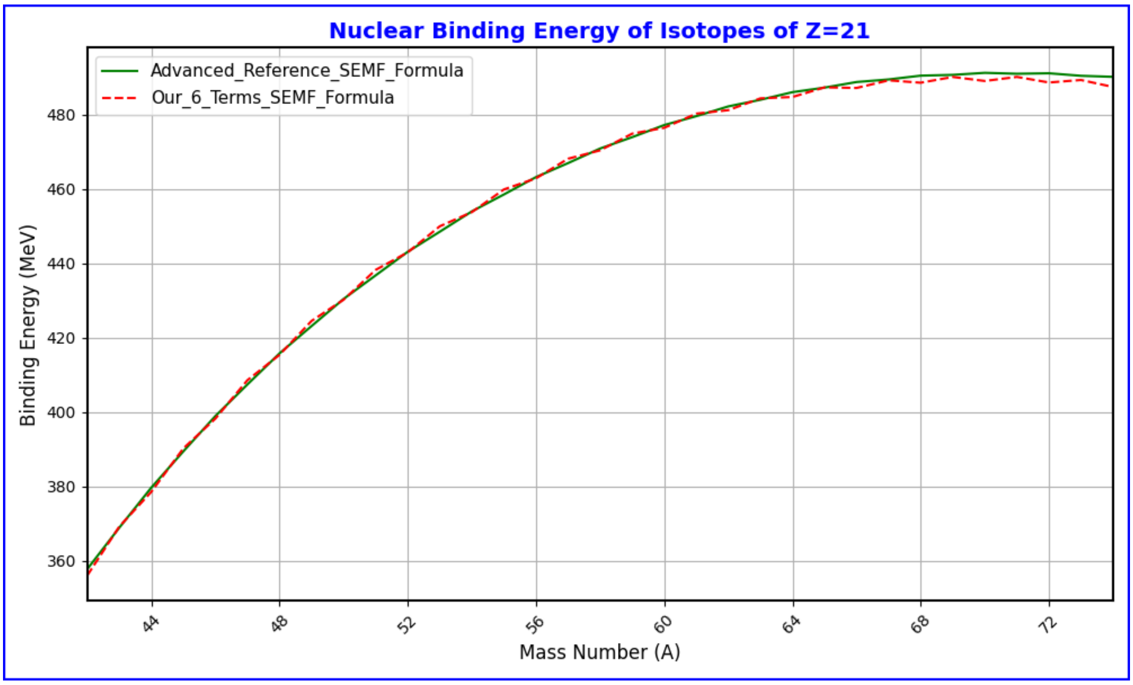

Figure 6. Nuclear binding energy of isotopes of Z=21 estimated with 6 terms SEMF.

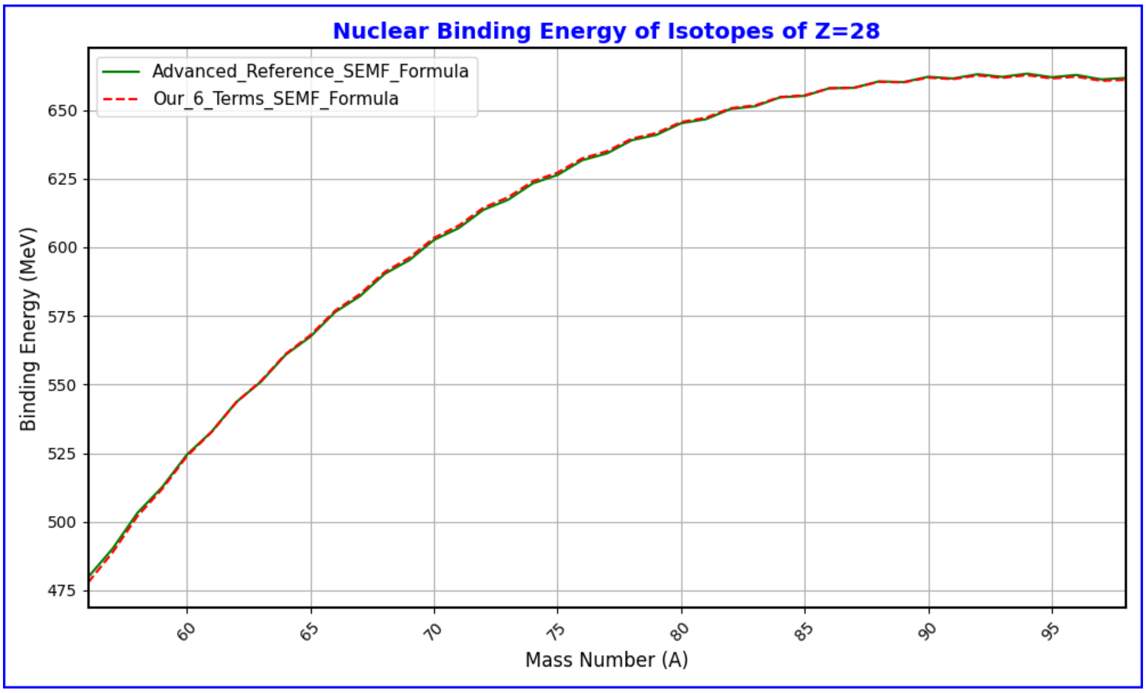

Figure 7. Nuclear binding energy of isotopes of Z=28 estimated with 6 terms SEMF.

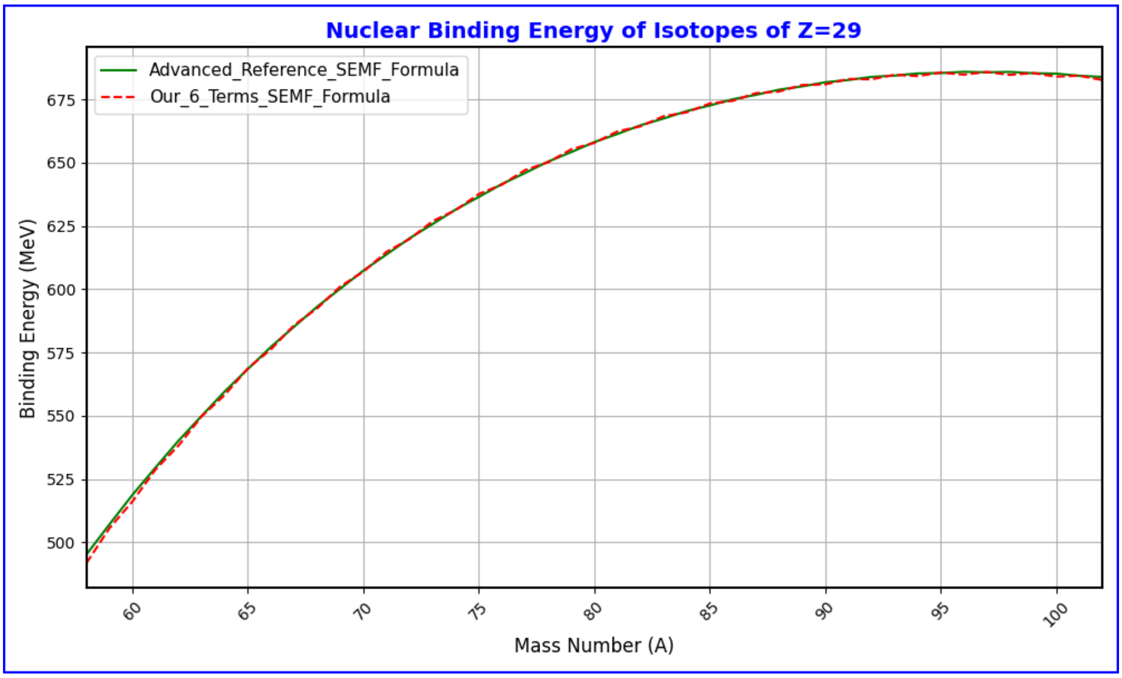

Figure 8. Nuclear binding energy of isotopes of Z=29 estimated with 6 terms SEMF.

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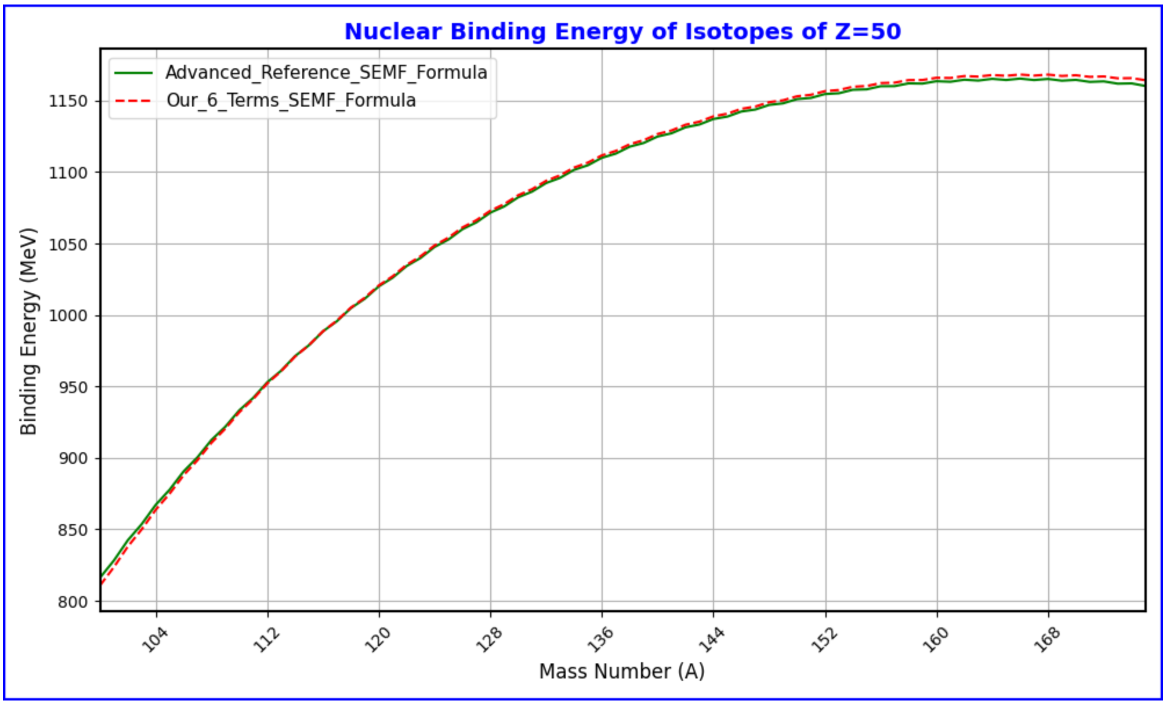

Figure 9. Nuclear binding energy of isotopes of Z=50 estimated with 6 terms SEMF.

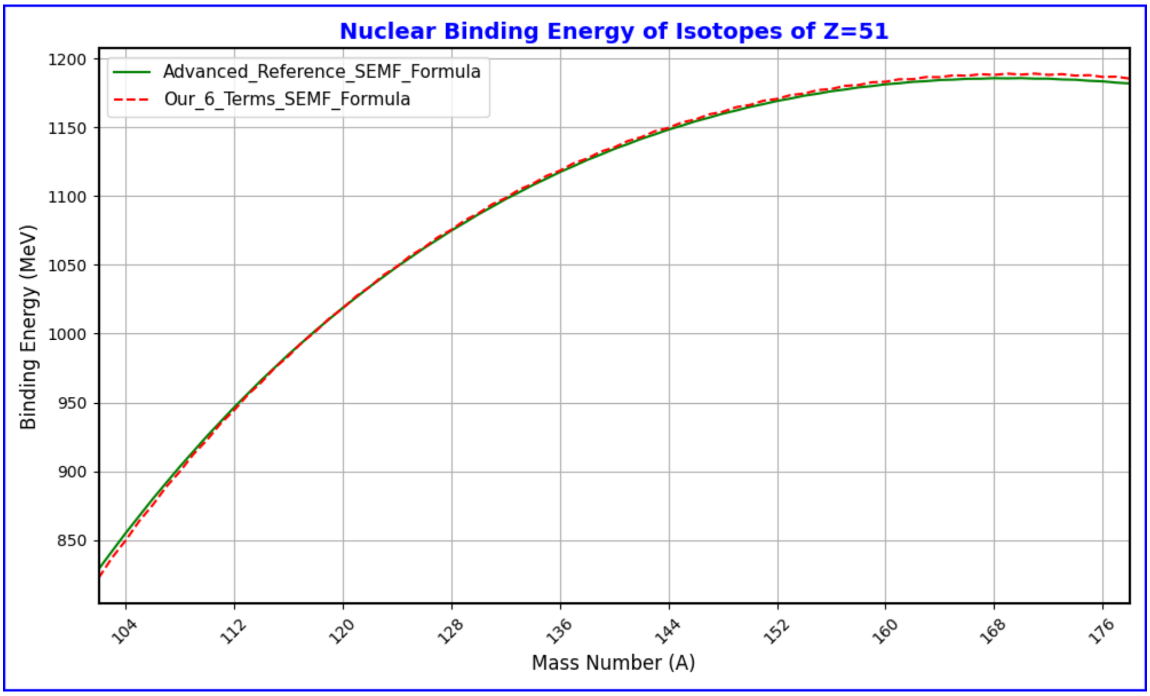

Figure 10. Nuclear binding energy of isotopes of Z=51 estimated with 6 terms SEMF.

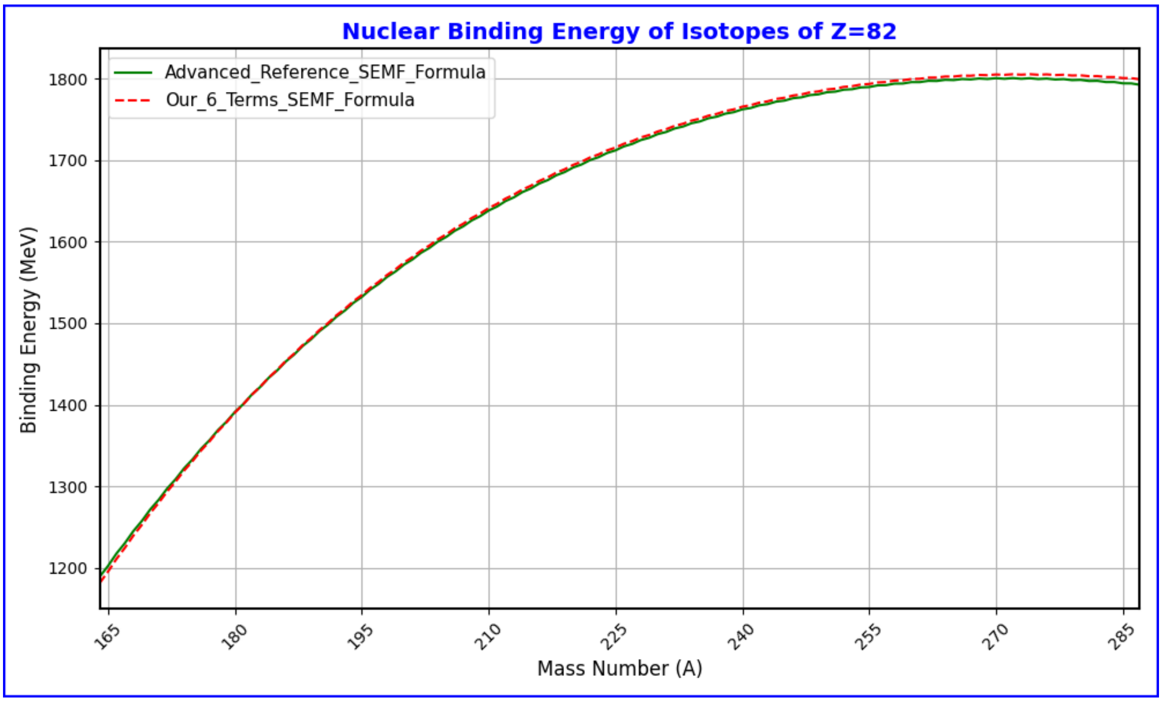

Figure 11. Nuclear binding energy of isotopes of Z=82 estimated with 6 terms SEMF.

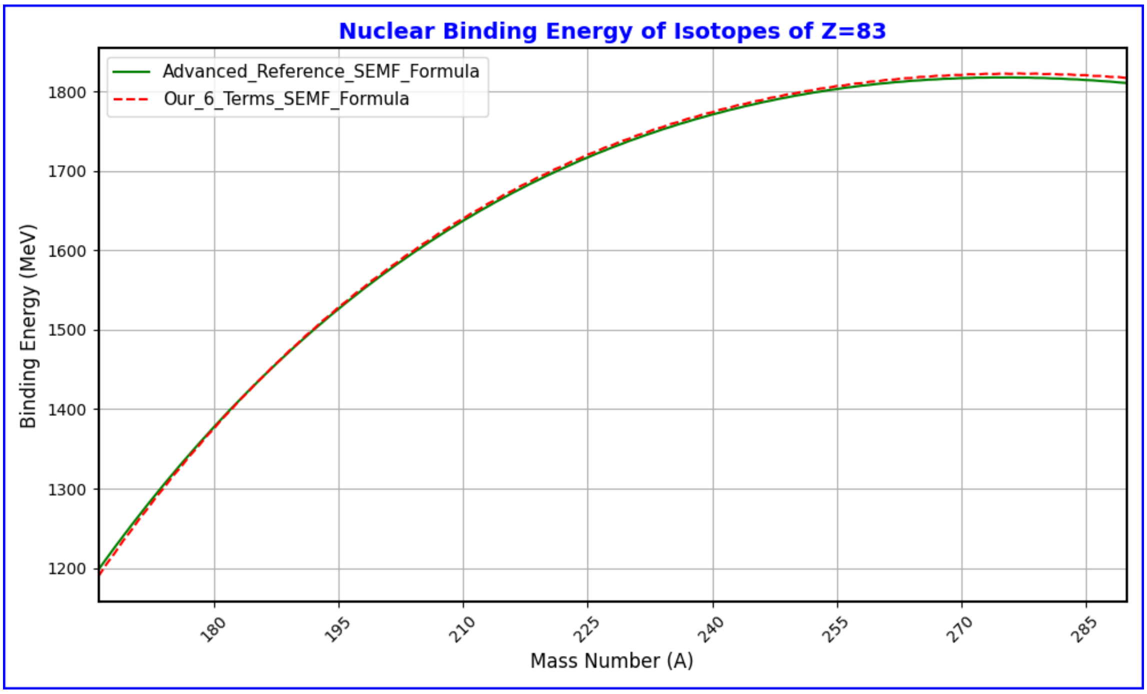

Figure 12. Nuclear binding energy of isotopes of Z=83 estimated with 6 terms SEMF.

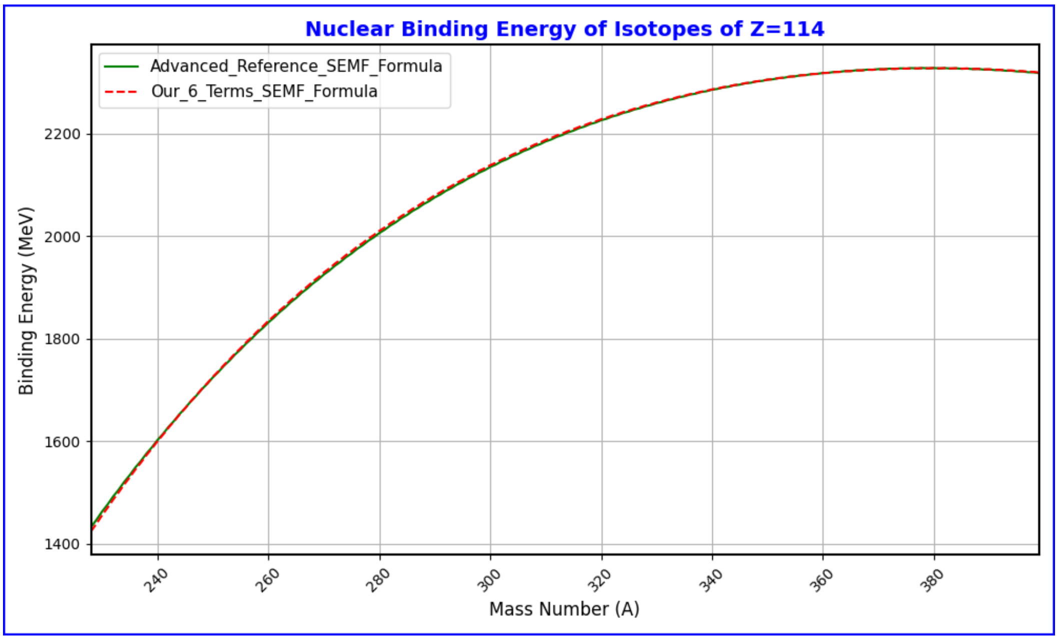

Figure 13. Nuclear binding energy of isotopes of Z=114 estimated with 6 terms SEMF.

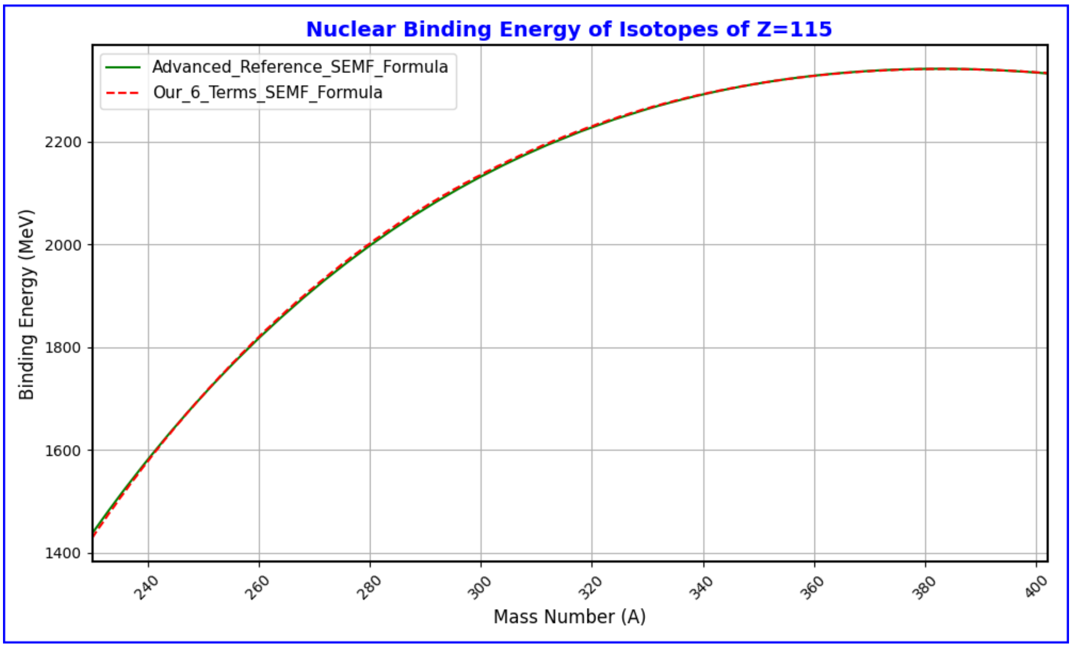

Figure 14. Nuclear binding energy of isotopes of Z=115 estimated with 6 terms SEMF.

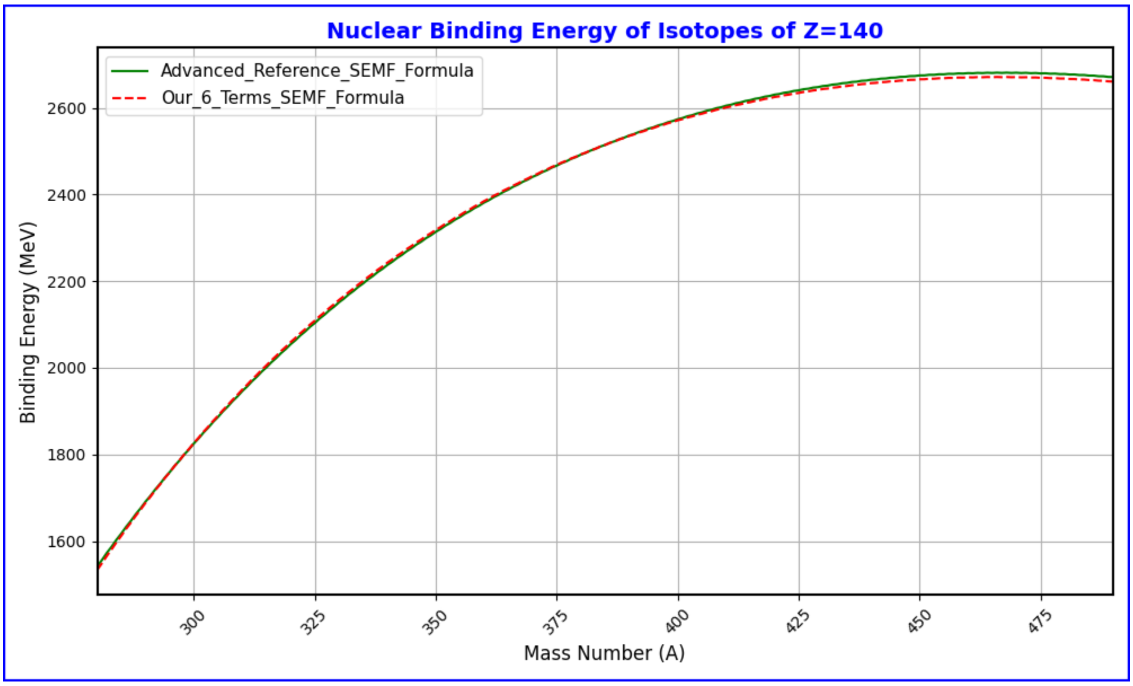

Figure 15. Nuclear binding energy of isotopes of Z=140 estimated with 6 terms SEMF.

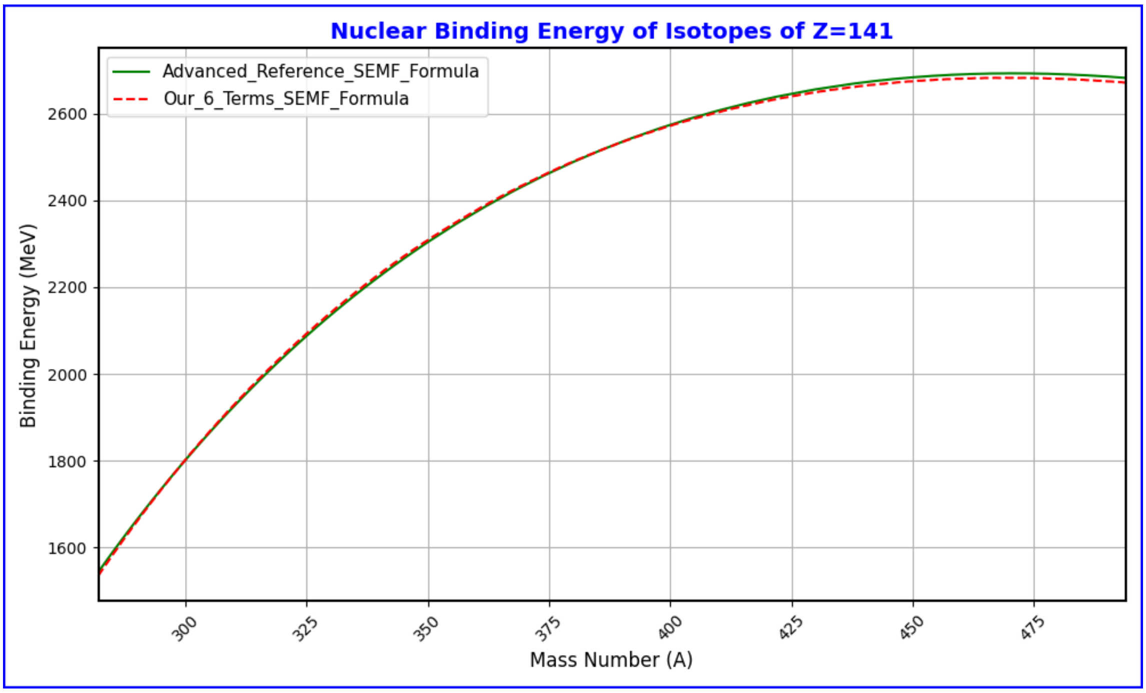

Figure 16. Nuclear binding energy of isotopes of Z=141 estimated with 6 terms SEMF.

It may be noted that, the 16 figures collectively demonstrate the enhanced accuracy and robustness of the proposed six-terms semi-empirical binding energy (SEMF) formula across a wide range of isotopes, including magic proton numbers 2, 8, 20, 28, 50, 82, 114, and heavy elements 140 and 141. They illustrate close agreement with experimental data and outperform existing models particularly for light, odd-A, neutron-rich, and superheavy nuclei. The red curves representing the current model generally show improved smoothness and fewer anomalies compared to reference models (green curves). These results highlight the applicability without region-specific tuning and its potential for reliable predictions even in experimentally sparse nuclear regions, critical for nuclear structure, astrophysical simulations, and superheavy element research. The graphical trends confirm

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the physical insights embedded in the model's refined corrections for asymmetry, surface, Coulomb, and congruence energies.

9. Scope for Machine Learning and AI-Based Refinement

Common ML models applied in nuclear mass and binding energy calculations include:

Artificial Neural Networks (ANNs): Capable of modelling complex nonlinear relationships across isotopic chains [32,33].

Bayesian Neural Networks (BNNs): Follow with BNNs since they are a probabilistic extension of ANNs, adding uncertainty quantification and improved precision [34,35].

Gaussian Process Regression (GPR): Offers probabilistic predictions along with uncertainty quantification [36].

Support Vector Machines (SVM): Used for regression and classification tasks in nuclear property predictions [37].

Ensemble Learning Methods (Random Forests, Gradient Boosting): Excel in reducing overfitting and improving robustness [38].

Deep Learning Architectures: Such as convolutional neural networks (CNNs) designed to capture hierarchical nuclear structure features [39,40].

Moreover, ML-based residual analysis can highlight where the current model deviates systematically from empirical trends, guiding targeted physical corrections (e.g., for deformation, shell closures, or pairing irregularities). As high-precision mass data become available from future experiments, such hybrid approaches combining physically interpretable models with data-driven refinements could significantly enhance predictive power and expand the utility of models in astrophysical and nuclear technology applications.

While the present model achieves strong agreement with experimental data using a compact, physically motivated structure, future refinements may benefit significantly from integrating machine learning (ML) and artificial intelligence (AI) techniques. AI/ML methods have become powerful tools in nuclear mass and binding energy modelling [41,42], helping to identify subtle patterns and dependencies beyond traditional regression or analytical optimization. For example, the machine-learned nuclear mass model by Gao et al. demonstrates competitive large-scale predictive power. However, purely data-driven models often face limitations extrapolating beyond their training domains, particularly for light nuclei or superheavy elements with sparse data.

The robust physical basis and unified formulation of the six-terms SEMF provide complementary strengths by maintaining stable and physically interpretable predictions across the nuclear chart. Future hybrid models that combine the explicit physics of the unified six-term formula with data-driven AI/ML optimization or residual correction hold promise to enhance prediction precision and extend applicability, especially as new experimental mass data become available.

10. Conclusions

The proposed 6-terms unified binding energy formula presents a significant advancement over the classical semi-empirical mass formula (SEMF), offering accurate mass predictions across the full range of nuclides starting form light nuclei (Z=1) to superheavy elements (Z=140). With deviations typically within 0.5–1.5% when compared to experimental data, the model demonstrates strong predictive power, particularly for asymmetric, odd-A, and superheavy nuclei.

Unlike conventional models that often require separate parameter sets for different nuclear regions, this approach maintains a single, consistent framework across the entire periodic chart. Its robustness and simplicity make it a promising tool for incorporation into modern nuclear modelling platforms, simulation engines, and astrophysical analysis toolkits.

The authors invite the global nuclear physics community to explore, validate, and apply the model across both experimental and theoretical settings. Such collaborative efforts will help refine its parameters, extend its applications, and deepen our collective understanding of nuclear matter.

The model's simplicity, unified structure, and good agreement with experimental data make it a strong candidate for use in modern nuclear physics research. Further refinements, as discussed in Section 8, may enhance its predictive power in light of new data and advanced computational methods.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

Data Availability Statement: The data that support the findings of this study are openly available.

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Conflict of Interest: Authors declare no conflict of interest in this paper or subject.

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