Random forest-based prediction of decay modes and half-lives of superheavy nuclei

Authors: CAI, Boshuai, YUAN, Cenxi, YUAN, Cenxi

Date: 2023-10-12T00:00:00+00:00

Abstract

How nuclides decay in the superheavy region is key information for investigating new elements beyond oganesson and the island of stability. The Random Forest algorithm is applied to study the competition between different decay modes in the superheavy region, including α decay, $\beta-$ decay, $\beta+$ decay, electron capture and spontaneous fission. The observed half-lives and dominant decay mode are well reproduced. The dominant decay mode of 96.9 % nuclei beyond 212Po is correctly described. α decay is predicted to be the dominant decay mode for isotopes in new elements Z = 119 − 122, except for spontaneous fission in some even-even ones because of the increased Coulomb repulsion and odd-even effect. The predicted half-lives show the existence of a long-lived spontaneous fission island at the southwest of 298Fl caused by the competition of nuclear deformation and Coulomb repulsion. More understanding of spontaneous fission, especially beyond 286Fl, is crucial to search for new elements and the island of stability.

Full Text

Preamble

Random forest-based prediction of decay modes and half-lives of superheavy nuclei∗ Bo-Shuai Cai1 and Cen-Xi Yuan İD 1, † 1Sino-French Institute of Nuclear Engineering and Technology, Sun Yat-sen University, Zhuhai, 519082, China Information on the decay process of nuclides in the superheavy region is critical in investigating new elements beyond oganesson and the island of stability. This paper presents the application of a random forest algorithm to examine the competition among different decay modes in the superheavy region, including α decay, $\beta-$ decay, $\beta+$ decay, electron capture and spontaneous fission. The observed half-lives and dominant decay mode are well reproduced. The dominant decay mode of 96.9% of the nuclei beyond 212Po is correctly obtained. Further, α decay is predicted to be the dominant decay mode for isotopes in new elements Z = 119–122, except for spontaneous fission in certain even–even

elements owing to the increased Coulomb repulsion and odd–even effect. The predicted half-lives demonstrate the existence of a long-lived spontaneous fission island southwest of 298Fl caused by the competition between the fission barrier and Coulomb repulsion. A better understanding of spontaneous fission, particularly beyond 286Fl, is crucial in the search for new elements and the island of stability.

Keywords: Decay Mode, Superheavy Nuclide, Random Forest

INTRODUCTION

Limitations of the nuclear landscape [1, 2] have always been an intriguing topic. Exotic nuclear properties, for example, the shell evolution [3–6], 4n resonant state [7, 8], and 4p unbound state [9], emerge at the limits of nuclear stability.

The discovery of new elements (nuclides) involves the following three problems: production, separation, and identification [10]. Because the nuclei are unstable and have relatively short half-lives, appropriate probes must be utilized. Characteristic decay modes [10, 11] are commonly employed as a probe to signal the existence of exotic nuclei. Therefore, investigating and predicting the dominant decay modes of the unknown nuclides is crucial. The nuclear binding energy and half-life are key parameters for determining the decay mode of a nucleus. The former measures the stability of nuclides by using energy criteria, and the latter describes the possibility of decay.

Both microscopic and macroscopic methods have been used to study the nuclear binding energy [12–16] and partial half-life of each decay channel, including α decay [17–19], β decay [20, 21], spontaneous fission [22, 23], protons emission [25] and neutron emission [24], etc. Microscopic theories begin with nucleon–nucleon interactions, which can be based on either realistic or phenomenological models. The macroscopic theory uses selected variables with physical considerations to construct semi-empirical formulas and fit the experimental data, and it entails the risk of overfitting and inappropriate parameters. In addition, exotic nuclei may significantly deviate from the general fitting and be identified as outliers. Decreasing the deviation between theoretical predictions and the observed results remains a critical issue.

With advances in computing and storage, efficacious machine learning algorithms with diverse applications have been proposed [26, 27], e.g., nuclear properties [28–30], fission yields [31–35], spectra decomposition [36], radiation effect [37], neutrino experiment [38], and other nuclear techniques [39–42]. As summarized in a recent colloquium, estimating the residuals of nuclear properties using machine learning algorithms is a powerful strategy [43]. A neural network has been used to compensate for the residuals of nuclear masses [44–47] and nuclear charge radii [48–50]; this has been achieved through structural optimization and careful selection of the input parameters with definite physical interpretations. The applicability of the decision tree (DT) has been verified via training and testing with residuals of the binding energies [51]. However, random forest (RF)

[52] algorithm, developed from the DT algorithm, has not been tested for determining the nuclear mass or the partial half-life of a specific decay channel; in this regard, semi-empirical formulas have suggested several major components but with residuals. Machine learning algorithms can include possible features to realize the training for residuals, whereas RF, with bootstrap sampling, not only avoids overfitting but also considers the correlation between the data combinations and several features. Thus, RF exhibits increased robustness and is conducive to extrapolation. The amount of computation increasing in accordance with the number of trees in the forest and size of the dataset, as well as the difficulty of model interpretability, may limit its applications.

This study entailed the application of an RF machine learning algorithm to analyze the major decay modes of heavy and superheavy nuclei. The competition between α decay, β decay, and spontaneous fission (SF) of new elements, as well as the possible long-lived island in the superheavy region were examined.

II. METHOD

This study focused on the region with Z > 84 and N > 128. The partial half-lives of α decay, $\beta-$ decay, $\beta+$ decay, electron capture (EC), and SF were calculated using semi-empirical formulas, and the residuals of each formula were then trained using the RF algorithm. The minimum partial half-life among the decay modes corresponds to the dominant decay mode of a nuclide.

A. Decay Half-life Formulas

The universal decay law (UDL) [53, 54] is used to fit the α-decay half-life. Zα, Aα, Qα, and µ = AαA/(A + Aα) denote the proton number, mass number of the α particle, α decay energy, and reduced mass, respectively. The channel is assumed to move from the ground state to the ground state.

A three-parameter formula (denoted as SF3) was used for the SF as follows:

$$\log_{10} T_{SF} = a\kappa I^2 + bA + c$$

which was proposed based on several existing formulas [22, 23, 55–58], where represents the blocking effect from unpaired nucleons; its value is 0 for even–even nuclei and 2 for other nuclei [55]. has a value of 2.6 [22, 59], I = (N − Z)/A and a, b, and c are the fitting coefficients. Eq (2) is separately fitted to nuclei with Z < 104 and the remaining because of a systematic difference, as shown in TABLE 1. T1/2,SF of the nuclei with Z < 104 increases significantly with a decrease in Z because the Coulomb repulsion decreases. The relatively long TSF (> 10^8 s) of certain nuclei in this region cannot be universally described currently and were not used to fit Eq.(2) because the competition for the SF is significantly weak compared to other decay modes.

The β decay half-life was estimated using the formula given in Refs. [21, 60]. Assuming that the ground state β decay is an effective Gamow–Teller (GT) transition, the partial half-life can be expressed as follows:

$$\log_{10} T_{1/2,\beta} = \log_{10} \kappa_1 - \log_{10} f_0 - \log_{10} B_{GT}$$

where $_1$ = $2\pi^3$ħ^7 ln 2 / (m ^{5}c^{4}G_F^2) = 6147 s, f_0 is the phase-space factor, and B_{GT} is the GT-reduced transition probability [60]. As regards EC, the phase-space factor is deduced as follows:

$$f_0 = \int_1^{E_0} pE(E_0 - E)^2 F(Z, E) dE$$

whereas for the $\beta\pm$ decay, it is:

$$f_0 = \int_{m_{ec}^2}^{E_0} pE(E_0 - E)^2 F(Z, E) dE$$

where E_0 is the renormalized β-decay energy. Because Qβ provided by AME2020 [61] is the difference in atomic masses, the electron mass should be reconsidered as follows:

$$E_{0,\beta^+} = Q_{\beta^+} + 2m_{ec}^2$$
$$E_{0,\beta^-} = Q_{\beta^-}$$
$$E_{0,EC} = Q_{EC}$$

Finally,

$$\log_{10} T_{1/2,\alpha} = aZ_\alpha \left(\frac{Z_d}{\sqrt{Q_\alpha}} \right) + b\sqrt{\mu Z_\alpha Z_d (A_d^{1/3} + A_\alpha^{1/3})} + c$$

where Z_d, A_d are the daughter nucleus proton and mass numbers, and = A_{{{dA}}{{ }}}/(A_d + A{ }) is the reduced mass.

B. Random Forest Method

RF is a fusion of the DT and bootstrap algorithms. DT is a non-parametric supervised learning algorithm. For a dataset consisting of S samples, each containing I features (variables) ($_1$, ..., _I), it establishes a binary tree structure that divides the dataset into L subsets based on feature values; each subset is called a leaf node. This partition seeks to minimize the RMSE of the entire dataset and the object (observable) by assigning a value to each leaf:

$$\text{RMSE} = \sqrt{\frac{1}{S}\sum_{s=1}^{S}(y_s - f(\theta_1, ..., \theta_I))^2}$$

Bootstrap is a statistical method based on random resampling with replacement, which automatically considers possible combinations and weights of the data [62, 63]. Each time a new dataset is obtained, a new DT is trained and used to predict the object for each sample in the entire dataset. By repeating this process M times, a forest of M trees is obtained. The final predicted value of the object for a sample is the average of the results calculated by all trees in the forest. Since each tree is trained on only part of the samples in the dataset, the forest's prediction for each sample is an average of interpolation and extrapolation; this reduces divergence when calculating for unmeasured nuclei. The open-source Python library scikit-learn [64] was used for machine learning in this study. The forest was assumed to be composed of 10^5 trees to reduce the dispersion of the RMSE.

III. RESULTS AND DISCUSSION

The residuals of the α decay, $\beta-$ decay, $\beta+$ decay, and EC decay formulas were trained using RF with features including Z, N, A, the parity of Z and N, and the decay energy. Since decay energy cannot be defined for SF, the fission barrier (FB) from Ref. [65] was used in the feature set instead of decay energy to consider deformation effects. The number of leaf nodes chosen for this study was 11, the same as that used for training binding energies in this region in our previous study [66]. Fig. 1 [Figure 1: see original paper] compares the residuals of these decay formulas before and after RF training. Two conditions were used to identify outliers: 1) located outside the dashed line of the corresponding color, indicating that the scatter deviates from the experimental $\log_{10}\mathrm{T}_1/_2$ by twice the RMSE; and 2) the value is greater than 3, indicating that the calculated value is three times the magnitude of the experimental value. This avoids missing (or adding) outliers due to excessively large (or small) RMSE. After training, the bias of outliers for these decay formulas was significantly reduced, and the RMSE of the formulas decreased (TABLE 1), as expected. The outlier condition is not too strict because the aim was not to maximally reduce the RMSE but to reach an appropriate scale where the dominant decay mode can be described. The same RF features and number of leaf nodes were chosen in this study to train the residuals of different decay formulas; this avoids overfitting while seeking an extremely small RMSE.

In total, 445 nuclides with measured partial half-lives and branching ratios for the five decay modes were obtained from NUBASE2020 [67]. The dominant decay modes and partial half-lives of these nuclides are illustrated in Fig. 2 Figure 2: see original paper. A long-lived α-decay valley extends from ^{226}Ra to ^{251}Cf, lying between a narrow $\beta+$/EC decay band and the neutron-rich $\beta-$ region. The half-life of a nuclide decreases with increasing distance from this valley. The southwest region is dominated by α decay, while the southeast region is dominated by $\beta-$ decay. In the northwest region, $\beta+$ decay and EC compete with α decay and lose out as Z increases. In the northeast region, α decay and SF compete with each other, and the region extending from the α valley appears to be dominated by SF. Although the distribution of dominant decay modes shows clear boundaries, the minimum partial half-life varies smoothly.

Among the 445 nuclides considered, 341 (104) nuclides had known (unknown) corresponding decay energies. The masses of nuclides without measured values were calculated using WS4 [12] and UNEDF0 [13] to estimate partial half-lives. The RF results are presented in Fig. 2(c–f). The calculated results agree well with experimental results, as the dominant decay mode was correctly described for 431 and 427 nuclides (96.9% and 96.0%) when the RMSE of $\log_{10}T_1/_2$ for the dominant decay mode was 0.62 and 0.67, respectively. Nuclides for which the dominant decay mode was inconsistently described generally have two competing decay modes. For example, the α and SF branching ratios of ^{255}Rf, ^{262}Db, and ^{286}Fl were approximately 50%. Meanwhile, the liquid drop model trained by RF [66] was also applied to obtain energies; this model yielded consistent results that are not presented here.

The accuracy of the obtained energy is crucial for half-life calculations. If the calculated energies from WS4 and UNEDF0 replace all experimental energies, the number of nuclides with consistent decay modes compared to experiment decreases to 72.6% and 64%, respectively, and the RMSE of $\log_{10}T_1/_2$ increases to 2.07 and 2.64. The difference in results obtained using the two models' energies is due to their different accuracies, as the RMSE of masses for WS4 is approximately 0.3 MeV [12], whereas that for UNEDF0 is approximately 1.45 MeV [13]. This also leads to differences during extrapolation. The consistency rate of dominant decay modes between energies calculated using these two models decreases from 82.2% to 66.2%. More accurate and precise measurements of decay energies will aid theoretical predictions. Furthermore, WS4 and UNEDF0 may lose their predictive power after training with machine learning. Training the WS4 and UNEDF0 binding energies with features Z, N, δ, and P, which sufficiently describe the residuals in Ref. [45], improves the energy description but decreases the consistency in dominant decay modes by several percent, which is considerable compared to the 23.4% rate of theoretical energies among all nuclides (104/445).

SF is important for investigating the half-lives of superheavy nuclei. As shown in Fig. 2(c, e), the dominant decay mode of unknown nuclides is determined by the competition among SF, α decay, and $\beta-$ decay. The main competition occurs between SF and $\beta-$ decay for neutron-rich nuclides, and between SF and α decay for neutron-deficient nuclides. Existing experimental data demonstrate a long-lived α-decay region from ^{226}Ra to ^{251}Cf, lying between the $\beta+$ and $\beta-$ decay regions and ending with SF. The proposed models correctly describe this phenomenon. In the long-lived region, after N exceeds 154, the blue band shown in Fig. 2(d, f) indicates half-lives of approximately 10^2–10^7 s. At the southwest corner of Z = 114 and N = 184, nuclides within the circle have longer half-lives than those in the surrounding area. This is due to the high FB in this region, which leads to longer $T_1/_2$,SF. Fig. 3 [Figure 3: see original paper] compares the evolution of FB and measured $T_1/_2$,SF along the mass number. FB decreases with A before A = 230 and subsequently behaves as a sinusoidal wave oscillating between 2 and 10 MeV. Apparently, an FB threshold exists, below which SF occurs. Nuclides with relatively long $T_1/_2$,SF generally have small SF branching ratios. Furthermore, the FB of nuclides with SF branching ratios less than 1% is mostly higher than that of nuclides with SF branching ratios greater than 1%, implying that the higher the FB, the weaker the SF. However, when considering only nuclides with SF branching ratios less than 1% or greater than 1%, the correspondence between FB and $T_1/_2$,SF becomes significantly more complex.

Nuclides with predicted partial half-lives longer than 10^4 s are marked with stars in Figs. 2(d, f), suggesting ^{250},^{252},^{254}Cm, ^{260},^{261}Es, $^{261-264}$Md, and ^{265}Lr for future measurements. No experimental half-life value for ^{250}Cm was suggested in NUBASE2020 and was thus extrapolated in this study. In the NNDC, SF was shown to be the dominant decay mode, and its half-life was recommended to be 8300 years, which is relatively long. Although the calculations in this study underestimate the NNDC value, the long half-life and dominant decay mode are reproduced. In addition, the upper limit of the half-life of ^{252}Cm was proposed to be two days in Ref. [69], which has not been updated since then (1966), whereas the current study estimates a half-life of 1.43 days. No experimental half-lives were previously reported for ^{260},^{261}Es, $^{261-264}$Md, and ^{265}Lr. However, their nearby isotopes have long half-lives, such as ^{257}Es (7.7 days), ^{260}Md (31.8 days), ^{259}Md (1.6 hours), ^{258}Md (51.5 days), ^{257}Md (5.52 hours), and ^{266}Lr (11 hours). Moreover, the Es, Md, and Lr isotopes are located in the extension of the narrow long-lived region from ^{226}Ra to ^{251}Cf, substantiating that the Es, Md, and Lr isotopes are candidates with long partial half-lives. Obtaining more measurements is also suggested; for example, the data for ^{252}Cm has not been updated for more than 50 years.

A comparison of all possible decay channels is limited by the accurate description of each channel and the availability of observed data; note that the SF mechanism remains unclear, such as its dependence on FB or deformation. The effect of the quadrupole deformation parameter ($_2$) [15] on half-life estimation was then investigated. If $_2$ replaces FB during RF training, more nuclides are predicted to have longer half-lives. Further investigations should be conducted to understand the dominant factors contributing to SF half-lives. FB combines the contributions of multipole deformations and thus exhibits stronger quantum effects compared to $_2$, as shown in Fig. 2(d, f). Fig. 3 demonstrates that FB increases when Z is large, indicating competition between FB and Coulomb repulsion in superheavy nuclides.

The extrapolation stops at the single-neutron (proton) and two-neutron (two-proton) drip lines. The UNEDF0 dataset stops at Z = 120. From the existing region to the neutron-deficient side, α decay and SF are predicted to compete. On the neutron-rich side, the calculations predict $\beta-$ decay as the dominant mode, while SF competes for specific nuclides. The latest results from most theoretical calculations of partial half-lives [17–20, 22, 23, 70–74] indicate that the α decay mode is dominant for new elements at N $\leq$ 184. As shown in Fig. 4 [Figure 4: see original paper], the partial half-lives of isotopes with Z = 117–122 were predicted in this study and compared with corresponding results from Refs. [18–20]. Although the partial half-lives of $\beta+$ decay and EC determined in this study are not longer than those indicated in Ref. [20], they remain approximately five orders of magnitude greater than that of α decay in this region, which does not change the dominant decay mode.

The $T_1/_2$,α values predicted in this study are longer than those indicated in Refs. [18–20]; this does not change the dominant decay mode of odd-Z isotopes but enhances the competition of SF in even-Z isotopes. Furthermore, the prediction in this study demonstrates strong odd–even staggering of $T_1/_2$,SF for even-Z isotopes. In other words, the $T_1/_2$,SF value of even–even nuclei is several times shorter than its two isotopic neighbors, which differs from the weak or unpredictable odd–even staggering effect obtained by other SF models, as shown in Fig. 4. Notably, all measured $T_1/_2$,SF values of even-Z isotopes demonstrate such odd–even staggering. Fig. 5 [Figure 5: see original paper] illustrates $T_1/_2$,SF and $T_1/_2$,α for isotopes with Z $\geq$ 92. For example, when Z is small in U, Pu, Cm, and Cf isotopes, SF is not competitive with α decay because Coulomb repulsion is not sufficiently strong. However, when Z is large, Coulomb repulsion increases, and this odd–even staggering makes SF competitive with α decay in even–even nuclides. Thus, α decay is suggested to be a key signal for detecting isotopes with Z = 119 and 121, whereas SF should also be considered for even-N isotopes of Z = 120 and 122. Moreover, odd–even staggering also exists in odd-Z isotopes, which can only be verified by $^{260-263}$Db due to limited data. Therefore, odd–even staggering of odd-Z isotopes was not predicted in this study. The DNS model predicted σ_{ER} values of hundreds of fb for the 3n or 2n channels producing ^{293119174} on a ^{243}Am target [75], which can be examined with the new CAFE2 and SHANS2 facilities in Lanzhou [76]. Given the odd–even effect of partial half-lives, nuclide candidates for new superheavy elements still require analysis based on cross-section and partial half-life.

IV. SUMMARY

In this study, the decay modes of superheavy nuclei were investigated using the RF algorithm. The partial half-lives of α decay, $\beta-$ decay, $\beta+$ decay, EC, and SF were studied and compared. The dominance of α decay in the neutron-deficient region was relatively evident. $\beta-$ decay is predicted to be dominant in neutron-rich regions. SF contributes to a long-lived circle at the southwest corner of Z = 114 and N = 184. More accurate and precise measurements of nuclear mass and decay energy can improve predictions of decay modes. The odd–even effect of SF was observed in even-Z nuclides. Combined with strong

Coulomb repulsion, SF and α decay become competitive in even–even nuclides. Thus, α decay is suggested to be a key probe for isotopes with Z = 119 and 121, whereas competition from SF should be considered in even–even isotopes with Z = 120 and 122. ^{250},^{252},^{254}Cm, ^{260},^{261}Es, $^{261-264}$Md, and ^{265}Lr with predicted half-lives longer than 10^4 s were suggested for future measurements. SF, influenced by the fission barrier and Coulomb repulsion, leads to a long-lived region during extrapolation. The results of this study indicate that research regarding SF, especially beyond ^{286}Fl, which is currently the heaviest nuclide with a significant SF branch ratio, is critical for studies on new facilities such as CAFE2 and SHANS2 in Lanzhou.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Bo-Shuai CAI. The first draft of the manuscript was written by Bo-Shuai CAI and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data Availability Statement The data that support the findings of this study are openly available in Science Data Bank at https://www.doi.org/10.57760/sciencedb.12102 and https://cstr.cn/31253.11.sciencedb.12102.

[1] W. Nazarewicz, The limits of nuclear mass and charge, Nat. Phys. 14, 537 (2018). doi:10.1038/s41567-018-0163-3 [2] J. Erler, N. Birge, M. Kortelainen et al., The limits of the nuclear landscape, Nature 486, 509 (2012). doi:10.1038/nature11188 [3] T. Otsuka, A. Gade, O. Sorlin et al., Evolution of shell structure in exotic nuclei, Rev. Mod. Phys. 92, 015002 (2020). doi:10.1103/RevModPhys.92.015002 [4] T. Otsuka, T. Suzuki, M. Honma et al., Novel Features of Nuclear Forces and Shell Evolution in Exotic Nuclei, Phys. Rev. Lett. 104, 012501 (2010). doi:10.1103/PhysRevLett.104.012501 [5] A. Ozawa, T. Kobayashi, T. Suzuki et al., New Magic Number, N = 16, near the Neutron Drip Line, Phys. Rev. Lett. 84, 5493 (2000). doi:10.1103/PhysRevLett.84.5493 [6] N. A. Smirnova, B. Bally, K. Heyde et al., Shell evolution and nuclear forces, Phys. Lett. B 686, 109 (2010). doi:10.1016/j.physletb.2010.02.051 [7] M. Duer, T. Aumann, R. Gernhäuser et al., Observation of a correlated free four-neutron system, Nature 606, 678 (2022). doi:10.1038/s41586-022-04827-6 [8] J. G. Li, N. Michel, B. S. Hu et al., Ab initio no-core Gamow shell-model calculations of multineutron systems, Phys. Rev. C 100, 054313 (2019). doi:10.1103/PhysRevC.100.054313 [9] Y. Jin, C. Y. Niu, K. W. Brown et al., First Observation of the Four-Proton Unbound Nucleus 18Mg, Phys. Rev. Lett. 127, 262502 (2021). doi:10.1103/PhysRevLett.127.262502 [10] S. Hofmann and G. Münzenberg, The discovery of the heaviest elements, Rev. Mod. Phys. 72, 733 (2000). doi:10.1103/RevModPhys.72.733 [11] S. A. Giuliani, Z. Matheson, W. Nazarewicz et al., Colloquium: Superheavy elements: Oganesson and beyond, Rev. Mod. Phys. 91, 011001 (2019). doi:10.1103/RevModPhys.91.011001 [12] N. Wang, M. Liu, X. Wu et al., Surface diffuseness correction in global mass formula, Phys. Lett. B 734, 215 (2014). doi:10.1016/j.physletb.2014.05.049 [13] M. Kortelainen, T. Lesinski, J.

Moré et al., Nuclear energy density optimization, Phys. Rev. C 82, 024313 (2010). doi:10.1103/PhysRevC.82.024313 [14] W. D. Myers, Development of the semiempirical droplet model, At. Data Nucl. Data Tables 17, 411 (1976). doi:10.1016/0092-640X(76)90030-9 [15] P. Möller, A. J. Sierk, T. Ichikawa et al., Nuclear ground-state masses and deformations: FRDM(2012), Atom. Data Nucl. Data 109-110, 1 (2016). doi:10.1016/j.adt.2015.10.002 [16] S. Goriely, N. Chamel, and J. Pearson, Hartree-Fock-Bogoliubov nuclear mass model with 0.50 MeV accuracy based on standard forms of Skyrme and pairing functionals, Phys. Rev. C 88, 061302 (2013). doi:10.1103/PhysRevC.88.061302 [17] G. Saxena, A. Jain, and P. K. Sharma, A new empirical formula for α–decay half-life and decay chains of Z = 120 isotopes, Phys. Scr. 96, 125304 (2021). doi:10.1088/1402-4896/ac1a4d [18] J. P. Cui, Y. H. Gao, Y. Z. Wang et al., Improved effective liquid drop model for α–decay half-lives, Nucl. Phys. A 1017, 122341 (2022). doi:10.1016/j.nuclphysa.2021.122341 [19] C. He, Z. M. Niu, X. J. Bao et al., Research on α–decay for the superheavy nuclei with Z= 118–120, Chinese Phys. C 46, 054102 (2022). doi:10.1088/1674-1137/ac4c3a [20] P. Sarriguren, Self-consistent calculations of electron-capture decays in Z = 118, and 120 superheavy isotopes, Phys. Lett. B 815, 136149 (2021). doi:10.1016/j.physletb.2021.136149 [21] Y. F. Gao, B. S. Cai, and C. X. Yuan, Investigation of $\beta-$–decay half-life and delayed neutron emission with uncertainty analysis, Nucl. Sci. Tech. 34, 9 (2023). doi:10.1007/s41365-023-01193-4 [22] X. J. Bao, S. Q. Guo, H. F. Zhang et al., Competition between α–decay and spontaneous fission for superheavy nuclei, J. Phys. G: Nucl. Part. Phys. 42, 085101 (2015). doi:10.1088/0954-3899/42/8/085101 [23] A. Soylu, Search for decay modes of heavy and superheavy nuclei, Chinese Phys. C 43, 074102 (2019). doi:10.1088/1674-1137/43/7/074102 [24] B. S. Cai and C. X. Yuan, Theoretical description of the decay width of neutron emission in light nuclei (in Chinese). Chin. Sci. Bull., 67, 2782–2789 (2022). doi:10.1360/TB-2022-0151 [25] Z. Zhang, C. Yuan, C. Qi, et al., Extended R-matrix description of two-proton radioactivity, Phys. Lett. B, 838, 137740 (2023). doi:10.1016/j.physletb.2023.137740 [26] P. Mehta, M. Bukov, C.-H. Wang et al., A high-bias, low-variance introduction to Machine Learning for physicists, Phys. Rep. 810, 1 (2019). doi:10.1016/j.physrep.2019.03.001 [27] W.-B. He, Y.-G. Ma, L.-G. Pang et al., High-energy nuclear physics meets machine learning, Nucl. Sci. Tech. 34, 88 (2023). doi:10.1007/s41365-023-01233-z [28] Z.-P. Gao, Y.-J. Wang, H.-L. Lü et al., Machine learning the nuclear mass, Nucl. Sci. Tech. 32, 109 (2021). doi:10.1007/s41365-021-00956-1 [29] T.-S. Shang, J. Li, Z.-M. Niu, Prediction of nuclear charge density distribution with feedback neural network, Nucl. Sci. Tech. 33, 153 (2022). doi:10.1007/s41365-022-01140-9 [30] W.-J. Xie, Z.-W. Ma, J.-H. Guo, Bayesian inference of the crust–core transition density via the neutron-star radius and neutron-skin thickness data, Nucl. Sci. Tech. 34, 91 (2023). doi:10.1007/s41365-023-01239-7 [31] Q.-F. Song, L. Zhu, H. Guo et al., Verification of neutron-induced fission product yields evaluated by a tensor decomposition model in transport-burnup simulations, Nucl. Sci. Tech. 34, 32 (2023). doi:10.1007/s41365-023-01176-5 [32] Z. A. Wang, J. C. Pei, Y. J.

Chen, et al., Bayesian approach to heterogeneous data fusion of imperfect fission yields for augmented evaluations, Phys. Rev. C 106, L021304 (2022). doi:10.1103/PhysRevC.106.L021304 [33] Q. Song, L. Zhu, B. Cai, et al., Image processing of isotope yield in neutron-induced fission, Phys. Rev. C 107, 044609 (2023). doi:10.1103/PhysRevC.107.044609 [34] Z.-A. Wang and J. Pei, Optimizing multilayer Bayesian neural networks for evaluation of fission yields, Phys. Rev. C 104, 064608 (2021). doi:10.1103/PhysRevC.104.064608 [35] Z.-A. Wang, J. Pei, Y. Liu et al., Bayesian Evaluation of Incomplete Fission Yields, Phys. Rev. Lett. 123, 122501 (2019). doi:10.1103/PhysRevLett.123.122501 [36] Y.-D Zeng, J. Wang, R. Zhao et al., Decomposition of fissile isotope antineutrino spectra using convolutional neural network, Nucl. Sci. Tech. 34, 79 (2023). doi:10.1007/s41365-023-01227-9 [37] B.-C. Wang, M.-T. Qiu, W. Chen et al., Machine learning-based analyses for total ionizing dose effects in bipolar junction transistors, Nucl. Sci. Tech. 33, 131 (2022). doi:10.1007/s41365-022-01107-w [38] Z.-Y. Li, Z. Qian, J.-H. He, et al., Improvement of machine learning-based vertex reconstruction for large liquid scintillator detectors with multiple types of PMTs, Nucl. Sci. Tech. 33, 93 (2022). doi:10.1007/s41365-022-01078-y [39] 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 [40] 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 [41] Y.-Y. Li, F., Zhang, J., Su, Improvement of the Bayesian neural network to study the photoneutron yield cross sections, Nucl. Sci. Tech. 33, 135 (2022). doi:10.1007/s41365-022-01131-w [42] F.-D. Qin, H.-Y. Luo, Z.-Z. He et al., Counting of alpha particle tracks on imaging plate based on a convolutional neural network, Nucl. Sci. Tech. 34, 37 (2023). doi:10.1007/s41365-023-01181-2 [43] A. Boehnlein, M. Diefenthaler, C. Fanelli et al., Colloquium: Machine learning in nuclear physics, Rev. Mod. Phys. 94, 031003 (2022). doi:10.1103/RevModPhys.94.031003 [44] R. Utama, J. Piekarewicz, and H. B. Prosper, Nuclear mass predictions for the crustal composition of neutron stars: A Bayesian neural network approach, Phys. Rev. C 93, 014311 (2016). doi:10.1103/PhysRevC.93.014311 [45] Z. M. Niu and H. Z. Liang, Nuclear mass predictions based on Bayesian neural network approach with pairing and shell effects, Phys. Lett. B 778, 48 (2018). doi:10.1016/j.physletb.2018.01.002 [46] Z. M. Niu, J. Y. Fang, and Y. F. Niu, Comparative study of radial basis function and Bayesian neural network approaches in nuclear mass predictions, Phys. Rev. C 100, 054311 (2019). doi:10.1103/PhysRevC.100.054311 [47] X.-C. Ming, H.-F. Zhang, R.-R. Xu et al., Nuclear mass based on the multi-task learning neural network method, Nucl. Sci. Tech. 33, 48 (2022). doi:10.1007/s41365-022-01031-z [48] R. Utama, W.-C. Chen, and J. Piekarewicz, Nuclear charge radii: density functional theory meets Bayesian neural networks, J. Phys. G: Nucl. Part. Phys. 43, 114002 (2016). doi:10.1088/0954-3899/43/11/114002 [49] D. Wu, C. L. Bai, H. Sagawa et al., Calculation of nuclear charge radii with a charge-trained feed-forward neural network, Phys. Rev. C 102, 054323

(2020). doi:10.1103/PhysRevC.102.054323 [50] X.-X. Dong, R. An, J.-X. Lu et al., Novel Bayesian neural network based approach for nuclear charge radii, Phys. Rev. C 105, 014308 (2022). doi:10.1103/PhysRevC.105.014308 [51] M. Carnini and A. Pastore, Trees and forests in nuclear physics, J. Phys. G: Nucl. Part. Phys. 47, 082001 (2020). doi:10.1088/1361-6471/ab92e3 [52] L. Breiman, Random Forests, Mach. Learn. 45, 5 (2001). doi:10.1023/A:1010933404324 [53] C. Qi, F. R. Xu, R. J. Liotta et al., Microscopic mechanism of charged-particle radioactivity and generalization of the Geiger-Nuttall law, Phys. Rev. C 80, 044326 (2009). doi:10.1103/PhysRevC.80.044326 [54] C. Qi, F. R. Xu, R. J. Liotta et al., Universal Decay Law in Charged-Particle Emission and Exotic Cluster Radioactivity, Phys. Rev. Lett. 103, 072501 (2009). doi:10.1103/PhysRevLett.103.072501 [55] Z. Z. Ren and C. Xu, Spontaneous fission half-lives of heavy nuclei in ground state and in isomeric state, Nucl. Phys. A 759, 64 (2005). doi:10.1016/j.nuclphysa.2005.04.019 [56] C. Xu, Z. Z. Ren, and Y. Q. Guo, Competition between α decay and spontaneous fission for heavy and superheavy nuclei, Phys. Rev. C 78, 044329 (2008). doi:10.1103/PhysRevC.78.044329 [57] K. P. Santhosh, R. K. Biju, and S. Sahadevan, Semi-empirical formula for spontaneous fission half life time, Nucl. Phys. A 832, 220 (2010). doi:10.1016/j.nuclphysa.2009.10.160 [58] K. P. Santhosh, C. Nithya, and T. A. Jose, Decay modes of superheavy nuclei using a modified generalized liquid drop model and a mass-inertia-dependent approach for spontaneous fission, Phys. Rev. C 104, 024617 (2021). doi:10.1103/PhysRevC.104.024617 [59] G. Royer, Alpha emission and spontaneous fission through quasi-molecular shapes, J. Phys. G: Nucl. Part. Phys. 26, 1149 (2000). doi:10.1088/0954-3899/26/8/305 [60] J. Suhonen, From Nucleons to Nucleus: Concepts of Microscopic Nuclear Theory (Springer, Berlin Heidelberg, 2007), pp. 1–636. [61] M. Wang, W. J. Huang, F. G. Kondev et al., The AME 2020 atomic mass evaluation (II). Tables, graphs and references, Chinese Phys. C 45, 030003 (2021). doi:10.1088/1674-1137/abddaf [62] B. Cai, G. Chen, J. Xu et al., α–decay half-life estimation and uncertainty analysis, Phys. Rev. C 101, 054304 (2020). doi:10.1103/PhysRevC.101.054304 [63] B. Cai, G. Chen, C. Yuan et al., Shell–model study on properties of proton dripline nuclides with Z, N = 30–50 including uncertainty analysis, Chinese Phys. C 46, 084104 (2022). doi:10.1088/1674-1137/ac6cd7 [64] F. Pedregosa, G. Varoquaux, A. Gramfort et al., Scikit-learn: Machine Learning in Python, J. Mach. Learn. Res. 12, 2825 (2011). doi:10.5555/1953048.2078195 [65] P. Möller, A. J. Sierk, T. Ichikawa et al., Fission barriers at the end of the chart of the nuclides, Phys. Rev. C 91, 024310 (2015). doi:10.1103/PhysRevC.91.024310 [66] B. Cai, T. Yu, X. Lin et al., Investigation of Nuclear Binding Energy and Charge Radius Based on Random Forest Algorithm, At. Energ. Sci. Technol. 57, 704 (2023). doi:10.7538/yzk.2022.youxian.0780 [67] F. G. Kondev, M. Wang, W. J. Huang et al., The NUBASE2020 evaluation of nuclear physics properties, Chinese Phys. C 45, 030001 (2021). doi:10.1088/1674-1137/abddae [68] Z. Wang, D. Bai, Z. Z. Ren, Improved density-dependent cluster model with anisotropic deformation-dependent surface diffuseness in α–decay calculations, Phys. Rev. C 105, 024327 (2022). doi:10.1103/PhysRevC.105.024327 [69] Combined

Radiochemistry Group, Nuclear Decay Properties of Heavy Nuclides Produced in Thermonuclear Explosions–Par and Barbel Events, Phys. Rev. 148, 1192 (1966). doi:10.1103/PhysRev.148.1192 [70] P. Sarriguren, Competition between weak and α–decay modes in superheavy nuclei, Phys. Rev. C 105, 014312 (2022). doi:10.1103/PhysRevC.105.014312 [71] C. Xu, X. Zhang, and Z. Z. Ren, Stability of superheavy nuclei against α–decay and spontaneous fission, Nucl. Phys. A 898, 24 (2013). doi:10.1016/j.nuclphysa.2012.12.022 [72] J. H. Liu, S. Q. Guo, X. J. Bao et al., Predictions of decay modes for the superheavy nuclei most suitable for synthesis, Chinese Phys. C 41, 074106 (2017). doi:10.1088/1674-1137/41/7/074106 [73] K. N. Sridhar, H. C. Manjunatha, and H. B. Ramalingam, Search for possible fusion reactions to synthesize the superheavy element Z = 121, Phys. Rev. C 98, 064605 (2018). doi:10.1103/PhysRevC.98.064605 [74] T. Sahoo and S. K. Patra, Search for the stable isotopes for Z = 119 and 121 superheavy elements using relativistic mean field model, Phys. Scr. 95, 085302 (2020). doi:10.1088/1402-4896/ab98b8 [75] F. Li, L. Zhu, Z.-H. Wu et al., Predictions for the synthesis of superheavy elements Z = 119 and 120, Phys. Rev. C 98, 014618 (2018). doi:10.1103/PhysRevC.98.014618 [76] L. N. Sheng, Q. Hu, H. Jia et al., Ion-optical design and multiparticle tracking in 3D magnetic field of the gas-filled recoil separator SHANS2 at CAFE2, Nucl. Instrum. Methods Phys. Res., A 1004, 165348 (2021). doi:10.1016/j.nima.2021.165348

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