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^{51}Cr Radyoizotopunun Üretim Tesir Kesitinin Yapay Sinir Ağları ile Elde Edilmesi

Serkan Akkoyun[1]*, Tuncay Bayram[2]

[1]Sivas Cumhuriyet Üniversitesi Fen Fakültesi Fizik Bölümü, Sivas
[2]Karadeniz Teknik Üniversitesi Fen Fakültesi Fizik Bölümü, Trabzon

ÖZET:
Amaç: Radyoizotopların tıpta teşhis ve tedavide kullanımları gün geçtikçe artmaktadır. Bu radyoizotopların üretimini verimli kılmak amacıyla, üretim tesir kesitlerinin doğru olarak hesaplanması gerekmektedir. Deneysel verilerin olmadığı durumlarda, tesir kesitleri çeşitli teorik yollarla hesaplanmakta ve istenilen enerji değerine karşı gelen değer elde edilmektedir. Çalışmamızda, farklı bir yaklaşım olarak yapay sinir ağları kullanılarak, bilinmeyen enerjilerdeki tesir kesitlerinin tahmininin yapılması için bir alternatif model ortaya koyulmuştur.
Gereç ve Yöntem: ^{51}Cr radyoizotoplarının nötron indüklenmiş reaksiyonlarla üretilmesine ait tesir kesitlerini elde etmek amacıyla, yapay sinir ağları metodu kullanılmıştır. Literatürde mevcut olan bu tesir kesiti verileri alınarak, %80'i ağın eğitiminde kullanılmış ve kalan %20'si ile ağın testi gerçekleştirilmiştir. Yapay sinir ağlarının girdileri, gelen nötron enerjileri olup çıktısı ise tesir kesitidir. Birçok denemeden sonra en iyi sonucu veren gizli katman nöron sayısı olarak 20 kullanılmıştır.
Bulgular: Elde ettiğimiz sonuçlara göre, yapay sinir ağları metodu, radyoizotop üretim tesir kesitlerini tahmin etmede alternatif bir yöntem olarak kullanılabilir. Eğitim verileri üzerinden yapılan tahminlere ait MSE değeri 0,178 barn olarak elde edilirken, test verileri üzerindeki MSE değeri ise 0,155 barn'dır. Ağın, eğitim ve test verileri üzerindeki tahminlerine ait korelasyon katsayı değerleri sırasıyla, 0,93 ve 0,95 olarak bulunmuştur.
Sonuç: Literatürdeki deneysel sonuçlarla kıyaslandığında, yapay sinir ağlarının verdiği sonuçların, tesir kesitini tahmin etmede alternatif olarak kullanılabileceği sonucuna varılmıştır. Bu metodun bir avantajı, karmaşık matematiksel formülasyona girmeden, hızlı bir şekilde sonuçları elde etmeye imkan tanımasıdır. Bu çalışmadan elde edilen sonuçlar, herhangi bir izotop kullanılarak gerçekleştirilecek her türlü reaksiyona ait tesir kesitlerinin, yapay sinir ağları yöntemi kullanılarak elde edilebileceğinin bir göstergesidir.
Anahtar Kelimeler: *Radyoizotop, Tesir kesiti, Cr izotopu, Yapay sinir ağları*

Production Cross-Section of ^{51}Cr Radioisotope Using Artificial Neural Networks

ABSTRACT:
Purpose: The use of radioisotopes in diagnosis and treatment in medicine is increasing day by day. In order to make the production of these radioisotopes efficiently, the production cross-sections must be calculated correctly. In the absence of experimental data, cross-sections are calculated in various theoretical ways and the data corresponding to the desired energy value is obtained. In our study, using artificial neural networks as a different approach, an alternative model is presented to estimate cross-sections at unknown neutron energies.
Material and Methods: Artificial neural networks method was used to obtain cross-sections of ^{51}Cr radioisotopes produced by neutron-induced reactions. By taking this cross-section data available in the literature, 80% of it was used in the training of the network and the remaining 20% was used in the test. The inputs of artificial neural networks are the incident neutron energies and the output is the cross-section. Hidden layer neuron number 20 was used that gave the best results after many trials.
Results: According to the results we have obtained, the artificial neural network method can be used as an alternative method to estimate the radioisotope production cross-sections. While the MSE value of the estimations made over the training data is 0.178 barn, the MSE value on the test data is 0.155 barn. Correlation coefficient values of the predictions of the network on training and test data were found as 0.93 and 0.95, respectively.
Conclusion: When compared with the experimental results in the literature, it is concluded that the results of artificial neural networks can be used as an alternative to estimate the cross-section. An advantage of this method is that it allows to obtain results quickly without going into complex mathematical formulation. The results obtained from this study are an indication that cross-sections of any reaction to be performed using any isotope can be obtained by using artificial neural networks method.
Keywords: *Radioisotope, Cross-section, Cr isotope, Artificial neural networks*
**Corresponding author: Serkan Akkoyun, email: sakkoyun@cumhuriyet.edu.tr*

INTRODUCTION

The use of radioactive isotopes used in the diagnosis and treatment of diseases in medicine has increased considerably today. In order to minimize the damage these radioisotopes can cause to the patient, it is preferred that their half-life is as short as possible and their energy is as low as possible. However, since short-lived radioisotopes cannot be stored, they must be produced using a generator during use if the health center is far from the production center. In order for the radioisotopes to be produced by the generators through nuclear reactions to be produced efficiently, it is necessary to know the production cross-sections. Knowing the reaction energies to realize the most efficient production is one of the key points. Therefore, the desired radioactive isotopes can be produced in the most efficient way with incident particles at energies suitable for the target material (Martin, 2013; Bailey et al., 2014).

Chromium has four naturally occurring stable isotopes which are ^{50}Cr, ^{52}Cr, ^{53}Cr and ^{54}Cr with the abundances of 4.35%, 83.79%, 9.50%, and 2.37%, respectively. We focused on the production of the ^{51}Cr isotope, which is used as red cell label and can also be used as a platelet label. This medical radioisotope can be produced by neutron-induced reactions performing on stable ^{50}Cr isotope. With a radioactive half-life of 27.7 days, it decays by electron capture. Gamma and x-ray radiation from this radioisotope can be fatal in large doses or sustained exposure. Therefore, ^{51}Cr should be stored in lead containers or behind lead shield and carried only with protective gear attached. In our study, we studied the determination of the values of the production cross sections of the production of the ^{51}Cr radioisotope from the stable Cr isotope by neutron-induced nuclear reaction according to different neutron energies (Kenny, et al., 1977; Kapchigashev and Popov, 1964).

Recently, ANN has been used in many fields in nuclear physics. Among them the studies performed by our group on the cross-sections are estimations of heavy-ion fusion reaction cross-section (Akkoyun, 2020), determination of photonuclear reaction cross-section on Ca isotopes (Akkoyun, and Kaya 2020) and p-shell nuclei (Akkoyun et al., 2020). For this purpose, we used artificial neural networks method, which is a machine learning method. Artificial neural networks are a mathematical method that models the work of the brain function of living beings in terms of learning. In the study where we estimated the production cross-section for ^{51}Cr using the cross-section data available in the literature (Kopecky, 1997), we saw that artificial neural networks are an alternative tool suitable for this purpose. Thus, production cross sections corresponding to energies not available in the literature can be rapidly produced without the need for complex mathematical operations. We also compared our results with the experimental data available in the literature for ^{51}Cr, and we found that our results were consistent with these data.

MATERIAL and METHODS

Artificial neural network (ANN) is a mathematical model that mimics the brain functionality. It consists of several processing units called neurons in mainly three different layers (Haykin, 1999). Because of it has layers, it is named as layered ANN. In one of the most common type of ANN, the data flow forward direction from input layer to output layer. Therefore this type of ANN, which is also used in this study, is named as layered feed-forward ANN. The neurons only in different layers are connected each other via weighted connections. The neurons in the input layer receive the data and the output layer neurons give the result. According to the problem variables, the numbers of the neurons in input and output layers are determined. Between these two layers there is a hidden layer which is seen as a black box. Besides, the number of the hidden layer can also be change from 1 to more leading deep-learning. There is no rule for the determination of the numbers of hidden layer and its neurons. After many trials for the problem, the numbers of hidden layer and the neurons can be taken into account that gives the results as close as to the desired values.

ANN consists of two main stages, one of which is the training and the other is the test stage of the results of the training. The data for the problem is usually divided into two parts, 80% and 20%, and 80% is used for training of ANN and 20% for the test of ANN. The main goal in training is to determine the weight values of the connections between each neuron in different layers. In the training stage of this work, Levenberg–Marquardt (Levenberg, 1955; Marquardt, 1963) back-propagation algorithm was used. After determining the weight values that gives the best results, the desired values in the training data is tried to be produced with the constructed network. The error between the outputs produced by the network and the desired outputs is determined by MSE. MSE gives the average of the squares of the difference between the desired and the neural network output values. It is not enough to see that the network gives successful results on the training data. It should also be determined whether the network can generalize on this type of data. This is done on the 20% data set previously allocated. The constructed network is applied on the test data and the outputs of the network are compared with the desired outputs. If the MSE values are below the desired level in the test stage also, it can be said that this network is successful in solving the given problem. In our study, we consider the reaction in which neutrons are sent on the ^{50}Cr stable isotope to produce the ^{51}Cr radioisotope. For different neutron energies, we tried to obtain the cross-section of this reaction with ANN. We obtained the data from the literature from a experimental data library (Kopecky, 1997). We took the neutron energies as inputs of ANN and logarithm of the production cross-section as output. We used the values of 1 as the number of hidden layer and 20 as the number of hidden layer neurons, which enabled us to give the closest results to the desired outputs of the problem. For further information about ANN, we refer to reader to the reference (Haykin, 1999).

RESULTS and DISCUSSIONS

The differences between literature data and the ANN estimations on the training data have been presented in Figure 1. As can be seen in the figure that the maximum differences are about +1 and -1 for the logarithm of the cross-sections in units of barn. From the low-energies to the about 10^3 keV, the differences decrease linearly. In energy values between 10^3 and 10^5 keV, fluctuations are observed in the differences between them. The differences in this range are the cause of the 1 barn difference, which is also the maximum. It is seen that the difference between the literature values and ANN estimates is concentrated around zero for the incident neutron energies after 10^5 keV. As a result of the similar examination on the test data (Figure 2), it is seen that the same behavior is observed. Again, maximum deviations from the literature data were observed in the range of 10^3 and 10^5 keV and it was found to be 1 barn.

We tried to see the reason of the differences by drawing the literature data and ANN estimations in the same plot for the training and test data separately. As seen in Figure 3, literature data have resonance peaks in the energy range of 10^3 and 10^5 keV. In our estimates made with artificial neural networks, it is seen that the general trend is caught, although it is naturally difficult to fully capture these peaks. However, the fact that the peak values were not fully reproduced led to the emergence of bigger differences in this region. In the low energy parts up to 10^3 keV, it is seen that the ANN estimates show values close to the literature, but in an opposite behavior. It is clearly seen that the ANN estimates are in a one-to-one agreement with the literature data at high energies above 10^5 keV. In Figure 4, similar inspection was carried out on the test data. It was observed that the similar behavior in the training data was observed here, and although the trend in the resonance region was caught, the peak values could not be obtained exactly. The MSE values for the training and the test data obtained as 1.178 and 0.155, respectively. The correlation coefficients are 0.93 and 0.95 for the training and test data which shows the method is quite useful for the estimation of production cross-sections.

Along with the literature data we use in our ANN calculations, the production cross-section values of ^{50}Cr(n,γ)^{51}Cr neutron induced reaction including the existing experimental data (Pomerance, 1952; Kapchigashev and Popovare, 1964; Sims and Juhnke, 1968; Stieglitz et al., 1971; Gleason, 1975; Kenny et al., 1977; Venturini and Pecequilo, 1977; Simonits et al., 1984) given in Figs. 5 and 6 together with the ANN results. It is clear from the figures that ANN results are generally compatible with the experimental data. In Figure 5, training data of ANN are shown in the same graph along with all experimental data in the literature. Especially in the high neutron energy part, it is seen that the ANN results are quite compatible with the experimental data. Figure 6 shows the comparison of test data with experimental data. In both graphs, it is seen that only one experimental value in the resonance region is far from ANN results. ANN results appear to be fairly close to all other experimental data points. It is seen that ANN produces values for cross-section data corresponding to many neutron energies for which there is no experimental data in the literature.

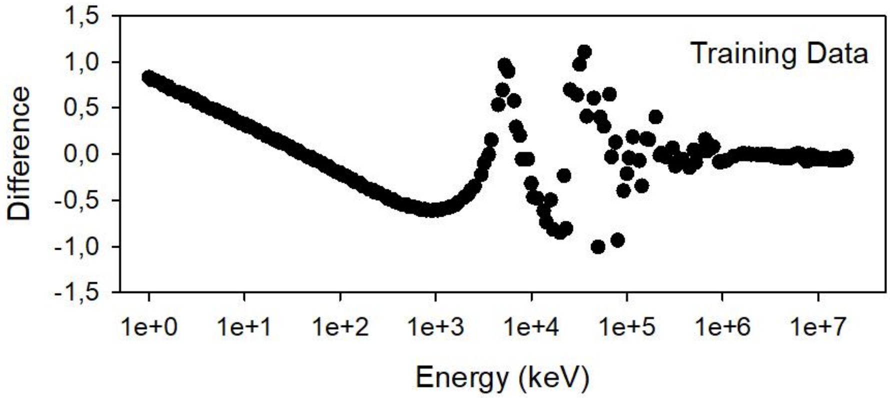

Figure 1. Differences between the literature data and ANN estimations on the training data for ^{51}Cr production cross-sections.

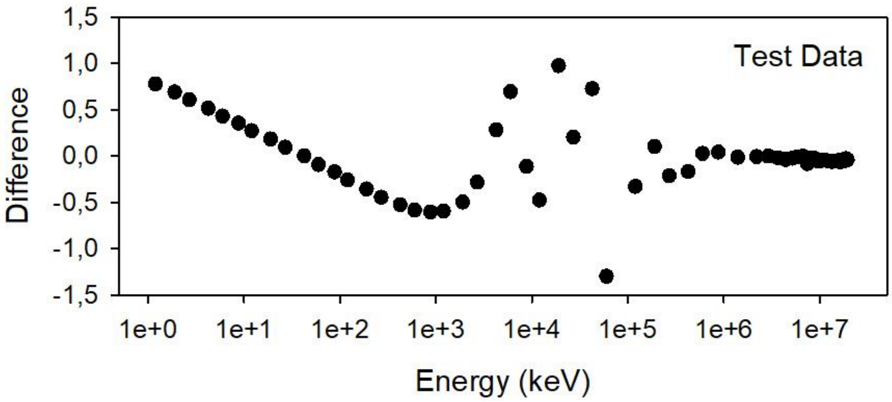

Figure 2. The same as Figure 1 but for the test data.

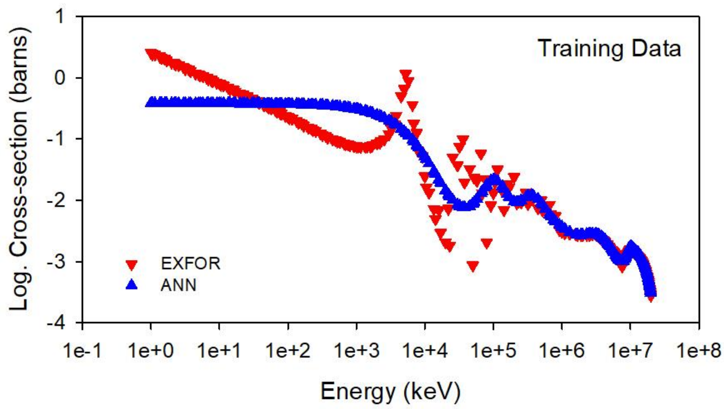

Figure 3. Logarithms of the literature data (Kopecky, 1997) and ANN estimations on the training data for ^{51}Cr production cross-sections.

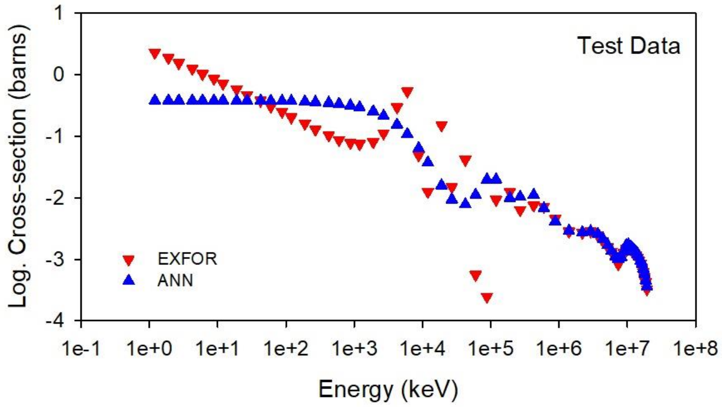

Figure 4. The same as Figure 3 but for the test data.

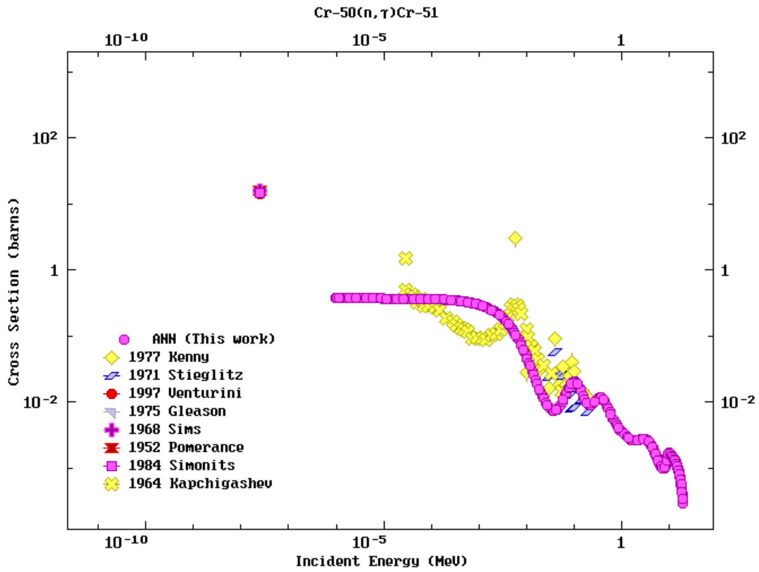

Figure 5. The ANN estimated cross-sections of training data for $^{50}Cr(n,\gamma)^{51}Cr$ reaction as a function of incident neutron energy together with the available experimental data.

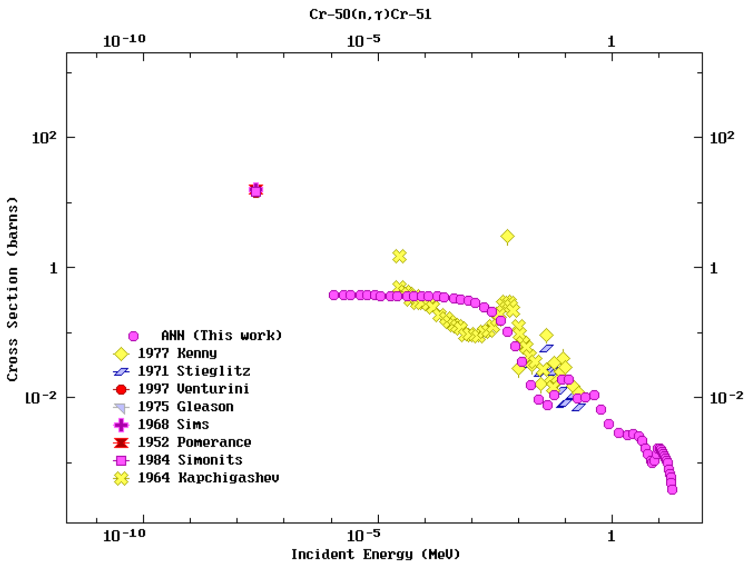

Figure 6. The ANN estimated cross-sections of test data for $^{50}Cr(n,\gamma)^{51}Cr$ reaction as a function of incident neutron energy together with the available experimental data.

CONCLUSION

In this study, we obtained the cross section values of ^{51}Cr radioisotopes from stable ^{50}Cr isotopes by neutron induced reaction by using artificial neural networks method. According to the results we have obtained, this method is a suitable method for this purpose. Apart from fluctuations in the resonance region, we have seen that with ANN, we can generally capture behaviors in the production cross-sections. As a result, by using the ANN method, the cross-section information required for any radioisotope production in a nuclear reaction can be easily obtained by using ANN. Thus, it has been seen that approximate values of cross-sections corresponding to energies that do not have experimental value in the literature can also be obtained easily and quickly by ANN.

Conflict of Interest

There is no conflict of interest.

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