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Neural network predictions of (n,2n) reaction cross-sections at 14.6 MeV incident neutron energy

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ABSTRACT

In this study, we have estimated the (n,2n) reaction cross-section for 14.6 MeV incident neutron energy by using the artificial neural network (ANN) method. We have also predicted the reaction cross-sections whose experimental data are not available in the literature. For the construction of the present ANN, available experimental data in the literature has been borrowed. The ANN estimations have been compared with the available experimental data and the results from a theoretical calculation and the two commonly used computer codes. According to the results that the ANN results are in good agreement with the experimental data than the codes and this shows that the method can be a powerful tool for the estimation of cross-section data for the neutron-induced reactions. Considering the predictions of the ANN of the cross-sections whose experimental data are not available in the literature, it is seen that they are in line with the trend of the experimental data, but far from the results given by the theoretical calculations and two computer codes.

1. Introduction

The nuclear activation cross-sections are very useful in the applications such as fusion research, radiation safety, neutron dosimetry, rare isotope production and material damage. Values of the neutron cross-section around 14.6 MeV energy are important for the design of fusion reactors in issues such as secondary particle generation, radiation damage to the first wall, toroidal coils and the prediction of surrounding materials (Konobeyev et al., 1996). A large amount of data is available in the EXFOR library (Otuka et al., 2014) regarding (n,2n) reaction cross-sections for fusion reactor applications. However, due to the lack of experimental data in the literature, theoretical models and computer codes based on these models have been developed in order to make better predictions in addition to using different techniques to measure reaction cross-sections experimentally. Also, the use of systematic formulas from semi-empirical approaches has also been used to predict the cross-section data.

In this work, ANN method as an alternative tool has been used for the estimations of the (n,2n) reaction cross-section data at 14.6 MeV incident neutron energy in the mass range between A = 48 and A = 209. The experimental data are taken from the literature (Yigit, 2020). By using experimental data for the training of the machine, we obtained ANN results for the (n,2n) reaction cross-section. Then, we compared the experimental values with the present ANN results, a theoretical model results and the two commonly used computer codes results. The considered codes in this study are TALYS-1.95 (Koning and Rochman, 2012) and EMPIRE-3.2 (Herman et al., 2017). Our results indicate that the ANN method is one of the successful tool for calculating cross-sections of (n,2n) reactions.

ANN is a machine-learning tool as a mathematical model that imitates brain functionality, which is composed of layers including neurons in each (Haykin, 1999). The method generates its own output as close as the desired values. One of the advantages of the method is that it does not need any relationship between input and output data variables. Another advantage of the method is that in the case of missing data, it can be completed automatically due to its learning ability. Recently, ANN has been used in many fields in nuclear physics. Among them, the studies performed by our group are developing nuclear mass systematic (Bayram et al., 2014), obtaining fission barrier heights (Akkoyun and Bayram, 2014), obtaining nuclear charge radii (Akkoyun et al., 2013),

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estimation of beta decay energies (Akkoyun et al., 2013), an approximation to the cross-sections of Z boson (Akkoyun and Kara, 2013; Akkoyun et al., 2014a,b), determination of gamma-ray angular distributions (Yildiz et al., 2018), estimations of radiation yields for electrons in absorbers (Akkoyun et al., 2016) and estimations of fusion reaction cross-sections (Akkoyun, 2020), estimations of the cross-section of (n,p) reactions at 14.5 MeV neutron energy (Akkoyun and Amrani, 2021). In the present study, by training ANN through the known experimental cross-section values with two inputs, we have predicted reaction cross-sections for different (n,2n) reactions at 14.6 MeV. According to the results, the ANN estimations are closer to the experimental data than the theoretical results. Also, we have predicted the cross-section values whose experimental data are not available in the literature and compared them to the results of a theoretical calculation (Konobeyev and Korovin, 1999) and the two computer codes (Koning and Rochman, 2012; Herman et al., 2017).

2. Material and methods

Artificial neural network (ANN) (Haykin, 1999) is one of the strong tools that can be handled when standard techniques fail. This mathematical method imitates the function of the human brain and nervous system. ANN can be in a layered structure with three main layers, which are the input, hidden and output layers. Each layer has its own processors, called neurons. The neurons in each layer are fully connected to each of the neurons in the next layer. This structure is called a fully linked ANN. The input neurons receive the data that are independent variables of the problem. The received data in the input neurons are transmitted to the hidden layer neurons by multiplying the weight values of the connections. At the entrance of the hidden neuron, all data going into the neurons are summed by using an appropriate function and the total net data are activated by an appropriate function before exiting the neuron. The hidden neuron activation function can be theoretically any well-behaved nonlinear function (Hornik et al., 1989). In this study, the tangent hyperbolic function has been used for the activation of the data in the hidden neurons. Data from hidden neurons is transmitted to output neurons. All data entering the output neurons is first summed and then activated, just like the process with hidden neurons. The data coming out of the output neuron are the dependent variables of the problem and include the desired results of the problem. In Fig. 1, we have shown the 2-10-1 ANN structure that is used in this study for the prediction of the (n,2n) reaction cross-sections.

In the present work, the input parameters are proton (Z) and neutron (N) numbers of the target material. The desired output parameter is (n,2n) reaction cross-sections for the targets at 14.6 MeV incident neutron energy. There is no rule in determining the hidden layer and the number of neurons in this layer, and the optimum numbers were determined after the trials. In this work, one hidden layer with 10 neurons structure is used which gives the optimum results for the problem.

The main goal of the ANN method is the assignation of the final weight values of the connections between the neurons. The constructed final ANN with the optimum weights can give the outputs as close as to the desired values. ANN calculations consist of two stages, and thus the data is divided into two separate sets. In the first stage, called the training stage, the inputs of the problem and the desired outputs are given to the network and the weight values are tried to be changed so that the network can reach these outputs. By the modifications of the weights, ANN modifies its weights until an acceptable error level between ANN outputs and desired values. The error function for this stage is the mean square error (MSE) in this study. The MSE gives the average of the squares of the difference between the desired and the neural network output values. In the training step, Levenberg–Marquardt (Levenberg, 1944; Marquardt, 1963) back-propagation algorithm using to solve non-linear least squares problems was used for the modification of the weights. Levenberg–Marquardt uses neural neighborhood to

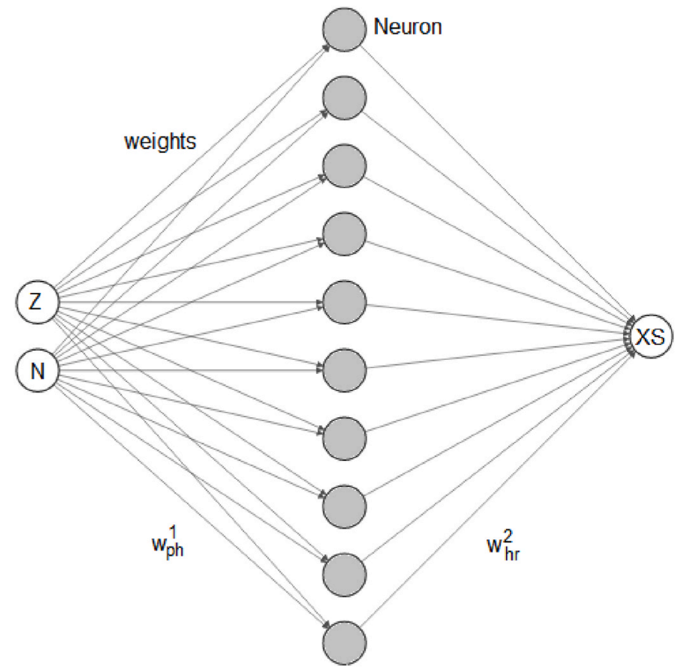

Fig. 1. The (2-10-1) ANN structure for the prediction of (n,2n) reaction cross-sections performed on different targets at 14.6 MeV incident neutron energy.

increase the behavior of both memory and time constraints. The Levenberg–Marquardt algorithm adaptively changes by updating the parameter between the Gaussian Newton update and the gradient descent update. Factors such as having highly correlated variables during the training phase and low diversity due to the uniformity of the training set may cause overfitting problems. Due to the fact that there were only 2 input parameters in our study and the number of data point was low, we prevented the occurrence of overfitting by stopping in line with our observations during the training phase.

In the second stage (test), another dataset of the problem is given to ANN and the results are predicted by using the final weights that are determined in the training stage after the modifications. If the predictions on the test data are good, the ANN is considered to have learned the relationship between input and output data. In this work, the data is divided into two separate sets for training (75% of the whole) and test (25% of the whole) stages. The whole experimental data were obtained from a previous study (Yigit, 2020).

Here we present some basic information about the ANN method. For ANN with a single hidden layer, the desired output vector $\vec{y}$ (XS in Fig. 1) is approximated by a network multi-output vector $\vec{f}$. The multi-output vector is defined by Eq. (1) as given below

$$\vec{f} : R^p \rightarrow R^r$$
$$: \vec{f}_k(\vec{x}) = \sum_{j=1}^{h_1} \beta_j G(A_j(\vec{x})), \vec{x} \in R^p, \beta_j \in R, A_j \in A^p, \text{and } k = 1, \ldots, r \quad (1)$$

where A^p is the set of all functions $R^p \rightarrow R$ defined by $A(\vec{x}) = \vec{w}.\ \vec{x} + b$, $\vec{w}$ is weight vector from the input layer to hidden layer, $\vec{x}$ is the input vector of ANN (2 inputs in Fig. 1), b is the bias weight and p (r) number corresponds to each input (output) variables. In this study, we have used two input layer neurons ($p = 2$), one output layer neuron ($r = 1$) and ten hidden layer neurons ($h = 10$) with no bias (see Fig. 1). The total number of adjustable weights (ΣW) is calculated as 30 by Eq. (2). The weights were randomly assigned in the beginning and modified accordingly with the algorithm used.

$$\Sigma W = p.h + h.r = h.\ (p + r) \quad (2)$$

In Fig. 1, the weight matrices w^1 and w^2 correspond to weight vectors defined in $A(\overrightarrow{x})$ and $\overrightarrow{\beta}$ in Eq. (1). However, as seen in Fig. 1 and Eq. (1) that the correspondences $w^1 \rightarrow A(\overrightarrow{x})$ and $w^2 \rightarrow \overrightarrow{\beta}$ are valid only for the ANN structure having a single hidden layer. For the ANN with more than one hidden layer, both Eq. (1) and the correspondences must accordingly be changed. The activation function for hidden neurons $G: R \rightarrow R$ in Eq. (3) can be theoretically any well-behaved nonlinear function. Commonly G is chosen as a nonlinear sigmoid type function which is defined by Eq. (3). The type of activation functions G in Eq. (3) is used hyperbolic tangent [tanh = $(e^x - e^{-x})/(e^x + e^{-x})$] for hidden and output layers.

$$G : R \rightarrow [-1, 1], \text{non}-\text{decreasing}, \lim_{\lambda \rightarrow \infty} G(\lambda) = 1, \text{and} \lim_{\lambda \rightarrow -\infty} G(\lambda) = -1 \quad (3)$$

3. Results and discussion

The total number of data used in the ANN calculations performed in this study was 149. Of these, 98 were obtained from the available experimental data and 51 of them included the results of theoretical calculations. 79 of the experimental data was used for the training of the ANN and the remaining part for the test stage. The theoretical data, whose experimental values for the studied reaction energy are not available in the literature, were used to compare the results generated by the constructed ANN through experimental data. ANN calculations were also made for the cross-section data, whose experimental data are not available in the literature, but theoretically calculated in the literature. The obtained ANN results were compared with both the theoretical results in the literature and the results of two commonly used computer codes.

In the training stage, the maximum number of epoch was chosen as 1000. After the determination of the final weights, the constructed ANN was first tested on the training dataset (Fig. 2). For the determination of the goodness of the results, the root mean square error (RMSE), minimum (MIN) and maximum (MAX) absolute error values were used as given in Eqs. (4)–(6).

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

$$MAX = \max\ (x_i - y_i) \quad (5)$$

$$MIN = \min\ (x_i - y_i) \quad (6)$$

where x_i and y_i are calculated and experimental values, N is the total number of data under consideration. The RMSE, MIN and MAX values, which show the deviation from the experimental data, were obtained as 95.2 mb, 2.1 mb and 407.2 mb, respectively. However, these values of the calculations performed with the TALYS-1.95 code were obtained as 225.4 mb, 2.4 mb and 550.5 mb, respectively. For the results of the calculations made with the EMPIRE-3.2 code, these values are 222.5 mb, 1.0 mb and 543.0 mb. If we look at these numerical data, we can conclude that the ANN predictions are better on the training data than the values given by the other codes used in this study. **But in our study, we used these codes with their default parameters without making any modifications suitable for our purpose. Therefore, this can be an expected situation. Our aim is not to emphasize that ANN is better than these, but to show that ANN also gives alternative acceptable results.** The rmse value of the ANN results is 2.4 and 2.3 times better than the rmse values of the results obtained from the TALYS-1.95 and EMPIRE-3.2 codes. It shows that ANN estimates are compatible with nonlinear experimental data and a useful alternative method for the (n,2n) reaction cross-section calculations.

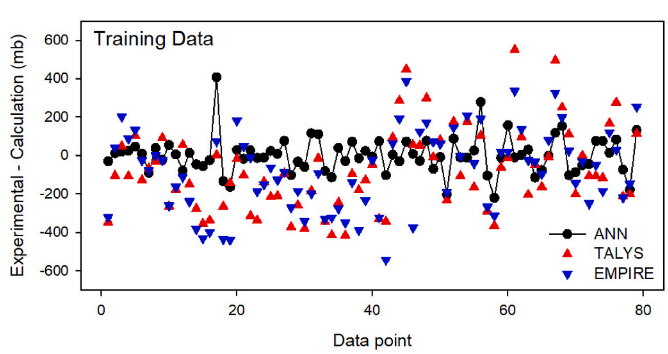

Fig. 2. Differences between theoretical results and experimental values on the training dataset for (n,2n) reaction cross-sections at 14.6 MeV incident neutron energy.

In Fig. 3, we give the estimates of the (n,2n) reaction cross-sections on the test dataset in comparison with the experimental data and the results of the calculations of the two computer codes. As can be seen from the figure, the ANN estimates are more compatible with the experimental data than the others. The RMSE, MIN and MAX values of ANN estimations on the test data set were obtained as 132.7 mb, 9.9 mb and 359.5 mb, respectively. The RMSE, MIN and MAX values of the calculations performed with the TALYS-1.95 code are 214.3 mb, 8.2 mb and 447.9 mb, respectively. However, the values of the results obtained from the EMPIRE-3.2 code were obtained as 229.4 mb, 9.0 mb and 476.0 mb. It is seen that the RMSE values of the ANN calculations are 1.6 and 1.7 times better, respectively, than the RMSE values of the TALYS-1.95 and EMPIRE-3.2 codes, which have not been modified or improved.

After the training and test stages, new estimates of the (n,2n) reaction cross-section data, which do not have experimental values in the literature, were made with the present ANN. It is worth remembering that for these predictions, the ANN trained using the experimental data is used. Therefore, we can expect that the new predictions of the ANN, learning the behavior at the experimental values of the cross-sections, will also be compatible with the experimental data. In order to see the success of the method and generate the new cross-section data to contribute to the literature, we have generated the (n,2n) cross-sections for different isotopes at 14.6 MeV incident neutron energy. In Table 1, these results obtained with ANN are given in comparison with the results of theoretical calculations and the results of two computer codes. As can be clearly seen from the table, the results of the theoretical calculations and the results of the calculations performed by using two computer codes are close to each other. On the other hand, it is seen that the ANN results are far from these values and generally have smaller numerical values. If we look at the experimental values given in the appendix in the form of tables containing the training and test data sets, it is seen that the ANN results are more in line with the experimental values as expected. When the experimental cross-sections of the isotopes in the close neighbors of the estimated isotopes in Table 1 are examined in the tables in the appendix, it can be concluded that the ANN results catch the experimental trends. Table 1 also shows that the convergence of the ANN results with the theoretical results and the results of the computer codes starts after the isotope where the Z and A numbers are 60 and 145. This may have pointed to the results of the theoretical calculations, which are compatible with the experimental data, only after this isotope approximation.

4. Conclusions

Since experimental data on (n,2n) reaction cross-sections are limited in the literature, obtaining cross-sections for these reactions can be done with the help of theoretical calculations and computer codes. In this study, we used an alternative approach, the ANN method, to obtain these cross-sections. We have seen that the cross-sections of the (n,2n) reactions that will occur as a result of the incoming neutrons with 14.6 MeV energies hitting different target materials can be obtained

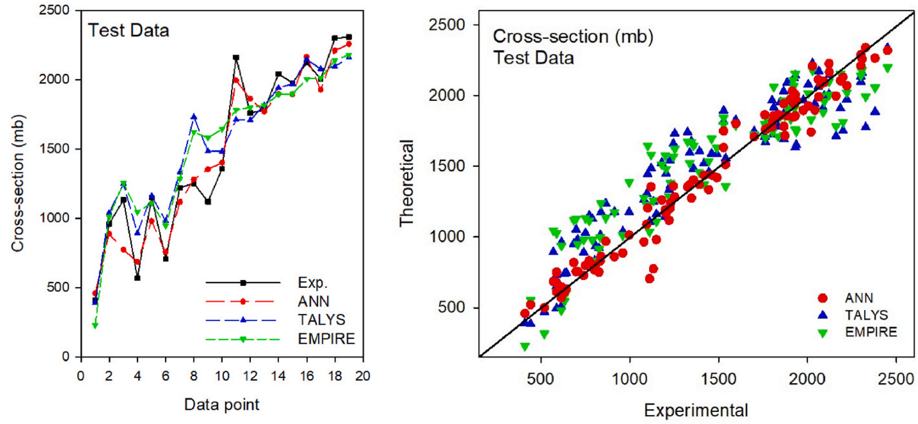

Fig. 3. The (n,2n) reaction cross-sections from ANN calculation and the computer codes in comparison with the available experimental data on the test dataset at 14.6 MeV incident neutron energy.

successfully with this method. First of all, we compared the results of ANN calculations and the results obtained from theoretical calculations with the experimental data available in the literature. In this comparison, we saw that the ANN results are closer to the experimental data than the results from other methods. After obtaining the confidence of the ANN, we generated new cross-section values for the reactions whose experimental data were not available in the literature. We have seen that the obtained ANN results are consistent with the trend in the experimental data, but far from the theoretical calculations. In this study, it was seen that the ANN results were 1.6–2.4 times closer to the experimental data than the results of the theoretical codes we used without any improvement. This was to be expected, as we did not make any effort to ensure that these codes yielded good results in our study. However, we presented our results in this way, aiming to emphasize that ANN can be an alternative tool.

CRediT authorship contribution statement

Serkan Akkoyun: Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Naima Amrani:** Writing – original draft, Validation, Investigation, Formal analysis. **Tuncay Bayram:** Writing – review & editing, Software, Methodology, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

APPENDIX

Table A1
The cross-sections of (n,2n) reactions on different targets at 14.6 MeV incident neutron energy for the training dataset.

Z	N	A	Experiment	ANN	TALYS-1.95	EMPIRE-3.2
20	28	48	616	645.9	1042.7	820.5
25	30	55	643	631.3	876.7	754.0
26	30	56	519	499.0	674.3	409.8
27	32	59	633	609.1	918.0	480.5
29	34	63	615	568.7	953.2	446.8
29	36	65	808	798.9	891.3	772.2
30	36	66	588	678.9	829.6	412.5
31	38	69	803	764.9	912.5	676.2
32	38	70	588	611.5	781.4	260.4
32	44	76	914	859.0	1257.3	928.8
33	42	75	835	830.1	1114.3	730.0
34	40	74	442	520.7	796.1	148.9
35	44	79	741	727.8	1141.6	784.2
35	46	81	751	797.1	1234.1	904.5
37	48	85	698	754.1	1248.0	891.4
37	50	87	838	862.4	1286.0	1074.6
39	49	88	1111	703.9	1165.8	975.0
39	50	89	685	818.3	1059.8	649.8
40	50	90	588	750.8	820.1	389.2
40	56	96	1539	1510.7	1492.2	1488.5
42	58	100	1418	1435.7	1543.8	1253.0
43	56	99	1227	1200.4	1484.6	1322.2
44	54	98	790	803.0	1302.4	1019.7
44	60	104	1230	1240.3	1475.2	1258.3
46	64	110	1392	1368.9	1511.1	1423.4

(continued on next page)

Table 1
The ANN cross-section data predictions for (n,2n) reactions on different targets at 14.6 MeV incident neutron energy. The results are compared to the theoretical calculation, TALYS-1.95 (Koning and Rochman, 2012) and EMPIRE-3.2 (Herman et al., 2017) results.

Z	N	A	Konobeyev	ANN	TALYS-1.95	EMPIRE-3.2
20	23	43	883	575.7	791.8	777.6
22	27	49	1000	725.9	895.2	904.4
23	27	50	739	617.9	814.2	644.7
24	29	53	1088	696.1	981.4	958.9
26	31	57	1150	653.4	1050.0	1002.7
28	33	61	1133	592.1	1008.3	966.1
30	37	67	1180	735.9	1113.6	1044.3
32	41	73	1368	799.5	1271.4	1327.9
34	43	77	1330	779.0	1325.6	1259.9
36	47	83	1409	821.4	1317.6	1316.1
38	49	87	1412	783.7	1169.8	1202.2
40	51	91	1507	733.3	1256.2	1409.1
42	53	95	1523	692.6	1391.5	1422.1
42	55	97	1578	1266.6	1417.1	1556.8
44	55	99	1525	1075.9	1482.2	1471.7
44	57	101	1613	1171.1	1536.6	1634.9
46	59	105	1604	1073.8	1505.3	1589.7
48	63	111	1666	1087.8	1584.6	1701.6
48	65	113	1702	1185.2	1640.7	1772.7
50	65	115	1664	1044.1	1436.1	1543.0
50	67	117	1716	1141.8	1597.0	1695.1
50	69	119	1751	1257.5	1657.1	1779.9
52	71	123	1744	1222.4	1646.7	1741.4
52	73	125	1783	1350.2	1702.2	1812.0
54	75	129	1793	1310.4	1620.1	1775.8
54	77	131	1837	1400.0	1687.7	1854.2
56	79	135	1834	1317.6	1673.4	1822.1
56	81	137	1854	1440.1	1716.4	1835.4
57	81	138	1820	1338.7	1683.9	1794.9
60	83	143	1921	1387.9	1786.4	1934.2
60	85	145	1944	1924.8	1752.0	2005.8
62	85	147	1931	1719.8	1807.4	2009.3
62	87	149	1985	1882.0	1804.8	2059.3
64	91	155	2000	1741.2	1844.7	2074.9
64	93	157	2013	1875.5	1953.0	2093.7
66	95	161	2041	1838.3	1972.6	2115.4
66	97	163	2068	1999.2	2035.1	2137.2
68	99	167	2080	1966.2	2035.0	2141.1
70	101	171	2092	1932.7	2036.5	2138.7
70	103	173	2119	2089.3	2084.7	2167.1
71	105	176	2145	2146.8	1898.1	2186.1
72	105	177	2144	2058.3	2112.1	2174.7
72	107	179	2179	2200.7	2037.8	2198.3
73	107	180	2164	2117.4	2065.6	2181.6
74	109	183	2199	2173.2	2127.0	2217.2
76	111	187	2224	2144.7	2140.5	2230.5
76	113	189	2265	2241.6	2122.5	2273.3
78	117	195	2294	2020.1	2083.7	2308.8
80	119	199	2257	1977.4	2094.2	2306.4
80	121	201	2320	2170.8	2174.9	2358.5
82	125	207	2273	2294.5	2295.2	2399.0

Table A1 (*continued*)

Z	N	A	Experiment	ANN	TALYS-1.95	EMPIRE-3.2
47	60	107	1096	1087.7	1247.5	1112.3
48	58	106	827	751.0	1000.0	679.9
48	60	108	865	967.9	1243.8	1051.9
48	68	116	1337	1368.8	1604.0	1468.5
50	62	112	772	831.6	1014.6	783.5
50	64	114	1080	964.1	1219.3	1109.6
50	70	120	1444	1333.3	1637.8	1497.6
51	70	121	1180	1260.9	1514.0	1468.4
51	72	123	1245	1358.9	1599.1	1031.0
52	70	122	1204	1165.1	1379.1	1113.1
52	78	130	1325	1353.7	1681.4	1694.9
53	76	129	1490	1418.8	1663.0	1643.0
54	70	124	997	1012.0	1105.7	1031.6
54	80	134	1460	1437.1	1714.4	1683.3
54	82	136	1700	1706.6	1544.2	1547.1

(*continued on next page*)

Table A1 (*continued*)

Z	N	A	Experiment	ANN	TALYS-1.95	EMPIRE-3.2
59	82	141	1347	1273.6	1601.7	1501.4
60	82	142	1101	1203.7	1428.6	1492.8
60	84	144	1763	1758.9	1820.3	1652.5
60	86	146	1937	1967.6	1735.6	1757.7
60	90	150	2200	2128.6	1510.6	1533.8
62	82	144	1200	1191.4	1027.2	1200.3
62	86	148	1835	1863.1	1786.7	1640.8
62	88	150	1931	1854.9	1680.0	1682.5
62	92	154	1905	1974.6	1877.0	1696.0
63	88	151	1803	1812.4	1733.9	1717.1
63	90	153	1596	1800.3	1817.4	1702.4
64	88	152	1867	1780.0	1652.0	1676.7
64	94	158	1846	1856.4	1937.9	1609.7
64	96	160	2087	2099.4	1785.7	1746.8
65	94	159	1801	1775.1	1901.2	1772.2
66	94	160	2020	1740.8	1841.9	1693.0
68	94	162	1527	1631.6	1588.2	1562.9
68	96	164	1528	1748.2	1829.2	1547.7
69	100	169	1926	1937.9	2017.7	1798.1
70	98	168	1873	1715.0	1780.4	1621.5
70	106	176	2327	2337.3	1559.4	1825.1
71	104	175	2094	2090.9	2045.2	1889.8
72	102	174	1886	1856.3	1925.1	1998.4
72	104	176	1915	2029.6	1990.5	2084.3
74	106	180	1866	1941.4	2012.8	2053.8
74	108	182	2076	2078.1	2063.2	2114.4
74	112	186	2380	2262.5	1742.5	2103.6
75	110	185	2221	2068.0	2093.2	2176.5
76	116	192	2121	2224.2	1912.5	2184.1
77	114	191	1923	2010.2	2119.7	2167.4
77	116	193	2062	2111.9	1974.0	2209.2
78	114	192	1810	1854.7	1798.6	2008.0
79	118	197	2064	1988.5	2024.9	2217.2
80	118	198	1920	1844.9	2061.1	2163.2
80	124	204	2300	2286.2	2142.4	2294.1
81	122	203	2185	2102.4	2173.3	2286.1
82	122	204	1931	2004.7	2164.1	2255.8
82	124	206	2028	2206.5	2277.2	2306.8
83	126	209	2450	2317.1	2279.9	2282.5

Table A2
The cross-sections of (n,2n) reactions on different targets at 14.6 MeV incident neutron energy for the test dataset.

Z	N	A	Experiment	ANN	TALYS-1.95	EMPIRE-3.2
28	32	60	410	458.7	602.2	443.2
31	40	71	961	886.3	1085.9	507.4
34	48	82	1133	773.5	1330.1	1233.4
38	48	86	570	685.5	1031.4	573.3
41	52	93	1150	979.8	1405.5	1122.9
46	56	102	707	755.8	1221.3	584.2
48	62	110	1221	1116.8	1410.4	1249.6
50	74	124	1253	1280.6	1703.0	1486.6
53	74	127	1120	1353.6	1522.3	1499.4
55	78	133	1359	1401.6	1655.0	1644.0
60	88	148	2160	1994.4	1617.0	1539.1
62	90	152	1760	1862.7	1825.8	1157.8
64	92	156	1780	1770.0	1878.0	1710.8
67	98	165	2042	1895.8	1976.1	1638.5
70	100	170	1976	1894.6	1981.1	1793.2
73	108	181	2122	2163.1	2072.8	2158.3
76	110	186	2004	1926.4	2048.6	2098.8
78	120	198	2300	2209.6	2061.9	2239.8
81	124	205	2307	2256.7	2205.6	2327.5

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