The use of artificial neural networks for the unfolding procedures in neutron activation measurements

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Contents

1. Introduction

Determination of the cross section functions for neutron reactions

- Application of different neutron induced nuclear reaction as well as theoretical research request the new measurements of cross section data in a wide energy range.
- **NAXSUN** technique (Neutron Activation X-Section determined using UNfolding) was developed at the JRC-Geel

Iterative methods such as SAND II, Gravel and Maxed algorithms have been used for the unfolding process.

We tried to apply **Artificial Neural Networks (ANN)** for unfolding.

Special attention is paid to the generation of data sets for network training (using Talys code).

The possibility of using ANN for this purpose is demonstrated on experimental data obtained for the $\mathbf{^{115}In(n,n`)^{115m}In}$ reaction.

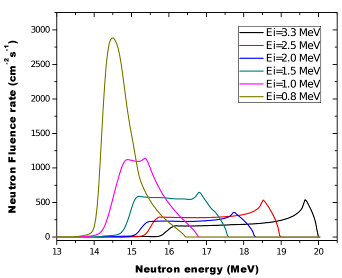
2. The NAXSUN method

$$A_k + \varepsilon_k = \sum_i \Phi_{ki} \cdot \sigma_i , i = 1,2 \ldots c, k = 1,2,..m$$

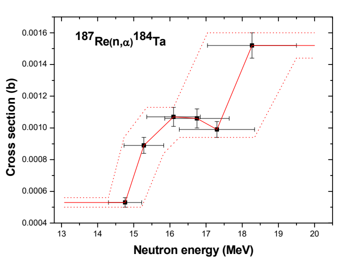
A_k = measured values
e_k = measurement uncertainties
s_i = cross sections
F_{ki}= neutron spectrum

Disk No	A (Br/atom)
1	
2	
…	

Measured disk activities



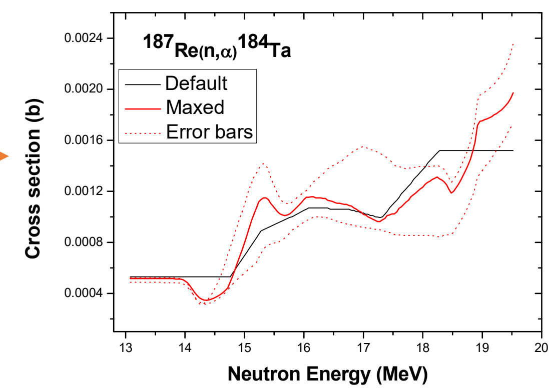
Neutron Fluence data



Default cross section function spectra

Spectrum unfolding

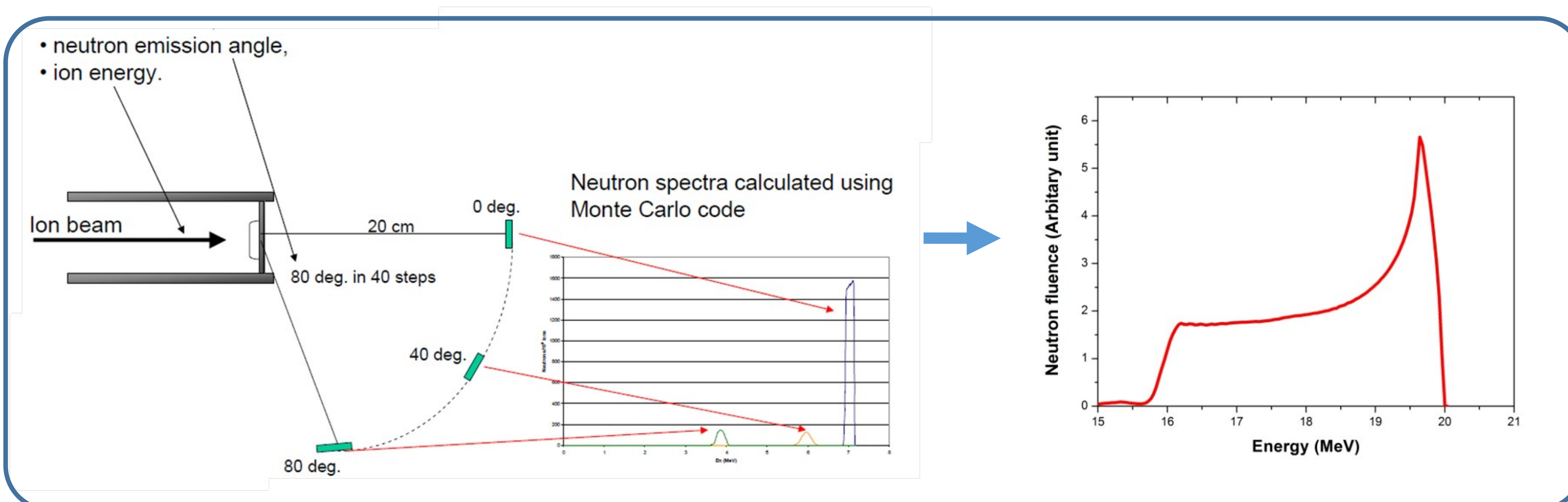
(MAXED, GRAVEL)



Cross-section excitation function

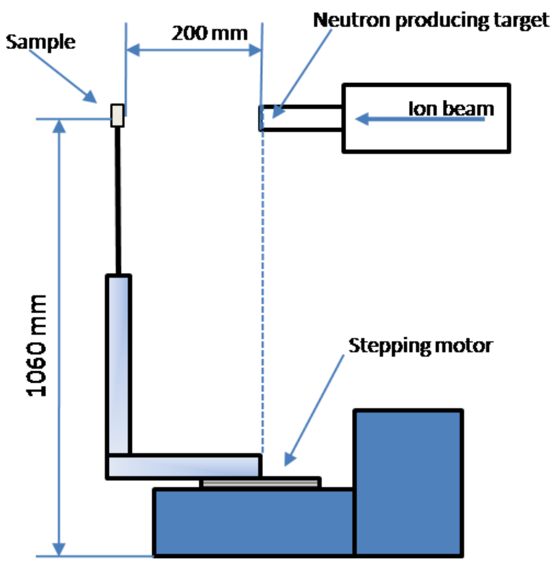
2. The NAXSUN method

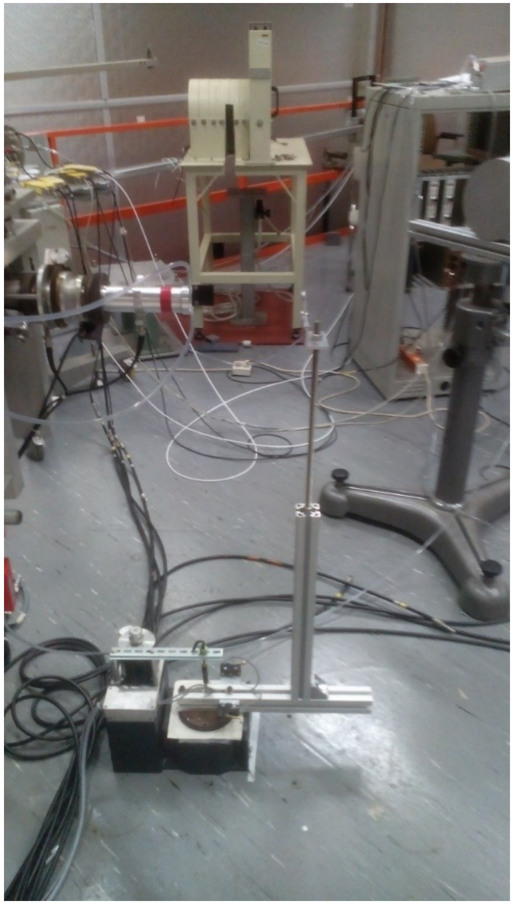
- Wide-energy overlapping neutron beams
- By **scanning of the disks over different angles** relative to the ion beam during irradiation, the samples were exposed to a total neutron spectrum over a broad-energy region.
- Neutron produce reaction (Van de Graff):
  - $^{7}Li(p,n)^{7}Be$, En: 0 - 5.3 MeV
  - $T(p,n)^{3}He$, En: 0 - 6.2 MeV
  - $D(d,n)^{3}He$, En: 1.8 - 10.1 MeV
  - $T(d,n)^{4}He$, En: 12.1 - 24.1 MeV



2. The NAXSUN method

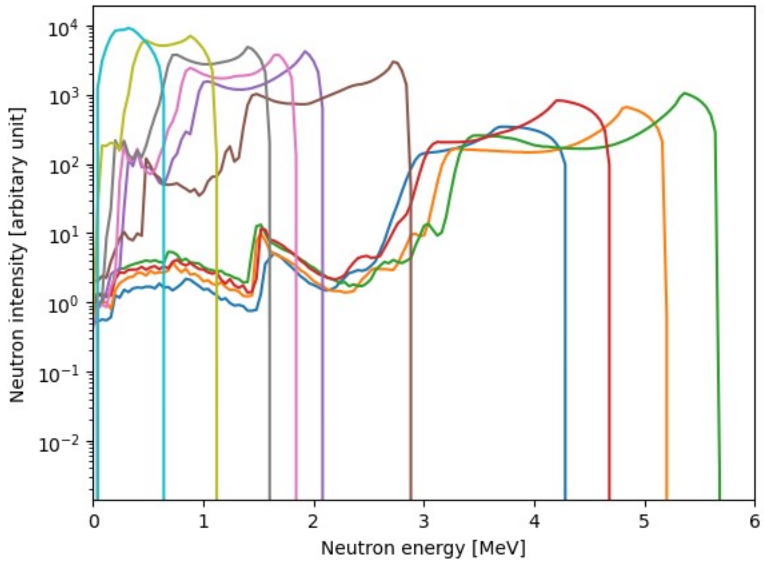
- Irradiation set up





3. Measurements od ^{115}In(n,n`)^{115m}In reaction cross section

The irradiation of the indium disks was done at the JRC-Geel at the Van de Graff neutron laboratory. All disks were made from natural indium. They had an identical shape with a diameter of 20 mm and 5 mm thick. The 2H(d,n)3He and 3H(d,n)4He nuclear reactions were used for production neutron flux of In discs activation. After irradiation, the gamma-ray measurements of the neutron-induced activities were carried out using low-background high-purity germanium detectors.



Spectra of neutron activation fluxes

Reaction	Activity concentration (10^{-21} Bq atoms^{-1})	
Id	^{113m}In	^{115m}In
Tp1463	–	0.11(1)
Tp1912	4.5(2)	4.1(2)
Tp2384	18.7(3)	24.6(11)
Tp2620	21.5(3)	14.9(7)
Tp2866	30.1(3)	36.4(17)
Tp3647	44.1(4)	29.8(14)
Dd1142	7.30(14)	4.02(19)
Dd1480	14.90(18)	8.5(4)
Dd1949	12.44(17)	7.5(3)
Dd2400	21.1(2)	25.6(12)

4. Data for training ANN

Data for training ANN is done in following way:

1. **The use of the TALYS code to generate cross-section values** for the neutron-induced reaction (n,n') for various nuclides in the energy range from 0 MeV to 5.6 MeV . Given that 115In (with Z = 49) was utilized as the target material, we expanded our scope to include nuclides within Z±4 compared to 115In. For each nuclide with a different Z value, we incorporated 10 different isotopes, resulting in a total of 90 nuclides considered as simulated targets for incident neutrons.
2. **The energy spectra of incident neutrons** were derived from 10 different neutron fields, corresponding to the experimental setup.
3. **We computed the theoretical neutron-induced activity for each nuclide across the 10 different neutron fluxes.** This yielded 10 distinct activity values for each nuclide, corresponding to the 10 different neutron fields.
4. **To train the Artificial Neural Network (ANN)**, these activities for each nuclide were utilized as input data. Meanwhile, the cross-section values calculated by TALYS for the (n,n') reaction for each nuclide within the energy range from 0 MeV to 5.6 MeV (with bin values of 0.04 MeV) served as the output values for the training set.
5. Additionally, to account for measurement uncertainties, **we introduced five random variations (up to 5 percent) to the activity values for each nuclide**. Importantly, for each of these five variations, the corresponding cross-section values were assumed to remain constant.

5. Artificial Neural Network Model

The input data in our model are saturated activity and the output data are cross section function.

A Sequential model is created, allowing us to build the model layer by layer.

Four dense layers are added:
1. **The first layer has 10 neurons and uses ReLU activation function**. The number correspond to the dimensionality of the input data – calculated activities.

2. The next three layers each have 450 neurons and also use ReLU activation function.

3. The final layer has 141 neurons, representing the output. The number correspond to the dimensionality of the output data, and no activation function is specified, indicating it's a regression problem.

Number of layers and neurons inside every layer is determined with a function that calculates the R2 score in the evaluation of the model and chooses parameters with the maximum R2 value

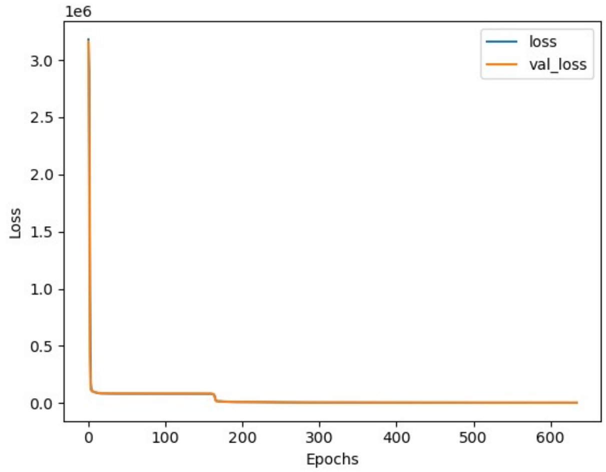
5. Artificial Neural Network Model

Model Training:

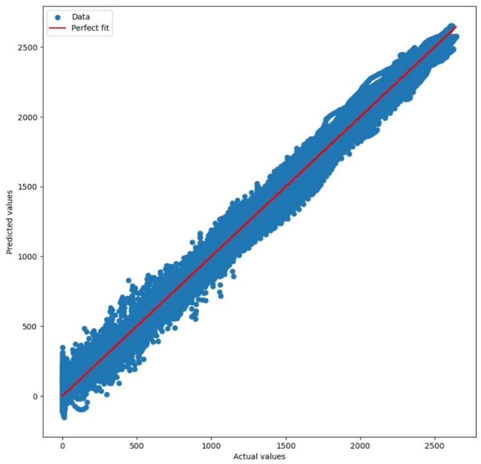
1. The model is trained using fit method on the training data (X_train and y_train). 2. Validation data (X_test and y_test) are specified for monitoring the model performance during training. 3. A batch size of 64 and a maximum of 1000 epochs are set for training. 4.EarlyStopping callback is employed to monitor the validation loss and stop training if it does not improve for 20 consecutive epochs.

Model Evaluation:

1. Predictions are made on the test data (X_test) using the trained model. 2. Mean squared error (MSE), mean absolute error (MAE), and R-squared score are computed using sklearn.metrics. 3. Printing Evaluation Metrics: MSE, MAE, and R-squared score are printed to evaluate the model's performance. **Average MSE: 3489.0786 (Arbitary units);Average MAE: 44.7822 (Arbitary units) ;R-squared Score: 0.9108**



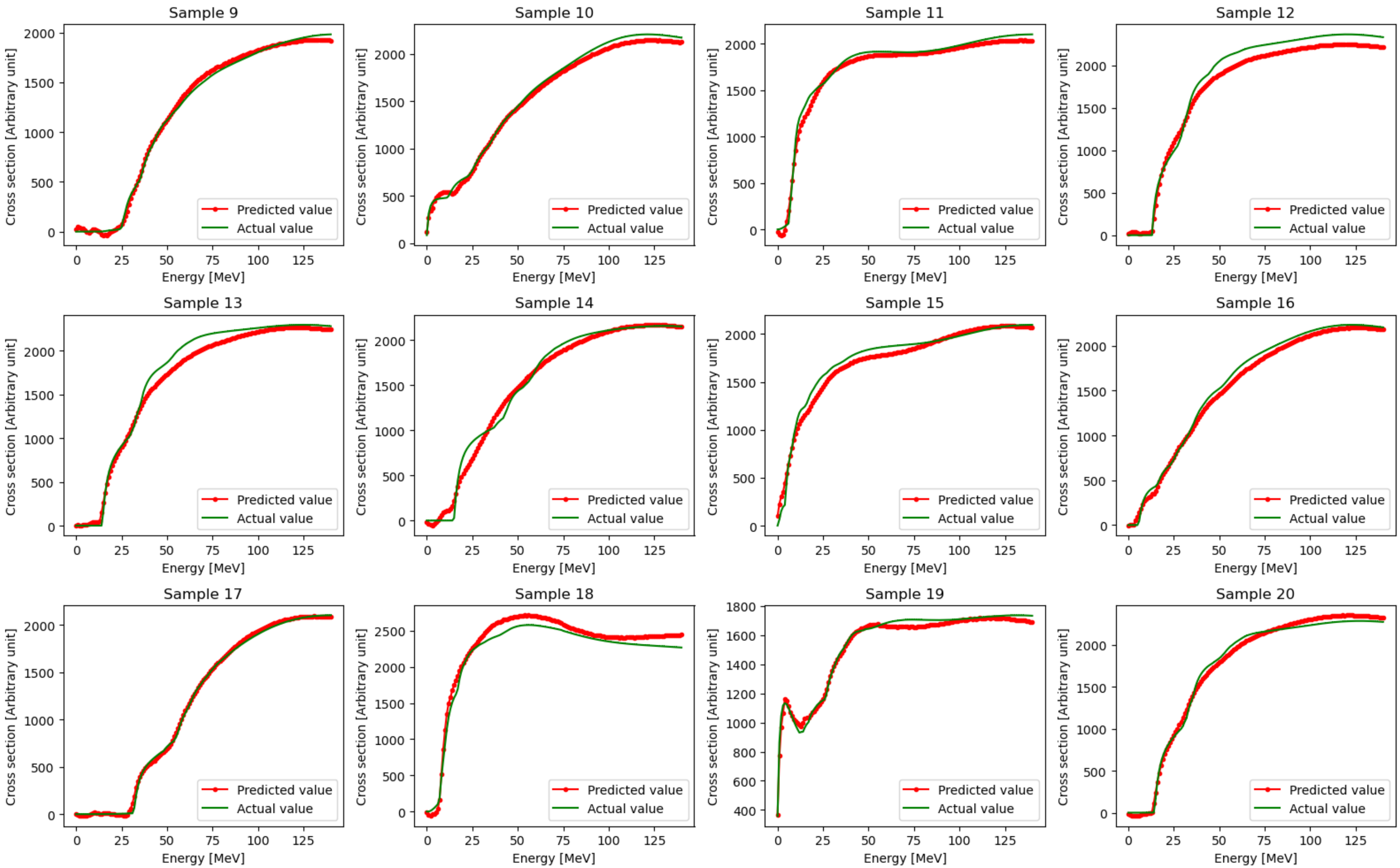
Training and validation losses.



Comparison of predict and actual values

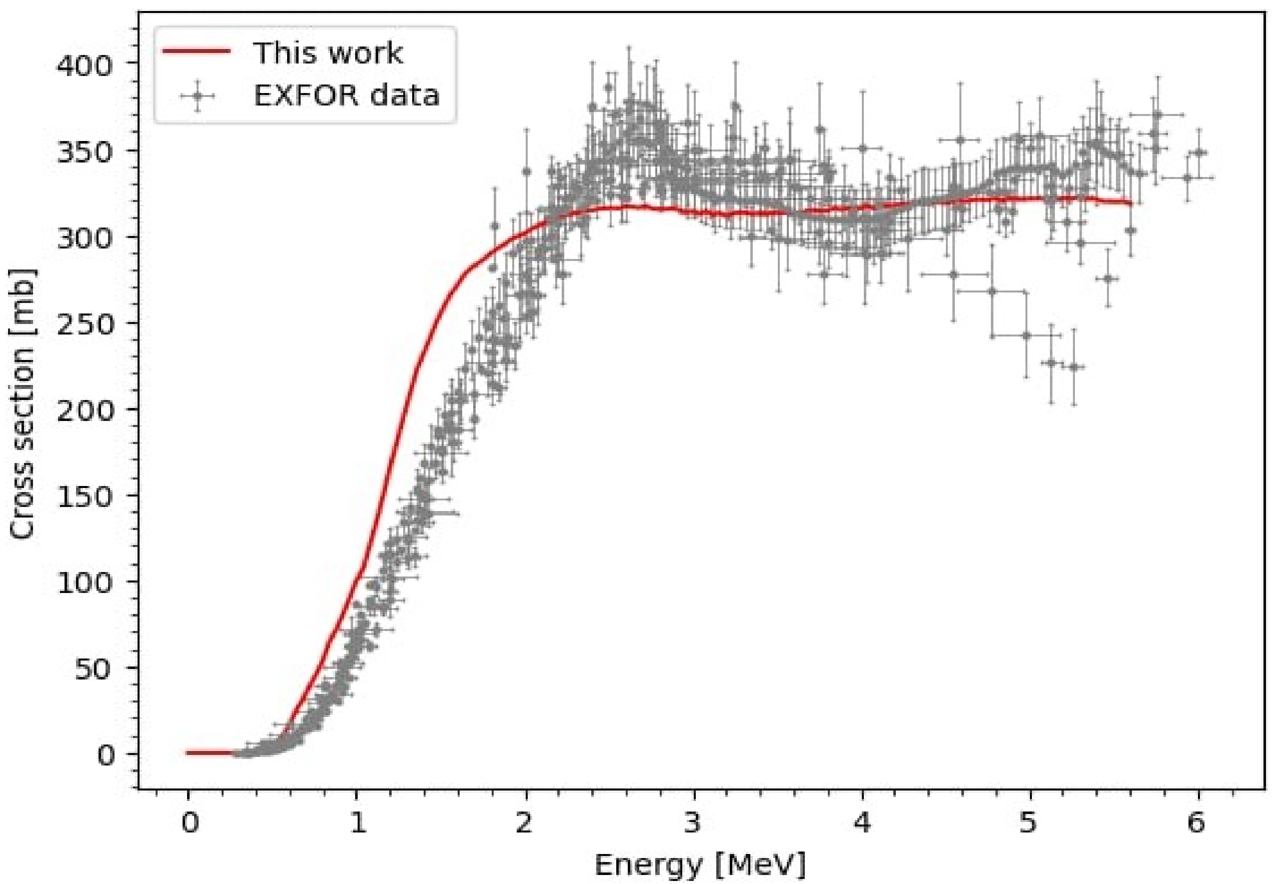
5. Artificial Neural Network Model

Example of comparison of predicted and actual cross section function for some



6. Testing model on real measured activities for $^{115}In(n,n`)^{115m}In$

Comparison of cross section function obtained in this work with the EXFOR experimental data.



7. **Conclusion**

We applied artificial neural networks to solve the unfolding problem during neutron activation measurements of effective sections.

Theoretically simulated data using the Talys code were used as training data.

The possibilities of the network are represented by the example of the $^{115}In(n,n`)^{115m}In$ reaction.

The obtained results show satisfactory agreement with existing experimental data and provide a good basis for further implementation of this method.

In the next phase, it is planned to include the existing experimental data in the training set, as well as to apply this method to other reactions for which there are experimental data obtained by the NAXSUM method.

Thank you for your attention!