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Research Article
Efficient Neuro-Fuzzy Inference System (ANFIS) and Neural Networks Systems for Different Beams Collisions with Light Nuclei

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Abstract

Background and Objective: The Neuro-fuzzy Inference System (ANFIS) and a Neural Networks (NNets) system are two effective and famous systems. This study aimed to study the behavior of the multiplicity distribution of shower particles for some metals and predict the behavior for others. In addition to make a comparative comparison between the two proposed systems. **Methodology:** The ANFIS and NNets systems are trained and tested to simulate and predict the non-linear relationship for multiplicity distribution of shower particles produced from the P, ^{2}H, ^{4}He, ^{6}Li,^{7}Li, ^{12}C, ^{16}O, ^{24}Mg,^{28}Si and ^{32}S with light (HCNO) emulsion at 4.5 AGev/c. **Results:** The simulation results from the ANFIS based model and NNets are compared with the corresponding experimented data for different beams collisions with light nuclei. **Conclusion:** The predicted values of the ANFIS and NNets are expected to be accurately as the experimental data. The ANFIS and NNets give the providing of extensive procedure in modeling of high-energy physics. However, the obtained results of ANFIS is better than the NNets in the test and predicted data.

Key words: ANFIS, neuro-fuzzy approach, high energy (light nuclei), neural networks

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

The ANFIS system well-organized for solving many problems related to classification, recognition and modeling of complex system. The fuzzy modeling has found numerous practical applications[1-3], prediction and inference[4,5]. Many models have been introduced in high-energy physics such as the fireball model[6], string model, the quark-gluon-string model[7] and the neural model[8-11].

The ANFIS is a class of adaptive networks that combine the processing of neural networks and fuzzy logic principles. ANFIS, as an adaptive multilayer feed-forward network. ANFIS is an effective approach to modeling/mapping the input and output relationship in complex and nonlinear systems[12,13]. It converges much faster and has the most efficient learning algorithm, comparing with other models[14].

The NNets algorithms are widely used for simulating/mapping many data-sets problems. The NNets have a number of advantages over established statistical classifiers such as the maximum likelihood classifier. The NNets structure has an effect on training time and simulating/mapping accuracy. The NNets architecture, which gives the optimal performance for a particular problem can only be specified using experimental processes. The NNets approaches are worked in iterative way, designed to minimize the difference between the actual output list of the network and the target output list in effective way[15,16].

This study aims to introduce the ANFIS and NNets systems to simulate and predict the multiplicity distribution of shower particles produced from P, ^{2}H, ^{4}He, ^{6}Li, ^{7}Li, ^{12}C, ^{16}O, ^{24}Mg, ^{28}Si and ^{32}S with light nuclei at 4.5AGev/c. Moreover, an effective comparison between the two proposed systems is done.

MATERIALS AND METHODS

The present experiment used stack of GOSNIHIMFOTOPRQENT Br-2 emulsion pellicles of dimension 10×20 cm^2 with 600 μm thick were open at the synchrophasotron of JINR, Dubna to beam nuclei of P, ^{2}H, ^{4}He, ^{6}Li, ^{7}Li, ^{12}C, ^{16}O, ^{24}Mg, ^{28}Si and ^{32}S at 4.5A GeV/c, except ^{7}Li at ~3A GeV/c (Table 1).

Table 1: The percentage of nuclei in the BR-2 emulsion

Elements	$^{1}_{1}H$	$^{12}_{6}C$	$^{14}_{7}N$	$^{16}_{8}O$	$^{80}_{35}Br$	$^{108}_{47}Ag$
Weight	39.52	17.72	4.96	11.99	12.99	12.99

The stack pellicles separately were checked around tracks, fastest in the frontward direction and low in the backward one. Attia *et al.*[11] preformed the analysis on about 1000 inelastic interaction[17-19] from ^{6}Li, ^{7}Li and ^{12}C ions under a high magnification.

In each event, the emitted secondary particles are classified in accordance with standard criteria into the following types:

- Relativistic singly charged particle called shower of relative ionization I/Io<1.4. Where, I represents the panicle track ionization and Io represents the lowest ionizing singly exciting particles ionization with each plateau. Many of them are π-mesons with very high velocity β (v/c) > 0.7. The multiplicity of these tracks is denoted by n
- Any charged fragment at an angle θ ≤ 3mm subject to many Coulomb-scattering calculation for determining momentum, without variation in ionization beside a distance at 2 cm as minimum value from the interaction vertex is occupied as singly exciting projectile fragment of Z = 1 (seen as shower) or Z = 2 (seen as grey) or $Z\geq3$ (seen as black) and therefore then separated. In order to see how the shower particle multiplicities produced from CNO (A = 14)[19]

Neural Networks (NNets): These systems consist of a set of neurons; they are connected via weighted links. The neurons are typically structured in some layers. These layers contain of one input layer, one/more hidden layer/layers and one output layer. The input one is the first layer. It takes two external activation vectors and sends them to the first hidden layer by weighted connections. Figure 1 shows R elements in the input layer, S neurons in two hidden layers (HLs) and one element in the output layer.

The proposed system is constructed to apply in automatic way without any help from user. The system is firstly created two lists, one for training functions names and the other for activation functions names. After that, the system is started with building initial NNets architecture with no hidden layer by choosing the training and activation functions from produced lists. Then, the start value of neurons and epochs are given. In random way, the weighted values are initialized. Then, the system is trained and tested. If it get the required performance, the obtained network is used for extracting the proposed features. Otherwise, this experiment is repeated

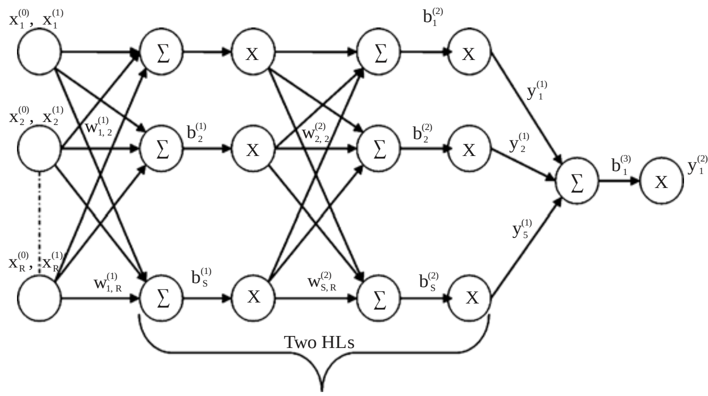

Fig. 1: Representative architecture of NNets with two HLs

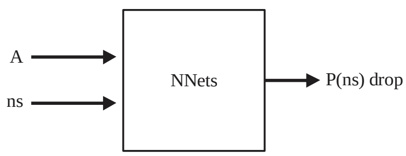

Fig. 2: NNets system construction

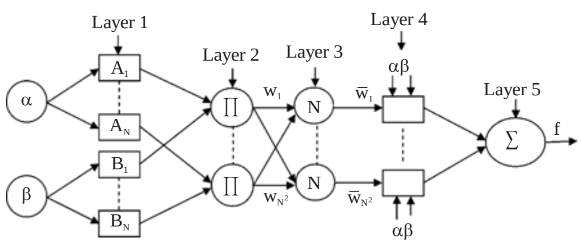

Fig. 3: Representative architecture of ANFIS

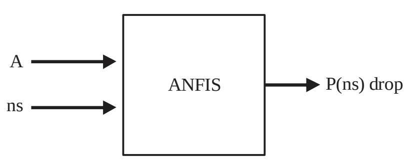

Fig. 4: ANFIS construction

again by rebuilding a new architecture of the NNets according to a linear combination among the NOEs, the number of neurons, training functions, activation functions and the number of HLs. This procedure is contained until the system has the required performance.

The studied problem has three inputs and one output. The inputs are the center of mass energy (C.M.S.), the number of shower particles (ns) and atomic mass number (A). The first one (mass energy) is constant and equals 4.5A GeV/c. The output is the multiplicity distribution of shower particles (P(ns)) (Fig. 2).

Neuro-fuzzy inference system (ANFIS): These systems are more efficient methods for classifications. The architecture of ANFIS is shown in Fig. 3. This architecture is produced using a Takagi-Sugeno FIS with a five layers. Layer-1 represents fuzzy MFs. The next two layers have nodes to create the antecedent parts for all rules. Layer-4 determines the first-order Takagi-Sugeno rules for every fuzzy rule. The last layer is used to calculate the global output[20].

The proposed system is organized to work automatically without any support from the users, starting by building the architecture of ANFIS. Then, it is trained and tested. After that, the obtained training, test performances and the workspace are stored. Next, the system re-designs the architecture of the ANFIS using a linear combination for selecting three parameters. They are MFs names, number of MFs for each input and number of epochs (NOEs). The training and test processes are continued until get the best training and test performances.

The utility of ANFIS is organized to identify a Preisach density function μ (α, β), where α and β are the input of the proposed system[21]. This system has two inputs; each one has N membership functions (MFs) and contains N^2 base rules as shown in Fig. 3.

The same problem is also simulated using the ANFIS system. The description of this system is shown in Fig. 4. The proposed system is implemented to find the best result by changing three bases parameters in a linear combination. They are type and number of MFs and the NOEs. When using extra numbers of MFs and epochs, more computations are required but may solve complicated problems. Moreover, many tries are done to train the best ANFIS using a minimum number of NOEs and MFs. In automatic way, the system is applied using 100 epochs and two MFs in the first try. In the next tries, the NOEs is incremented by 100, while the other parameter incremented by one. It found that, 2000 epochs and 7 MFs are sufficient to have the optimal solution as seen in the Fig. 8-10.

RESULTS

In order to make an effective comparison between the NNets and the ANFIS systems, they are selected to be applied on the same studied problem. The used programs are designed using the Matlab software.

NNets system: This system is trained using eight cases. The cases values are 1, 2, 4, 6, 12, 16, 24 and 28. The proposed system is working in automatic way for 100 experiments and stops when the best network is obtained. Where, the previous mentioned parameters are chosen in a linear combination way. The system is continued until excellent training and test are reached. After the training, it is noticed that the proposed system is working in an efficient way. It is found that, three Hls using 133 neurons for the first two HLs and 99 neurons for the third HL at 2000 epochs are enough for reaching the optimal solution as specified in Fig. 5. While Fig. 6 presents the performance of the trained NNets system. The NNets results are given in Fig. 7 having eight cases of training and two cases of prediction. It is noticed that, the proposed NNets system shows excellent results matched with the experimental data. The trained system is predicted the behaviour of P at the value of A equals 7 and 32.

ANFIS: This system is carried out and simulated to the experimental data using the proposed values of the three

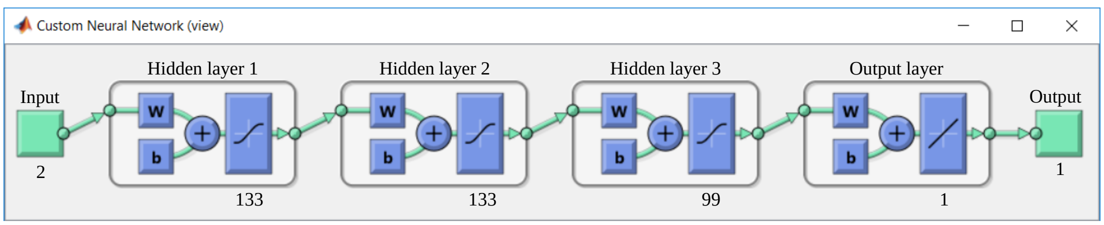

Fig. 5: The architecture of the NNets system

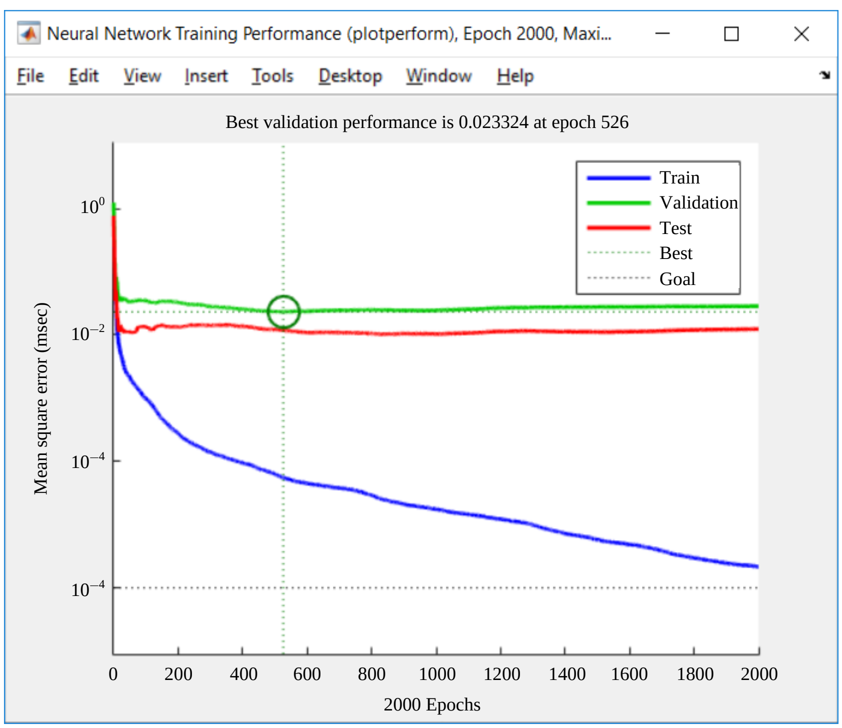

Fig. 6: The performance of the NNets system

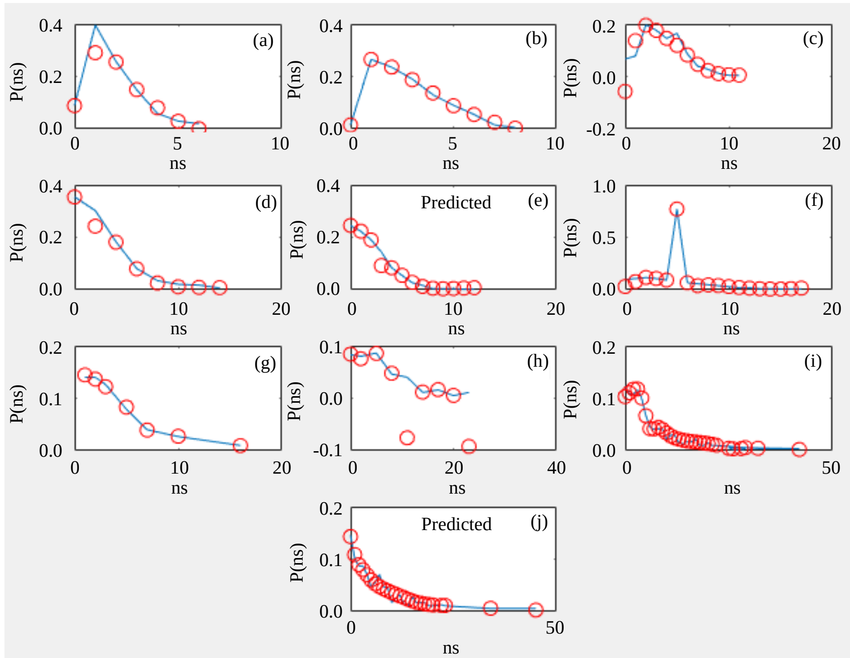

Fig. 7(a-j): Simulation results of NNets for the multiplicity distribution of shower particles produced from the (a) P, (b) ^{2}H, (c) ^{4}He, (d) ^{6}Li, (e) ^{7}Li, (f) ^{12}C, (g) ^{16}O, (h) ^{24}Mg, (i) ^{28}Si and (j) ^{32}S with light (HCNO) emulsion at 4.5 AGev/c using No. of HLs = 3 and NOEs = 2000

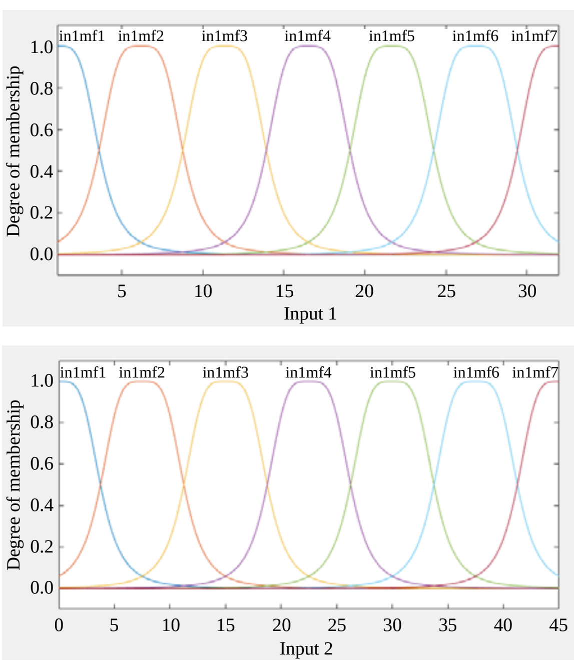

Fig. 8: Structure of MFs before training

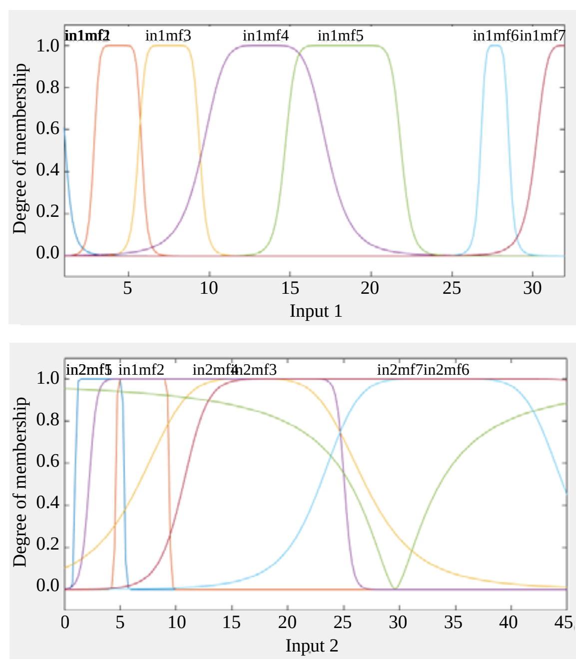

Fig. 9: Structure of MFs after training

mentioned parameters. The system is also trained on the previous eight cases. They are the same training data that are used for training with the NNets system. These cases values are 1, 2, 4, 6, 12, 16, 24 and 28. After the training, the trained system is predicted the behaviour of P at the value of A equals 7 and 32. It is found that the obtained results are

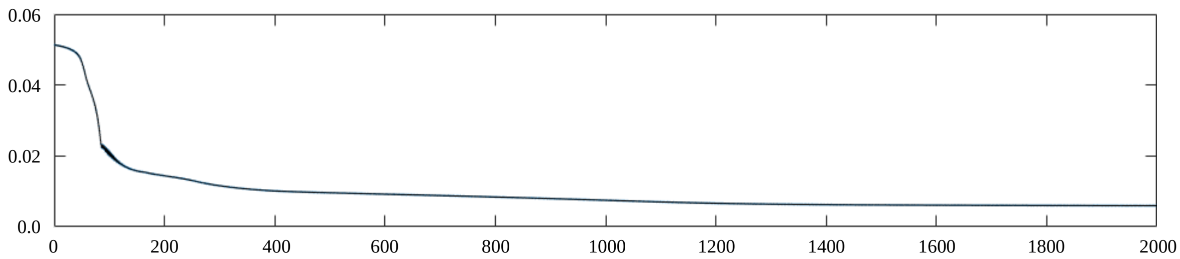

Fig. 10: The best trained ANFIS using MFs = 7 and NOEs = 2000

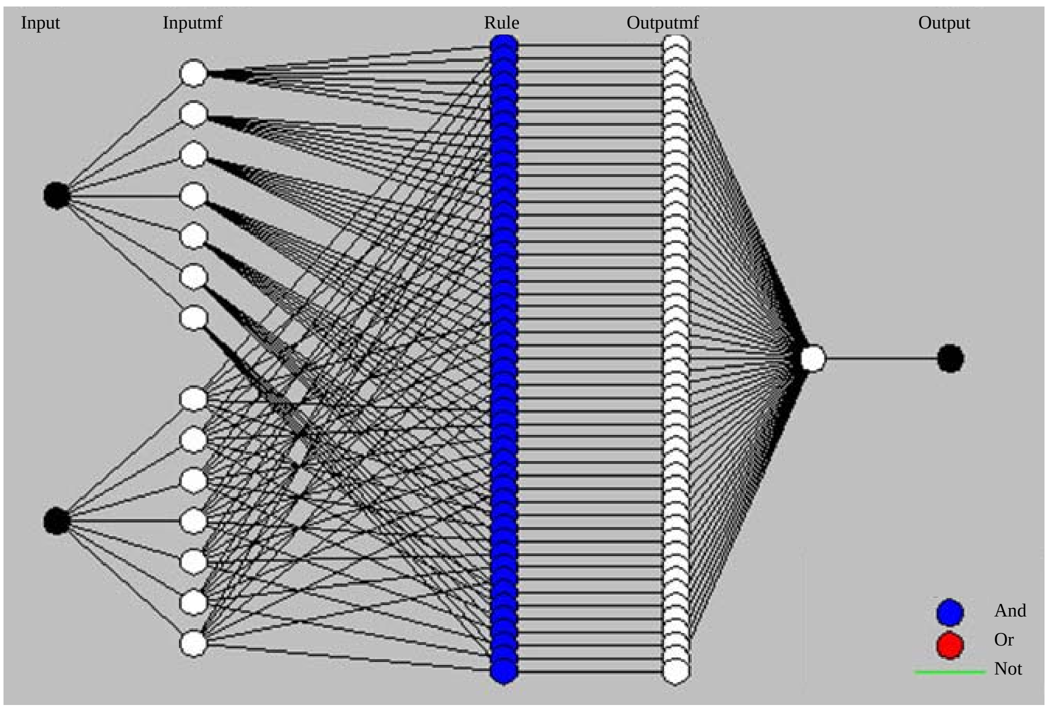

Fig. 11: The ANFIS architectures of the best network

affected by the number of MFs, the results are not good using the values from 2 up to 6, specially the predicted results. The results are better using 7 MFs and 2000 epochs.

The MFs before training are shown in Fig. 8. After training, they are given in Fig. 9. While, Fig. 10 shows the performance of the trained ANFIS. The architecture of the best-trained ANFIS is shown in Fig. 11.

The system results using 7 MFs at 2000 epochs are presented in Fig. 12. These results contain eight cases of training and two cases of prediction.

DISCUSSION

In this study, two effective systems are applied on the multiplicity distribution of shower particles produced from the P, ^{2}H, ^{4}He, ^{6}Li, ^{7}Li, ^{12}C, ^{16}O, ^{24}Mg, ^{28}Si and ^{32}S with light (HCNO) emulsion at 4.5 AGev/c for ten cases of P(ns). Two of them are used for prediction and eight for training and test. They are ANFIS and NNets systems. This problem is firstly processed with the NNets system. Then, the other system (ANFIS) is applied on the same problem, in order to make an effective comparison between them. The two systems are trained, tested and validated on the same data.

After training them, they are used to predict the behaviour of P(ns) at the values for ^{7}Li and ^{32}S. It is found that, the obtained results specify that ANFIS and NNets are effective models for prediction the other representation not given in the training data and matched them accurately. While, the obtained results of ANFIS is slightly better than the NNets especially for test and predicted phases; (Fig. 7, 12). The ANFIS system got its optimal performance

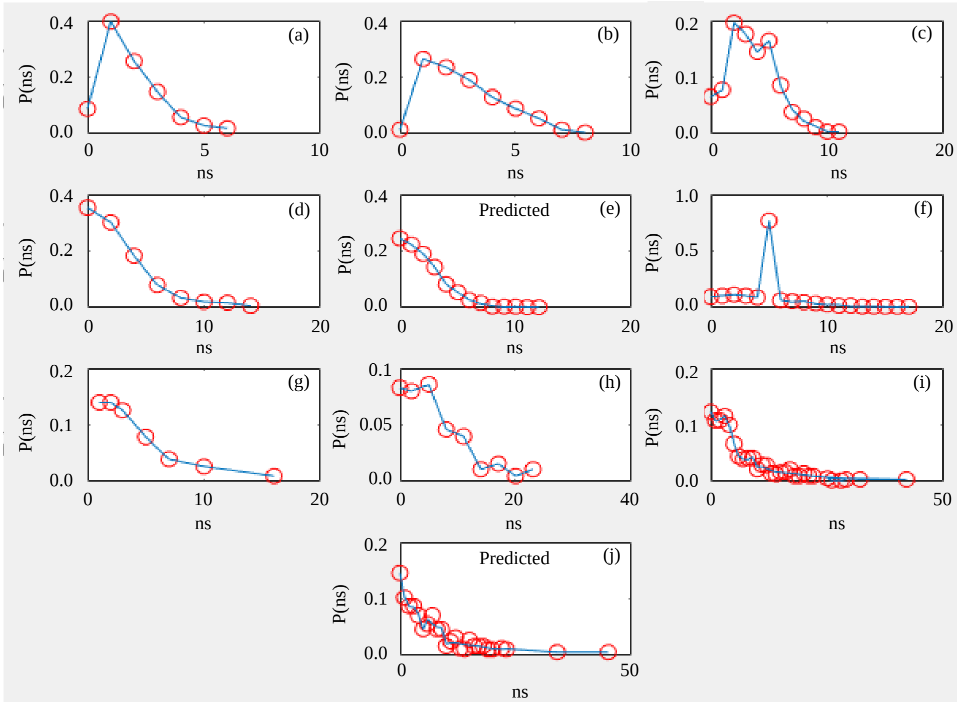

Fig. 12(a-j): Simulation results of ANFIS for the multiplicity distribution of shower particles produced from the (a) P, (b) ^{2}H, (c) ^{4}He, (d) ^{6}Li, (e) ^{7}Li, (f) ^{12}C, (g) ^{16}O, (h) ^{24}Mg, (i) ^{28}Si and (j) ^{32}S with light (HCNO) emulsion at 4.5 AGev/c using MFs = 7 and NOEs = 2000

with 7 MFs at 2000 epochs. While, the NNets got its optimal performance with 3 HLs and 2000 epochs.

It is also seen that, the ANFIS system is more faster than the NNets system specially in the training phase; this agreed with Gaur *et al.*[22]. This affected by many computations in the training phase, the NNets repeats every experiment of the same architectures many tries for obtaining the optimal performance. Moreover, the training time was increased for NNets system comparing with the ANFIS. As well as, any repeated experiment of the ANFIS system or the NNets system using the same setting, the obtained results are not changed of ANFIS, while, the results of the NNets system will be different in every repeating. Thus, the ANFIS is the fastest for having trained system.

CONCLUSION

The ANFIS is developed to work in the field of theoretical energy physics. This system is applied to get the best trained ANFIS that has the capability to have the best test and prediction with varying the number type of MFs and the NOEs. Therefore, a lot of tries is carried out to find the best ANFIS having low NOEs and MFs. The proposed systems (ANFIS and NNets) are applied and tested on different beams collisions with light nuclei. They can compute the multiplicity distribution of shower particles produced from the P, ^{2}H, ^{4}He, ^{6}Li, ^{7}Li, ^{12}C, ^{16}O, ^{24}Mg, ^{28}Si and ^{32}S with light (HCNO) emulsion at 4.5 AGev/c. After the training, the obtained systems are predicted the behaviour of P(ns) at the values for ^{7}Li and ^{32}S. It is found that, the results of ANFIS is better than the NNets in the test and predicted data. In addition to, the ANFIS has fastest trained comparing with NNets system. The ANFIS system gets the optimal results with low MFs using 'gbellmf' function. Simulation results using the ANFIS of training particles are tested with training data points showed perfect fitting to the data given by the experimental data. The ANFIS system has predicted the data with good performance, although this data is not represented in the training data. The results sufficiently show the feasibility of such technique for extracting the collision features and prove its effectiveness. The proposed ANFIS is more effective model for predicting the behaviour of different beams collisions with light nuclei.

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