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Estimations of Radiation Yields for Electrons in Various Absorbing Materials

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Abstract. In this paper radiation yields for electrons in various absorbing material water, Carbon, Aluminum, Copper, Lead and Uranium in the initial electron energy range between 10 keV to 1 GeV have been estimated. For this purpose artificial neural network method has been used. It has been seen that the results are in good agreement with the available theoretical values. The root mean square error values have been found between 0.00031 and 0.0071 MeV.

Keywords: Radiation yield, atomic number, artificial neural networks

Çeşitli Soğurucu Malzemelerde Elektronlar için Radyasyon Verimlerinin Kestirimleri

Özet. Bu makalede, su, Karbon, Aluminyum, Bakır, Kurşun ve Uranyum soğurucu malzemelerinde, 10 keV ile 1 GeV enerji aralığında elektronların radyasyon verimleri kestirildi. Bu kestirim için, yapay sinir ağları metodu kullanıldı. Çalışmada elde edilen sonuçların, mevcut teorik değerler ile uyumlu olduğu görüldü. Kare ortalama karekök hata değeri, 0,00031 ile 0,0071 MeV aralığında bulundu.

Anahtar Kelimeler: Radyasyon verimi, atom numarası, yapay sinir ağları

1. INTRODUCTION

While a light charged particle slowing down in an absorbing material, a fraction of its initial kinetic energy is emitted as radiation. The fraction of electron initial kinetic energy lost to radiative losses is defined as radiation yield [1, 2]. The radiation energy is generally in the form of bremsstrahlung. Therefore this yield is sometimes called as bremsstrahlung yield. Furthermore it can also be from positron annihilation and in the form of characteristic radiation. The radiation yield is almost zero for heavy charged particles. For the light charged particles, the radiation yield and energy radiated per charged particle are determined from stopping power data as

$$Y[(E_K)_0] = \frac{\int_0^{(E_K)_0} \frac{S_{rad}(E)}{S_{tot}(E)} dE}{\int_0^{(E_K)_0} dE} = \frac{1}{(E_K)_0} \int_0^{(E_K)_0} \frac{S_{rad}(E)}{S_{tot}(E)} dE \tag{1}$$

$$E_{rad} = (E_K)_0 \cdot Y[(E_K)_0] = \int_0^{(E_K)_0} \frac{S_{rad}(E)}{S_{tot}(E)} dE \tag{2}$$

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The estimation of the radiation yield gives a sign of the potential bremsstrahlung hazard of an electron source. In order to keep bremsstrahlung to a minimum, the materials with low Z numbers can be used as a shield to stop electrons. This shield can be surrounded by a high Z number material to absorb the bremsstrahlung photons.

In this study, the radiation yields for various absorbing material were estimated for different initial electron kinetic energies. In recent years, ANN has been used in many fields in nuclear physics [3, 4], such as, discrimination between neutron and gamma-rays [5], developing nuclear mass systematic [6], estimating beta decay half-lives [7], beta decay energies [8], determination of alpha decay energies [9], determination of gamma dose rates [10], determination and mapping the spatial distribution of radioactivity of natural spring water [11] and obtaining nuclear charge radii [12].

2. MATERIAL and METHODS

ANN is a mathematical model that mimics the human brain. They consist of several processing units named as neurons. The neurons are connected to each other via adaptive synaptic weights [13]. ANN is a very powerful tool which can be used when standard techniques fail to estimate the correlation between the data. The ANN is composed of three main layers. The first layer corresponds to the input layer, the intermediate layer is called the hidden layer and the last one is the output layer. The number of the neurons in these layers depends on the problem. Input and output layer neuron numbers depend on the input and output variable numbers. There is no rule for the numbers of the hidden layer and neuron. Generally one hidden layer is enough for all type of the problem. The number of the neurons in this layer differs to the problem nature.

In this study, one input layer with 1 neuron, 1 hidden layer with 4 neurons (h = 4) and 1 output layer with 1 neuron ANN structure were used (Fig. 1). The total adjustable weights were 8. The input layer neuron receives the data from outside and the output layer neuron gives the results. The data is transmitted via weighted connections between the neurons. The sigmoid like tangent hyperbolic functions (Eq.3) were used for hidden and output units. It has been proven that one hidden layer and sigmoid like activation function in this layer are sufficient to approximate any continuous real function [14].

$$\tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

ANN process has two main step: training and test. In this work, a backpropagation algorithm with Levenberg–Marquardt [15, 16] for the training of the ANN was used. The whole data belonging to the problem is divided into two parts. One of them is used for the training and the other is used for the test. In this study, 80% and 20% of the data was used for the training and the test, respectively. In the training stage, ANN modifies their weights until an acceptable error level between desired and predicted outputs is attained. The error function which measures this difference was mean square error. After an acceptable error level, the trained ANN is tested over the data of interest. The error is calculated by the difference between desired and the ANN outputs. This is done by using root mean square error (RMSE) formula given in Eq.4. For further and general background for ANN, the reader is referred to [15].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - d_i)^2} \tag{4}$$

In Eq.4, d_i and y_i are desired and estimated results, respectively. N is the total number of data points. After the successful construction, ANN has been tested on the test data in the test stage by using the 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.

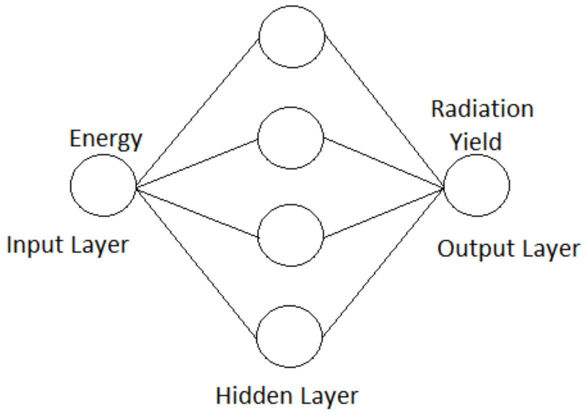


Fig. 1 ANN architecture of 1-4-1 for estimation of radiation yield for various materials

3. RESULTS and DISCUSSIONS

In this study, we have estimated radiation yield (Y) values for the absorbing materials in the energy ranges from 10 keV to 1 GeV. The data has been taken from [17]. In this reference, the Y values were calculated by using ESTAR computer program. The ESTAR calculates stopping power, density effect parameters, range, and radiation yield tables for electrons in various materials. In this computer program, radiation yield which is average fraction of the initial kinetic energy of an electron that is converted to bremsstrahlung energy as a particle slows down to rest, calculated in the continuous-slowing-down approximation [18, 19]. This is important only for electrons.

The absorbing materials have been chosen as water, carbon, aluminum, copper, lead and uranium. In the left columns of Fig. 2 and 3, the train results have been shown. As can be seen from these figures that the ANN results are in good agreement with the theoretical results. The root mean

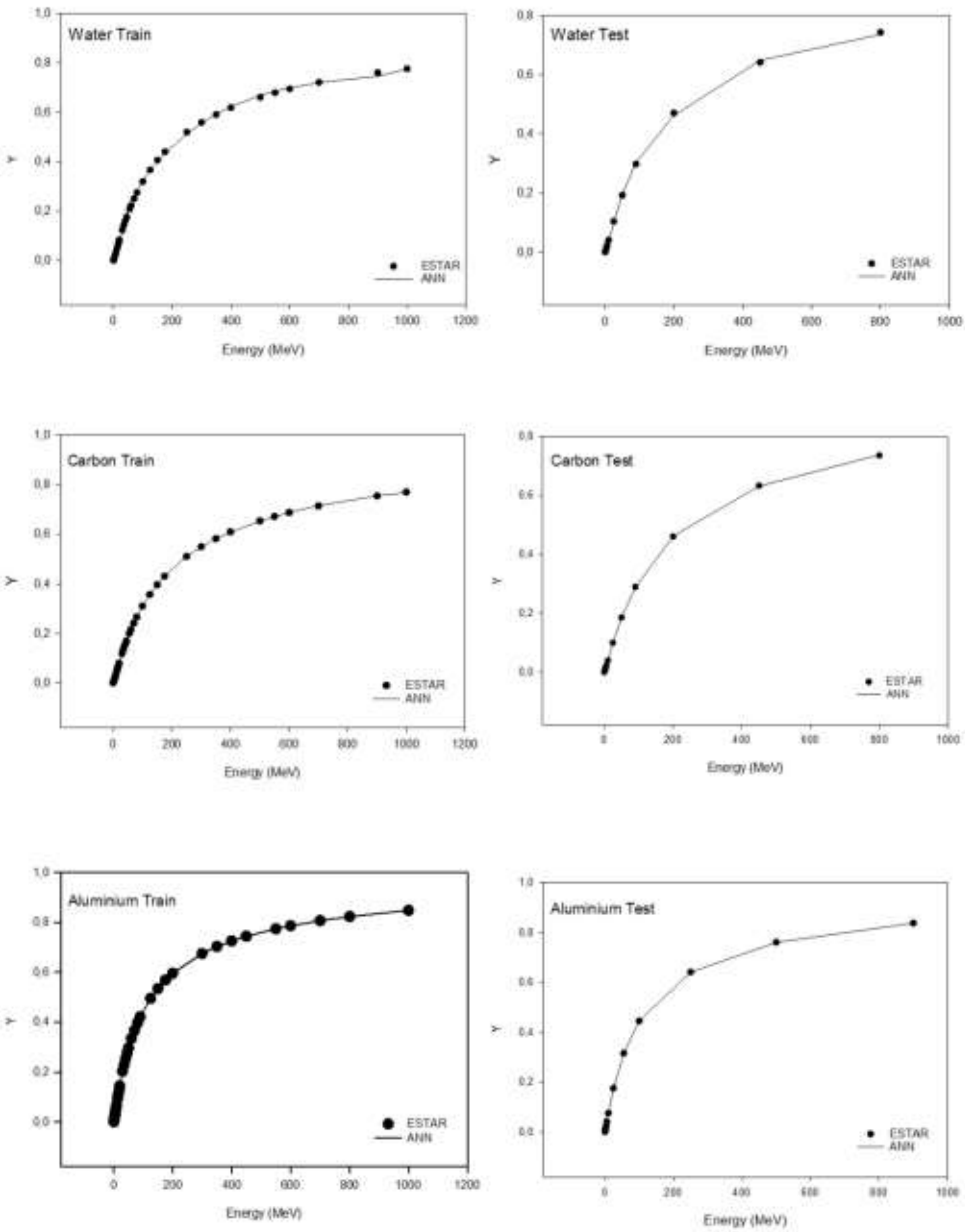


Fig. 2 Radiation yields (Y) for water, carbon and aluminum materials for train (left) and test (right) data

square error values are, 0.0038 for water, 0.00057 for carbon, 0.00031 for aluminum, 0.0015 for copper, 0.0071 for lead and 0.0063 for uranium. It is clear in the figures that Y values increase with electron energy. The increase is faster until about 100 MeV, especially for high Z materials such as lead and uranium. After 100 MeV, the value starts to become stable.

After testing the constructed ANN over the train data, we have tested the network on the test data which has been never seen in the training stage. In the right columns of Fig. 2 and 3, the test results have been shown. As can be seen in these figures that the ANN results are in good agreement with the theoretical results. The root mean square error values are, 0.0042 for water, 0.00076 for carbon, 0.00031 for aluminium, 0.0014 for copper, 0.0068 for lead and 0.0070 for uranium. It is clear in the figures that Y values increase with electron energy. The increase is faster until about 100 MeV, especially for high Z materials such as lead and uranium. After 100 MeV, the value starts to become stable. As is seen in Fig. 4 that the radiation yield increases with Z number of the absorbing material.

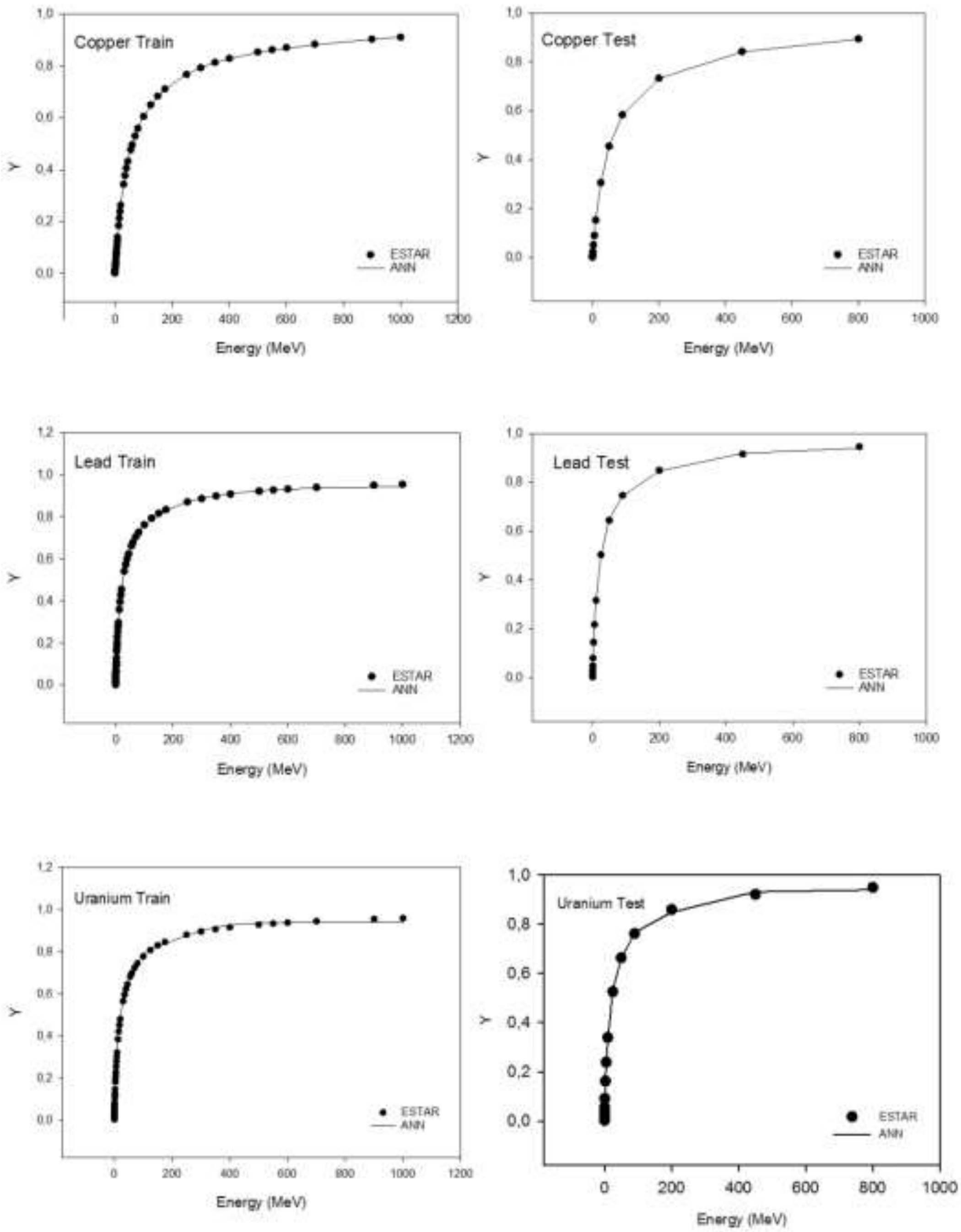
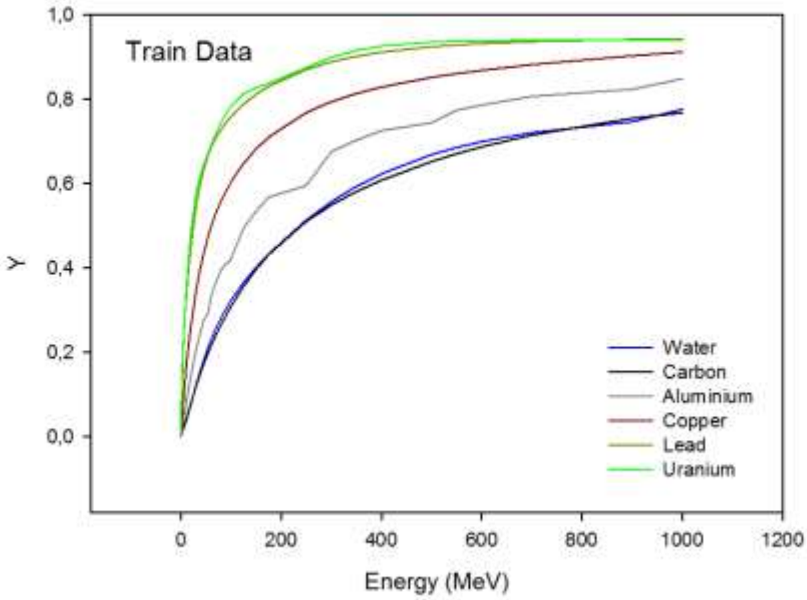


Fig. 3 Radiation yields (Y) for copper, lead and uranium materials for train (left) and test (right) data



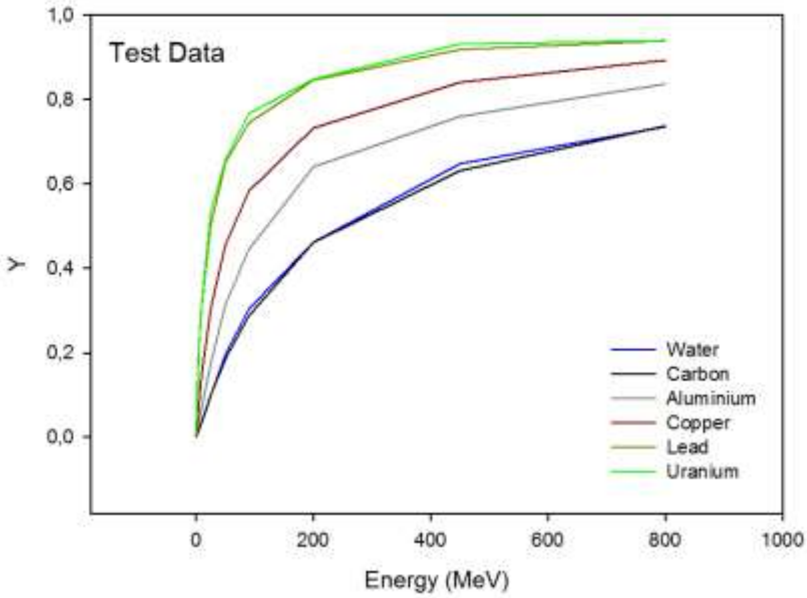


Fig. 4. Comparison of Y values for all absorbing materials investigated in this work. Train (upper) and test data (lower) results.

4. CONCLUSION

As a conclusion, the radiation yields for water, carbon, aluminum, copper, lead and uranium obtained from theoretical studies have been taken as inputs for ANN training in this study. After successful application of ANN for these data sets, ANN predictions for radiation yields with respect to the energy of incident electrons have been calculated. The results have been found as to be in agreement with the literature data. One can confidently concluded that ANN is a helpful tool for estimation of the radiation yields.

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