Neural Network-based Machine Learning Approach to Unfasten Universal Fusion Function

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Introduction: Heavy-ion fusion reactions are of great research interest due to their applicability to produce and study the nuclei away from the stability line. At energies around the Coulomb barrier, complete and incomplete fusion reactions are the dominant mode of reactions. To investigate the fusion mechanism several experiments have been performed using weakly as well as strongly bound projectiles. Data analysis indicates a significant contribution from incomplete fusion (ICF) processes[1]. Moreover, ICF has started competing with complete fusion (CF) and does not have a well-defined threshold energy. Hence, the investigations of CF and ICF using heavy ion-induced reactions are still a subject of investigation from theoretical as well as experimental points of view. However, the ascendancy of ICF has been observed with the increase in projectile energy where CF is curtailed. Further, to understand the behaviour of low-energy ICF reactions, various systematics based on entrance channel parameters have been reported[1], as well as some theoretical models have also been proposed. It is not out of place to mention that no theoretical model is available to explain the low-energy ICF data for tightly bound projectiles. One of the theoretical models is suggested by Canto et.al[2] where a system-independent generalized fusion function is reported in subsequent sections. In the present work, the artificial neural network (ANN) model is trained for the Universal Fusion Function (UFF). Using this model the available experimental data have been utilized to train the neural network and then a prediction of fusion suppression for a new system has been made. The results thus obtained are satisfactory. Moreover, it may be promising to predict the behaviour of UFF and further, this may be experimentally verified, or it can be a promising gadget to evaluate the experimental data. Further investigations may unfold the dynamical and geometrical effects in CF and ICF reaction dynamics near the Coulomb barrier.

Universal Fusion Function: Canto et.al. [2], proposed a universal fusion function model which can unfasten the coupling effects associated with the reaction process by studying the dynamic and static effects and can be used to study the breakup fusion as well. Several attempts have been made to probe the target dependence on experimentally modified fusion function as suggested by Canto et al. [2] . In this model, the dimensionless parameter $\chi = \frac{E-V_B}{\hbar\omega}$ is served as an independent variable, Where E is the projectile energy, V_B is the Coulomb barrier of the interacting partner and $\hbar\omega$ is the barrier curvature of radius R_B, at which the cross-section of fusion is occurring and the cross-section is given by σ_{CF}. However, the UFF is considered as the dependent variable as given below ;

$$F(\chi) = 2 \times \frac{E \times \sigma_{CF}}{\hbar w R_B^2}$$

To the best of my knowledge, it is the first time reporting the prediction for UFF using machine learning in heavy ion reaction mechanisms in the low-energy region. It may not be out of place, to propose a dimensionless parameter χ named as "Rutherford Energy" on the name of the father of Nuclear Physics British physicist "Sir Ernest Rutherford" [3].

Artificial Neural Network (ANN): It is an advanced mathematical gadget for the estimation of various parameters related to the different fields in science and technology. New fashioned ANN has been widely used in different fields in nuclear physics, for example, estimation of proton separation energies, beta decay energies, ground state energies of the nuclei, unfolding of neutron charge radius, prediction of impact parameters, and fusion evaporation cross sections in heavy ion[4], unfolding of spectrum etc., ANN mimics the human brain functionality. It comprises neurons associated with different layers, namely input, hidden, and output neuron layers. Due to the layered structure, it is called layered ANN. Input and output layer neurons are connected with the hidden layer neurons via weighted connections. First, input layer neurons receive data from an external source and then forward it to the hidden layer then output layer neurons, thus

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unidirectional neural network known as feed-forward ANN. However, to manage uncertainty and generalization Bayesian Regularization neural network along with backpropagation uses to Jacobian of performance with respect to the weight and bias variables. These are adjusted according to Levenberg-Marquardt.

In order to train the neural network, a feed-forward Levenberg-Marquardt network of one hidden layer with 10 neurons along with 7 input neurons and one output neuron is used, a pictorial representation is shown in Fig.1. For the estimation of UFF, 70% of data points were used for training, 15 % for validation and 15 % for test. After several attempts, results were obtained with the R^2 (=0.99703) values.

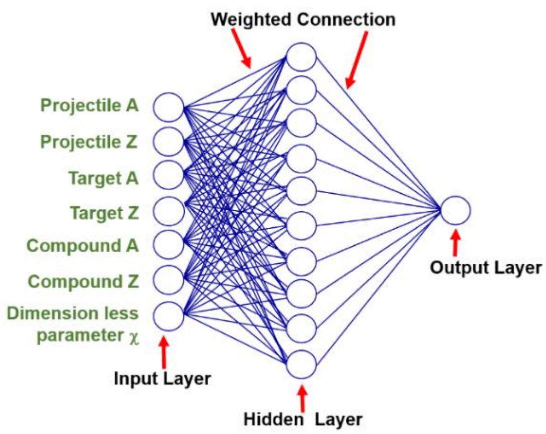

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Figure 1: The used 7-10-1 type ANN structure for the estimation of the Universal Fusion Function

The output vector is approximated by a network multioutput vector. The multioutput vector is defined elsewhere [4]. The total number of weights is calculated by the following equation.

$$\Sigma W = p.h + h.r.$$

Where p is the number of input neurons, h is the number of hidden layer neurons and r is the output layer neurons. The activation function for the hidden layer is the sigmoid-type function given as,

$$tanh = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})}$$

Result and Discussion

In the present work, to determine the number of hidden layer neurons several trials are performed, and 10 neurons in a single layer are found to be best suited. The measured data of UFF for ^{19}F induced reactions using ^{175}Lu, ^{169}Tm, and ^{159}Tb are taken from reference [7]. The inputs of the ANN are the beam energy, atomic numbers, neutron numbers, and mass numbers of the beam, target, and compound nuclei.

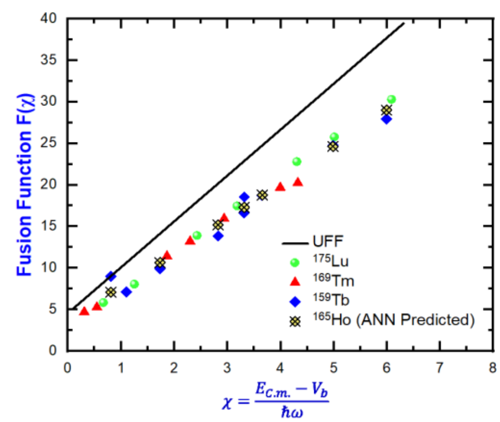

Figure 2. ANN predicted Fusion Function for $^{19}F+^{165}Ho$ reaction is shown by the symbol crossed diamond filled with yellow color ( ). The experimental fusion function data obtained from range integrated cross section and comparison with the UFF data of other systems taken from Ref.[7]

The ANN output is the total fusion reaction cross-section for $^{19}F+^{165}Ho$. For training the ANN, a Levenberg–Marquardt[4-6] backpropagation algorithm was used. By performing appropriate modifications, final weights are obtained after an acceptable error level between the estimated and desired outputs is attained. All experimental data were randomly divided into two separate parts 70 % for training and 30% for test stages. For the ^{165}Ho, it has been observed that it is following similar trends of other targets like ^{175}Lu, ^{169}Tm, and ^{159}Tb. The values of the dimensionless parameter are taken randomly. Further, experimental verification will be done using the measured values of UFF for this system and will be presented during the symposium.

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