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^{116,117,118,119,120,124}Sn ve ^{233,234,235,236,238}U İzotopları İçin Dev Dipol Rezonans Enerjilerinin Kestirimi

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Anahtar kelimeler
Dev dipol rezonans,
E1 geçişi,
yapay sinir ağları

Özet

Dev dipol rezonans (GDR) parametrelerini elde etmek için birçok deneysel ve teorik metot uygulanmaktadır.Bu çalışmada, Sn ve U izotopları için GDR enerjileri, yapay sinir ağları (YSA) metodu ile tahmin edilmiştir. Sonuçlara göre, YSA'nın eğitiminde deneysel verilerden ortalama sapma, %1 seviyesindedir. Sn ve U izotopları için tahmin edilen enerjilerdeki ortalama kare hata, 0,034 MeV'dir.Teorik bir model için ise hata, 0,061 MeV'dir.Bu sonuç, GDR enerjileri üzerinde ANN tahmininin, teorik hesaplamalardaki sonuçlardan daha iyi olduğunu göstermektedir.

Giant Dipole Resonence Energy Predictions For ^{116,117,118,119,120,124}Sn and ^{233,234,235,236,238}U Isotopes

Keywords
Giant dipole resonance,
E1 transition,
artificial neural networks

Abstract

Several experimental and thoretical methods are applied for obtaining giant dipole resonance (GDR) parameters. In this study, GDR energies for Sn and U isotopes have been predicted by using artificial neural network (ANN) method. According to the results, in the training of the ANN, the mean deviations from the experimental values are in the order of 1%. The mean square error for the estimated energies of Sn and U isotopes is 0.034 MeV. Similar error value belonging to a theoretical model calculation is 0.061 MeV. This result indicates that ANN predictions on GDR energy give better results according to the theoretical results.

1. Introduction

Although it has been about 70 years since the discovery of giant dipole resonance (GDR), this interesting phenomenon has been still extensively treating by many researchers. GDR name is given to the broad peaks appearing in gamma-ray spectra. These peaks are lied in about 15-25 MeV energy range with about 3-10 MeV peak width. The resonance is originated from collective motion of the nucleon inside the nucleus (Spicer, 1969). The GDR were first observed by Bothe and Gentner in 1937 (Bothe ve Gentner 1937) and the existence of this resonance were shown first by Baldwin and Klaiber (1948) in photonuclear reactions. In order to get information about GDR, many experiments have been performed by using gamma-rays. When gamma-rays are passing near the atomic nucleus, the nucleus is excited and a GDR occurs. The protons inside the nucleus are pulled to one side of the nucleus because of gamma-rays and the neutrons stay in their places. From this effect, protons oscillate and by the nuclear force neutrons are forced to the protons to bring their original place. After oscillating is stopped, the excess energy is emitted via gamma-rays or neutrons (Kawatsu ve Shevin, 2003).GDR corresponds to the main frequency for the absorption of electric dipole radiation by the nucleus.

Dipole electric (E1) gamma-transitions are dominant among the other multipolarities. GDR are strongly displayed in E1 gamma-transitions of photoabsorption and gamma-decay of the nucleus. Thus, GDR parameters can be obtained from investigations of the E1 gamma transitions. An experimental database including accurate GDR parameters is very important in nuclear reaction codes for good modelling of E1 gamma-ray cascades in highly excited nuclei (Plujko et al. 2011). The GDR can be observed in lightest (3He) and heaviest (^{232}Th) nuclei (Chomaz, 1997). Almost all the information about GDR comes from photoabsorption experiments. The energy of the GDR (E_{GDR}) depends on the mass number of the nucleus as given below (Berman ve Fultz, 1975)

$$E_{GDR} = 31.2A^{-1/3} + 20.6A^{-1/6} \text{ (MeV)} \quad (1)$$

Several experimental and theoretical methods are applied for obtaining GDR parameters indluding E_{GDR} (Schiller ve Thoennessen, 2007). In this work, we used compiled experimental GDR energy parameters (Int. Kyn.1) for predictions of EGDR. The used parameters have been obtained by Lorentzian curves fit to the total photoneutron cross section data from EXFOR library (Int. Kyn. 2) for about 110 nuclei (Dietrich ve Berman, 1998, Jianfeng ve Zongdi, 1995). By applying artificial neural network (ANN) method on the data, we predicted E_{GDR} for some Sn and U isotopes. After obtaining the energies, we have compared ANN results with theoretical results (Int. Kyn. 3). Theoretical predictions of the GDR energies are for about 6000 nuclei with 14<=Z<=110 lying between the proton and the neutron driplines. These GDR parameters have been provided by Goriely et al. (Goriely, 1998) and resulted from a fit of microscopic calculations of the Lorentzian functions. It has been seen that the ANN results give better results than the theoretical calculation for EGDR. This method is recently used in many fields on nuclear physics such as determination of nuclear binding energies (Bayram et al., 2014), identification of nuclear radius (Akkoyun et al. 2013), estimation of beta decay half-lives (Costris et al., 2007), estimation of glabal radiation (Günoğlu et al., 2011), obtaining gamma dose rates (Yeşilkanat ve ark., 2014), prediction of alpha decay half-lives of superheavy nuclei (Bayram et al., 2014), predictions of potential energy curves of Ti isotopes (Akkoyun et al., 2013), estimation of electric quadrupole transitions probability in nuclei (Akkoyun et al., 2015) and predictions of fission barrier of some superheavy nuclei (Akkoyun and Bayram, 2014).

2. Material ve Methods

As a nonlinear mathematical method, ANN mimics the human brain functionality and consists of several processing units called neurons (Haykin, 1999). ANN is composed of layers. From this property, it is named as layered ANN. Also, because the data flows forward direction from input layer to output layer, this is named layered feed-forward ANN. In the layers, thereare neurons. The neurons in different layers are connected each other via adaptive synaptic weights. Input layer neurons receive the data from environment and the output layer neurons give the result as close as to the desired ones. The number of the neurons in input layer depends on the problem variables. Also, the number of the output neurons depends on what the desired result. Furtermore, there is no rule for the numbers of hidden layer and neuron. One hidden layer is generally enough for all type of the problem. The neuron number in this layer differs to the problem nature.

ANN includes two main stages. These stages are training and test. First, the data belonging to the problem is divided into two parts. One of them is for the training of ANN and the rest is for the test of ANN. In this study, the GDR energy data except for Sn and U isotopes was used for the training. The test data includes GDR energies for Sn and U isotopes. In the training stage by given data, the adaptive weights between neurons are adjusted to construct ANN. Because of this, the weights play an important role for solving the problem. If weight is adjusted well, it works for all similar type data which have never seen in the training stage. Therefore, this training stage continues until the acceptable error level. The error is calculated by the difference between desired and the ANN outputs. This is done by using mean square error (MSE) formula given below.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(D_i - O_i)^2 \tag{2}$$

where D_i and $O_i$are desired and estimated results, respectively, N is the total number of data points. This formula can be applied for training and test stages separately. After the successful construction with acceptable error, ANN has been tested on the test data in the test stage by using the adjusted weights. The data used in this stage is new for the ANN. If the constructed ANN by the weights gives the result well for the test data, one can confidently say that ANN has generalized the data. For further information about ANN, we refer to reader to Haykin (1999).

In this study, one input layer with three neurons, one output layer with one neuron ANN topology has been used. The input neurons correspond to the proton number (Z), neutron number (N) and mass number (A) of the nuclei. The aim of the work is to obtain GDR energies of ^{116,117,118,119,120,124}Sn and ^{233,234,235,236,238}U isotopes. The type of hidden neuron activation function was hyperbolic tangent. The learning rule was Levenberg-Marquardt (Levenberg, 1944, Marquardt, 1963) algorithm. In the present study, neural network software NeuroSolutions v6.02 (Int. Kyn. 3) has been used for the calculations.

3. Results and Discussion

GDR energies (E_{GDR}) of Sn and U isotopes have been estimated by using ANN method. Different neuron numbers (h) in the hidden layer have been tried for obtaining good results. The better ones have been for h=4,6 and 8. Because it is 3 and 1 variables in input and output layers, respectively, the used structures of the ANN have been (3-4-1), (3-6-1) or (3-8-1). The number of the weights are 16, 24 or 32 according to the formula given below.

$$\text{Number of weights} = p \times h + h \times r \tag{3}$$

where p, h and r are neuron numbers in input, hidden and output layers, respectively. In figure 1, the (3-8-1) ANN topology has been shown as an illustration.

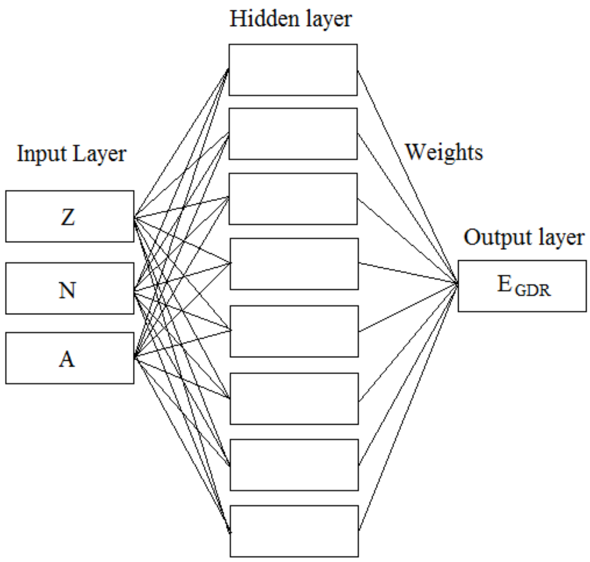

Figure 1. The (3-8-1) ANN topology with 32 weighted connections.

After adjusting the weights in training stage, the estimations have been first performed onthe training data. The MSE values are 0.272, 0.221 and 0.172 MeV for h=4,6 and 8, respectively. This indicates that among these hidden neuron numbers, h=8 gives best results due to its small MSE value. But we can not say that the bigger the neuron number is the best the results are. Because the results for the big h numbers in trying for finding optimum value have not give the better estimations. In figure 2, the difference between experimental values and the ANN predictions on EGDR on training data has been shown for h=8. The largest deviations have been seen in small mass numbers. The maximum absolute error is 2.09 MeV for ^{16}O. As can be seen in the figure that the errors are generally lied between 0.05 and 0.2 MeV.

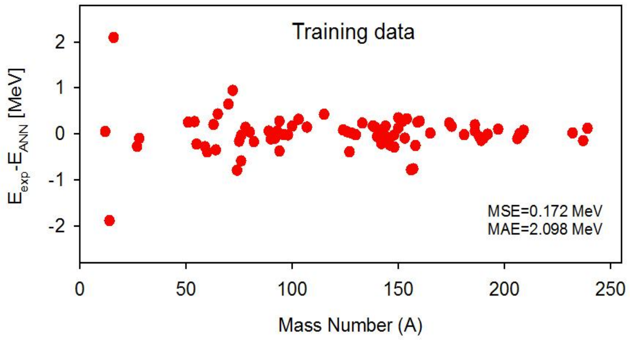

Figure 2. Difference between experimental values and ANN predictions on GDR energies for h=8.

By using the adjusted weights, the ANN has been tested on the test data which has been never seen before by the ANN. The data was for ^{116,117,118,119,120,124}Sn and ^{233,234,235,236,238}U isotopes. In Table 1, ANN estimations for EGDR have been listed. The smallest deviation from experimental data has been obtained as 0.05 MeV for 116Sn isotope. Besides larger one has been 0.28 MeV for 235U. The MSE value is 0.034 MeV for h=8. The mean value of $E_{GDR}$is 13.6 MeV. Therefore, this MSE value corresponds to about 0.25% error levelan done can confidently say the method is successful in prediction of EGDR.

Similar tests have been done for h=4 and 6. The corresponding MSE values are 0.065 and 0.054 for h=4 and h=6, respectively. This relatively big values still acceptable for the prediction due to their small error percentages of 0.48% and 0.40%. Additionally we have compared the results from theoretical calculation and experimental values. The MSE value is 0.061 MeV. This value is close to the results for h=4. The minimum and maximum deviations are 0.04 and 0.35 MeV for 238U and 234U, respectively.

4. Conclusions

The ANN method has been used for prection of giant dipole resonance energies of the selected Sn and U nuclei. The results indicate that the method is capable for this task. Different nuclei has been used for the estimations instead of Sn and U. Similar results have been obtained with small MSE values. Therefore, the method does not work for only these istopes, but works for all the desired nuclei. Therefore, if someone wants to estimate this energy value with no experimental value, the method is confidently used. The MSE values for the predictions are in the order of about 0.25-0.50%.

Table 1. Experimental data, ANN predictions and theoretical data of E_{GDR} forSn and U isotopes.

Z	N	A	Experimental Energy [MeV]	ANN Prediction Energy [MeV]	Difference[MeV]	Theoretical Energy [MeV]	Difference[MeV]
50	116	66	15.56	15.51	+0.05	15.85	-0.29
50	117	67	15.64	15.41	+0.23	15.81	-0.17
50	118	68	15.44	15.33	+0.12	15.78	-0.34
50	119	69	15.53	15.26	+0.27	15.74	-0.21
50	120	70	15.37	15.21	+0.16	15.70	-0.33
50	124	74	15.28	15.20	+0.08	15.55	-0.27
92	233	141	11.08	11.20	-0.12	10.80	+0.28
92	234	142	11.13	11.19	-0.06	10.78	+0.35
92	235	143	10.90	11.18	-0.28	10.84	+0.06
92	236	144	10.92	11.17	-0.25	10.83	+0.09
92	238	146	10.94	11.15	-0.21	10.90	+0.04

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