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Estimation of proton-boron reaction cross-sections by neural networks

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Abstract – The proton-boron fusion reaction is one of the interesting reactions in nuclear energy production. The fact that neutrons and radioactive products do not come out as a result of the reaction makes these reactions special. However, the realization of this reaction is very difficult due to the low reactivity of the plasma and high radiation losses at temperatures achievable in today's fusion devices. Therefore, it is important to determine the cross-sections of these reactions. In our study, we obtained the cross-sections of proton-boron fusion reactions using the machine learning methods after performing machine learning with the limited data available in the literature.

Keywords – Nuclear Reaction, Cross-Section, Machine Learning

I. INTRODUCTION

Proton-boron fusion is gaining renewed interest as a possible energy source. The reaction is aneutronic and does not contain radioactive species. Proton-boron fusion has been induced by high-power lasers. The proton-boron fusion reaction produces three alpha particles with Q=8.6 MeV. The reaction is of interest for work in the field of stellar evolution, as well as for application in an emerging form of enhanced-effect proton therapy [1-4].

The correct determination of the reaction cross-section is an important issue. In addition to the experimental determination of cross-sections, cross-sections can also be calculated using many theoretical models. As alternative approach to the methods, machine learning was performed using experimental cross-section data in the present study. Thus, it is aimed to obtain reliable cross-sections for energies for which available experimental data are not available. Estimates were made using three different machine learning models: Random Forest, Support Vector Regression and Extreme Gradient Boosting. The obtained results were compared with each other and with the available experimental data.

II. MATERIALS AND METHOD

In order to obtain the cross-sections of proton-boron reactions, machine learning was performed using the experimental data available in the literature. The reaction of the protons on the ^{11}B target causing the formation of alpha particle and ^{8}Be is discussed. Experimental cross-section data of the proton beam in the energy range of 200 keV to 3.5 MeV were taken from the EXFOR database [5]. 73 of the 98 data were used in the training phase. In this study, random forest (RF), support vector regression (SVR) and extreme gradient boosting (XGBoost) models were used in machine learning calculations.

The Random Forest (RF) algorithm based on many decision tree structures was first created by Brieman [6] as a combination of bagging and random subspace approaches. The training dataset is randomly divided into sub-data. The RF final estimate is determined by averaging all the results from each tree to produce an estimate. However, to increase forecast success, trees that fail the forecast result are pruned and their level of influence on the final forecast result is reduced. By increasing the weight coefficients of the trees that make the correct prediction, more contribution is made to the correct prediction.

Support Vector Regression (SVR) is a supervised machine learning model with associated learning algorithms that analyse data for regression analysis and classification [7]. SVR is one of the popular machine learning models that can be used in classification problems or class assignment where data cannot be separated linearly. A kernel is a function that places a low-dimensional plane into a higher-dimensional space where it can be broken up using a plane. That is, data that is not linearly separable is converted into separable data by adding more dimensions. There are three cores that SVM uses most. Linear kernel is dot product between two given observations, polynomial kernel allows curved lines in input space, radial basis function creates complex regions in feature space.

Extreme gradient boosting (XGBoost) initially started as a research project by Tianqi Chen [8] as part of the Distributed (Deep) Machine Learning Community group. Notable features that make XGBoost different from other gradient boosting algorithms include, intelligent punishment of trees, proportional shrinkage of leaf nodes, Newton upgrade, extra randomization parameter, application and non-core computing on single, distributed systems and automatic Feature selection. XGBoost works as a Newton-Raphson in function space, unlike gradient boosting which works as a gradient descent in the function space, a quadratic Taylor approximation is used in the loss function to con-nect with the Newton Raphson method.

III. Results and Discussion

According to the results obtained from the calculations performed with the RF model, the RMSE value of the estimates is 4.02 mb, the MAE value is 2.37 mb and the R^2 value is 0.92. Comparative graph of the obtained estimates (predicted) with the available experimental data in the literature (observed) is as seen in Fig. 1.

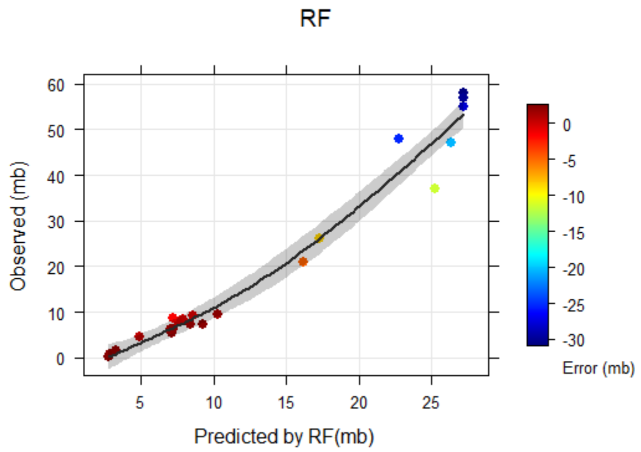

Fig.1 Proton-boron reaction sections from the RF model versus experimental literature data

When the results obtained from the SVR model, where the graph of the estimations against the experimental data are given in Fig. 2, are examined, it is seen that the RMSE, MAE and R^2 values are 2.45 mb, 1.57 mb and 0.79, respectively.

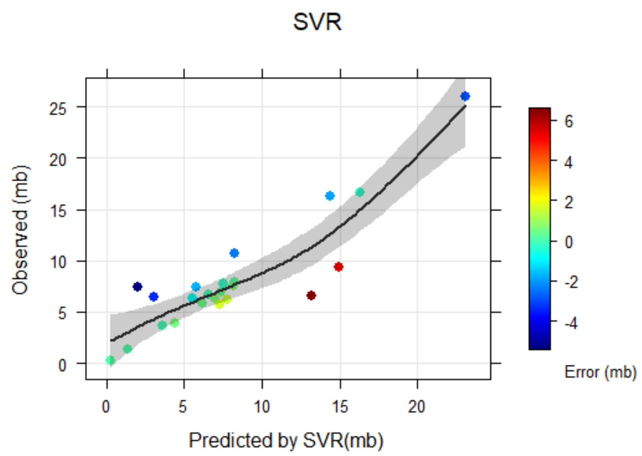

Fig.2 Proton-boron reaction sections from the SVR model versus experimental literature data

In Fig. 3, the predictions obtained from the XGBoost model are presented in comparison with the available experimental data in the literature. According to the estimation results obtained, the RMSE, MAE and R^2 values are 4.38 mb, 2.59 mb and 0.92, respectively.

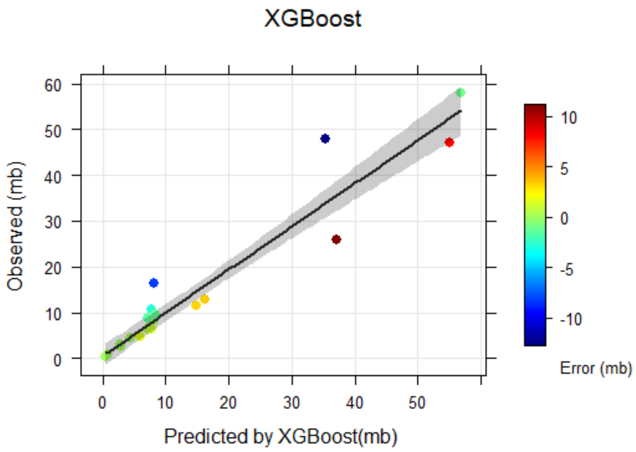

Fig.3 Proton-boron reaction sections from the XGBoost model versus experimental literature data

According to the results obtained from three different machine learning models, it is seen that the smallest RMSE value is not obtained by the SVR model in the predictions of the cross-sections of the proton-boron reactions. It is seen that the other successful model following this model is RF. When MAE values are examined, it is seen that SVR is the most successful model and RF follows it. Looking at the R^2 values, it was seen that RF and XGBoost had the highest R^2 values, while SVR lagged behind them.

IV. CONCLUSION

In this study, the cross-section of the alpha particle and the ^{8}Be product nucleus, which is formed after the nuclear reaction that occurs as a result of the proton beam in the energy range of 200 keV and 3.5 MeV, on the ^{11}B target was investigated. The cross-sections of these reactions were estimated using three different machine learning models. According to the results obtained, it was concluded that all three models can be used for this purpose, and the most successful among them is the SVR model.

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