α-decay half-life calculations of superheavy nuclei using artificial neural networks

2014 J. Phys.: Conf. Ser. 490 012105

(http://iopscience.iop.org/1742-6596/490/1/012105)

α-decay half-life calculations of superheavy nuclei using artificial neural networks

Tuncay Bayram[1,*], **Serkan Akkoyun**[2], **S. Okan Kara**[3]

[1] Department of Physics, Sinop University, Sinop, Turkey
[2] Vocational School of Health Services, Cumhuriyet University, Sivas, Turkey
[3] Bor Vocational School, Nigde University, Nigde, Turkey

E-mail: *tbayram@sinop.edu.tr

Abstract. Investigations of superheavy elements (SHE) have received much attention in the last two decades, due to the successful syntheses of SHE. In particular, α-decay of SHEs has a great importance because most synthesized SHE have α-decay and the experimentalists have evaluated the theoretical predictions of the α-decay half-life during the experimental design. Because of this, the correct prediction of α-decay half-life is important to investigate superheavy nuclei as well as heavy nuclei. In this work, artificial neural networks (ANN) have been employed on experimental α-decay half-lives of superheavy nuclei. Statistical modeling of α-decay half-life of superheavy nuclei have been found as to be successful.

1. Introduction

One of the hottest research subjects in nuclear physics is superheavy nuclei beyond Fermium ($Z = 100$). Better understanding of structures and properties of superheavy nuclei can provide quite significant knowledge for the area of existing nuclei and chemical elements. Furthermore, this can make a change in our conception of the material world's boundaries [1]. Many nuclear research centers have started preparing experiments for the synthesising SHE since 1970. Due to the successful synthesizing of SHEs in the laboratory, some of them has been stimulated, such as $Z = 107-112$ at GSI [2, 3, 4], $Z = 110-113$ at RIKEN [5, 6] and $Z = 113-118$ at Dubna [7, 8, 9]. From theoretical side, some properties of superheavy nuclei, such as binding energy, α-decay energy and α-decay half-lives have been intensively studied by using various nuclear models, such as the macroscopic-microscopic models, Skyrme-Hartree-Fock and relativistic mean field (RMF) models. The authors refer to read [10, 11] and references therein. In particular, α-decay half-lives of SHE are important because most synthesized SHE have α-decay. The theory of α-decay was firstly interpreted as a consequence of quantum penetration of α particle by Gamow [12] in 1928. Since then various models for description of α-decay have been proposed. On the other hand some simple semi-empirical formulas have been introduced for the estimations of the α-decay half-lives because experimentalists evaluate the values of the α-decay half-life during the experimental design (See [13] and references therein). It should be noted, however, that phenomenological formulae cannot replace theoretical studies of α-decay which provide a microscopic description of α-decay process.

In recent years, artificial neural networks (ANN) have been employed in nuclear physics research ([14] and references therein) as in the many field of sciences. Discriminating between neutron and gamma-rays [15], developing nuclear mass systematic [16, 17] and obtaining nuclear charge radii [18] have been done by using ANN. In this work, feed-forward ANN have been used in order to obtain α-decay half-lives of superheavy nuclei. The fundamental task of ANN is to give outputs through computation of the inputs. The method does not need any relationship between input and output data. The main purpose of the present study is to show success of ANN in describing of the unknown α-decay half-lives of superheavy nuclei.

2. Artificial Neural Networks (ANN)

ANN are nonlinear, nonalgorithmic and parallel processing systems that mimic the human brain functionality. They consist of several processing units called neurons which have adaptive synaptic weights [19]. ANN are known as very powerful tools that are used when standard techniques fail to estimate the correlation between the variables. ANN have several advantages, such as requiring less formal statistical training, ability to detect complex highly non-linear relationships between input and output variables and ability to detect all possible interactions between predictor variables.

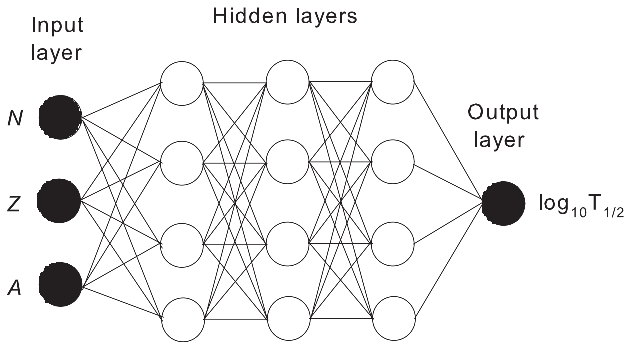

Figure 1. Used ANN topology (3-4-4-4-1) in the present study.

The layered feed-forward ANN consist of input, hidden and output layers. In this study, one input layer with three neurons ($p = 3$), three hidden layers with four (h) neurons in each and one output layer with one neuron ($r = 1$) ANN topology has been used for accurate prediction of the α-decay half-lives of superheavy nuclei (Figure 1). The number of total adjustable weights, which can be calculated by $p \times h_1 + h_1 \times h_2 + ... + h_i \times r$ (i=1 to maximum number of hidden layers), has been 48 with no bias. Three ANN inputs are neutron N, proton Z and mass A numbers and the desired output is logarithm of the α-decay half-lives ($\log T_{1/2}$) for superheavy nuclei. The neurons in the input layer collect the data from environment and transmits via weighted connections to the neurons of the hidden layers which are needed to approximate any non-linear function. In this work, the chosen type of hidden neuron activation function is hyperbolic tangent. In the present study, neural network software NeuroSolutions v6.02 has been used.

ANN are composed of two stages, training and test stages. In the training stage in which Levenberg-Marquardt back-propagation algorithm was used, the weights are adjusted to construct ANN. Because of this, these weights play a key role for solving the problem considered. This stage continues until the acceptable error level which is calculated by the difference between desired and ANN outputs. After the construction, ANN have been tested on the data in the test stage. The data used in this stage has never been seen by ANN before. In this work, all data has been partitioned into two separate sets: one for the supervised training of ANN and the rest (belonging to the Z=107 nuclei) for the test.

3. Results and discussions

In the present study, the available experimental data for α-decay half-lives of 154 superheavy nuclei starting from $Z = 100$ to 118 has been obtained from [7, 8, 9, 20, 21]. These values except those of Bh ($Z = 107$) nuclei have been used as output of ANN in units of second while related proton Z, neutron N and mass A numbers have been used as inputs. However, ANN have been found as unsuccessful for understanding connections between these variables. The α-decay half-lives $T_{1/2}$ performed in the Viola-Seaborg phenomenological formula [22] is given by

$$\log T_{1/2}(Z,N) = (aZ+b)Q^{1/2} + cZ + d + h_{log} \tag{1}$$

where Z is proton number, N is neutron number and Q is the α-decay energy of a parent nucleus. In this equation, $T_{1/2}$ and Q are in units of second and MeV, respectively. The quantities a, b, c, d and h_{log} are adjustable parameters. By considering equation (1), we have used the logarithm of the experimental $T_{1/2}$ values as output of ANN instead of the $T_{1/2}$ values. In this case, ANN has been found as to be successful in detecting relationships between inputs (Z, N and A) and the output ($\log T_{1/2}$). In Figure 2, ANN training results (open symbols) for the logarithm of the $T_{1/2}$ values for some superheavy nuclei ($Z = 100, 103, 105, 108, 110, 114$ and 117) are shown as in comparison with experimental values (filled symbols). The data error sizes are smaller than those of symbols. The maximum deviation between ANN training results and experimental ones is 1.001. The root mean square error (RMSE) value of ANN training results is 0.636 for 147 nuclei. As can be seen in Figure 2, ANN training results are close to the available experimental data for the $\log T_{1/2}$ values of superheavy nuclei. Also, ANN can be found as to be successful in understanding the general tendency of experimental data points for isotopic chains of superheavy nuclei.

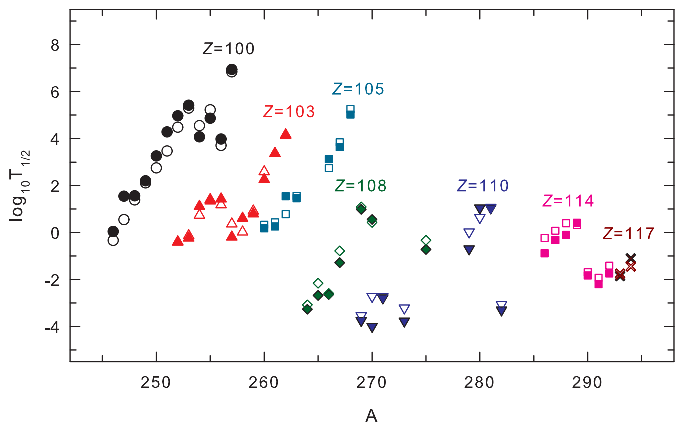

Figure 2. The logarithm of $T_{1/2}$ values for some superheavy nuclei as a function of mass number A. The experimental values [7, 9, 20, 21] are represented by filled symbols while ANN training results are denoted by open symbols. Units of the half-lives are in second.

Properties of superheavy nuclei, such as binding energy, α-decay energy and α-decay half-life are strongly influenced by the shell effects. Various theoretical models predict different proton and neutron magic numbers in superheavy region. The macroscopic-microscopic models predict that $^{270}\mathrm{Hs}_{162}$ ($Z = 108$) is a doubly magic nucleus and this prediction has been favored by experiments ([10] and references therein). One can expect that the fission barrier near this region is high because of the large shell correction energy. This leads to the fact that the spontaneous fission half-life will be increased. This indication is clearly visible in Figure 2. Generally, ANN results for the $\log T_{1/2}$ values for an isotopic chain of superheavy nuclei is increasing around neutron number $N = 162$ as in agreement with the experimental $\log T_{1/2}$ values.

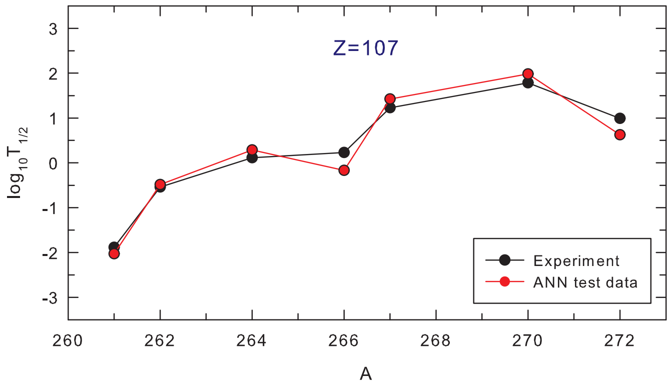

Figure 3. ANN test results for the $\log T_{1/2}$ of superheavy Bh ($Z = 107$) nuclei in comparison with the available experimental data. Units are in second and the experimental data error size are smaller than those of symbols.

After training of ANN, we performed the test of ANN. The training had been practised on the data without taking the experimental $\log T_{1/2}$ values of Bh ($Z = 107$) isotopes into account. Later, we have obtained ANN results for these isotopes which have never been seen by ANN. In Figure 3, ANN test results for the $\log T_{1/2}$ values of superheavy Bh isotopes are shown as in comparison with the available experimental data [8, 20, 21]. The maximum difference between the logarithm of the experimental and ANN $T_{1/2}$ values is seen at mass number $A = 266$ and its value is 0.399. The RMSE value of ANN test results is 0.246. As can be seen in Figure 3, ANN results are close to the experimental data points. This indicates that ANN has predictive power for the $\log T_{1/2}$ of superheavy nuclei. On the other hand, ANN method cannot be replaced by microscopic or macroscopic-microscopic approaches which provide deep descriptions of α-decay process. It should be noted, however, that ANN gives a practical value, for an easy prediction of not yet measured values of $T_{1/2}$.

4. Conclusions

ANN has been employed to investigate $T_{1/2}$ of superheavy nuclei starting from $Z = 100$ to 118. ANN results have been found to be in agreement with the experimental data. ANN method has also been performed for estimating $T_{1/2}$ of Bh ($Z = 107$) isotopes without introducing their original data to the network. The results show that in the region $Z = 100 - 118$, ANN is a practical tool for obtaining unmeasured $T_{1/2}$ values and it can be useful for describing systematics of α-decay half-lives.

References

[1] Oganessian Y 2013 *Nuclear Physics News* **23** 15
[2] Hofmann S 1998 *Rep. Prog. Phys.* **61** 639
[3] Hofmann S and Münzenberg 2000 *Rev. Mod. Phys.* **72** 733
[4] Hofmann S *et al* 2004 *Nucl. Phys.* A **734** 93
[5] Morita K *et al* 2004 *J. Phys. Soc. Jpn.* **73** 2593
[6] Morita K *et al* 2007 *J. Phys. Soc. Jpn.* **76** 045001
[7] Oganessian Y *et al* 2006 *Phys. Rev.* C **74** 044602
[8] Oganessian Y 2007 *J. Phys. G: Nucl. Part. Phys.* **34** R165
[9] Oganessian Y *et al* 2010 *Phys. Rev. Lett* **104** 142502
[10] Dong T and Ren Z 2010 *Phys. Rev.* C **82** 034320
[11] Bayram T and Yilmaz A H 2013 *Mod. Phys. Lett.* A **28** 1350068
[12] Gamow G 1928 *Z. Phys* A **51** 204
[13] Zhang Di-Da *et al* 2010 *Phys. Rev.* C **81** 044319
[14] Medhat M E 2012 *Ann. Nucl. Energy* **45** 73
[15] Akkoyun S 2013 *Ann. Nucl. Energy* **55** 297
[16] Athanassopoulos S, Mavrommatis E, Gernoth K A and Clark J W 2004 *Nucl. Phys.* A **743** 222

[17] Bayram T, Akkoyun S and Kara S O 2014 *Ann. Nucl. Energy* **63** 172
[18] Akkoyun S, Bayram T, Kara S O and Sinan A 2013 . *J. Phys.* G **40** 055106
[19] Haykin S 1999 *Neural Networks: A Comprehensive Foundation* (International: Prentice-Hall)
[20] Audi G, Bersillon O, Blachot J and Wapstra A H 2003 *Nucl. Phys.* A **729** 3
[21] Gupta M and Burrows T W 2005 *Nucl. Data Sheets* **106** 251
[22] Viola V E and Seaborg G T 1966 *J. Inorg. Nucl. Chem.* **28** 741