Artificial neural network for prescission neutron multiplicity

Biswajit Sarkar[1,3] and Jhilam Sadhukhan[2,3]*
[1] *Computer & Informatics Group, Variable Energy Cyclotron Centre, Kolkata - 700064, INDIA*
[2] *Physics Group, Variable Energy Cyclotron Centre, Kolkata - 700064, INDIA and*
[3] *HBNI, Training School Complex, Anushaktinagar, Mumbai - 400094, INDIA*

Introduction

Evaporated neutrons from the nuclear fission process play a crucial role in basic sciences related to nuclear astrophysics and engineering applications such as the control and running of power reactors. A precise estimation of neutron multiplicity also helps to understand the dynamical characteristics of the fission decay. Theoretical prediction of fission neutron multiplicities is essential as several fissioning nuclei of astrophysical importance and strategic applications are not easily accessible in laboratories. However, due to the intricacies involved in the inter-nucleonic interactions, the theoretical prediction of fission neutron multiplicities is often model-dependent and may contain significant uncertainties. For example, the nuclear dissipation strength is often used as a free parameter and adjusted locally to reproduce the measured prescission neutron multiplicities (n_{pre}). No theoretical model exists that can accurately predict n_{pre} over the whole chart of fissioning nuclei in a parameter-independent way.

Machine learning (ML) based techniques are now widely used for fast and accurate prediction of complicated scientific phenomena [1] where the inherent mechanism governing the phenomena is not known precisely, but sufficient data describing them are available. Therefore, an ML algorithm, properly trained with the experimental n_{pre}, can resolve the above-mentioned problem. In one of our previous works, we employed the $k-$nearest neighbour (kNN) algorithm to model n_{pre} [2].

*Electronic address: jhilam@vecc.gov.in

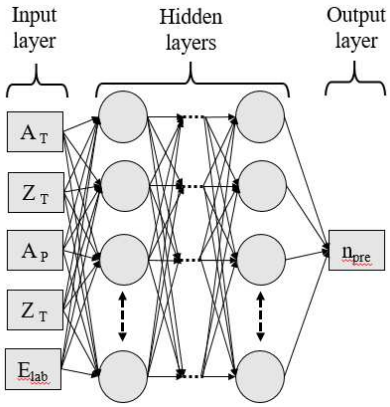

FIG. 1: Schematic diagram of an artificial neural network (ANN) with five inputs and one output, as discussed in the text.

kNN is an instance-based learning method for classification and regression problems [3]. We used the Euclidean distance norm from the four nearest instances to determine n_{pre} at an unknown instant. Although this algorithm achieved unprecedented accuracy, large deviations were observed at the boundaries of the measured data set and near the regions where data density is sparse.

Model

In the present work, we designed an artificial neural network (ANN) to predict n_{pre}. We used a fully-connected neural network with five inputs, viz., mass numbers (A_T, A_P) and atomic numbers (Z_T, Z_P) of the target and the projectile nuclei and the energy of the projectile (E_{lab}) in the lab frame. A schematic

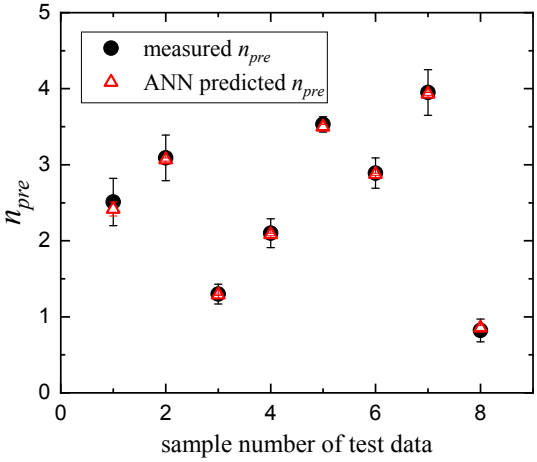

FIG. 2: Predictions made by the ANN juxtaposed against the experimentally measured n_{pre}s. Black error bars are associated with the experimental data. Refer to Table 1 for details of the sample data.

diagram of the ANN with the five inputs (A_T, A_P, Z_T, Z_P, E_{lab}) is illustrated in Fig. 1. A four-fold cross-validation method was used to arrive at a satisfactory architecture of the network. The chosen architecture was finally trained by minimizing the mean square error with *early stopping*. The results reported in this paper are based on an independent test data set not seen by the network during the training phase.

Results

The comparison of ANN-predicted n_{pre}s with the actual (experimentally obtained) n_{pre}s is shown in Fig. 2. The reactions are chosen randomly for the actual data, and the corresponding beam energies are given in Table I. It is observed that there is an excellent agreement between the ANN-based predictions and the experimental data, and the predicted values lie well within the error bars of the experimentally obtained data. Moreover, the predictions are dependent only on the model parameters, calculated from the input-output data and independent of any domain-specific prior knowledge. In the present analysis, we have chosen only those reactions with negligible possibility of non-compound events. Therefore, the ANN can distinguish the non-compound reactions by assessing the n_{pre} data of those reactions. We plan to extend the network to include multiple outputs with larger training and test data sets. More details on these aspects will be discussed during the Conference.

TABLE I: The input values (A_T, A_P, Z_T, Z_P, E_{lab}) for the test data set plotted in Fig. 2

sample	reaction	$E_{lab}(MeV)$
1	^{19}F+^{169}Tm	67.7
2	^{19}F+^{181}Ta	84.9
3	^{12}C+^{194}Pt	49.3
4	^{12}C+^{198}Pt	62.2
5	^{16}O+^{198}Pt	79.0
6	^{16}O+^{204}Pb	52.1
7	^{16}O+^{208}Pb	57.7
8	p+^{237}Np	20.1

References

[1] Amber Boehnlein et. al., Rev. Mod. Phys. **94**, 031003 (2022).

[2] Proceedings of the DAE Symp. on Nucl. Phys. **67**, 625 (2023).

[3] Tom Mitchell, Machine Learning, McGraw Hill (1997)

[4] Christopher M. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, Inc. (1995)