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Artificial neural network for Au- Au collision at different Centrality

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Abstract-An artificial neural network (ANN) was used to study experimental particles ratios for Au-Au collisions at different centrality (0-5 , 20-30 and 40-60 %) and different energies ($\sqrt{S_{NN}}$=39 , 11.5 and 7.7 GeV). The neural network was designed to simulate particles ratios . The system was trained on the available data in three cases. Therefore we designed the system for finding the best performance. Simulation results are compared with experimental results.High precision was found as well as good performance of the ANN model.

Index Terms-Neural networks, Centrality dependence.

1 INTRODUCTION

When two nuclei collide they can overlap more or less. The degree of overlapping is called centrality. If the overlap region is large the number of nucleons which interact inelastically, called participants, is important and the system formed is a hot and highly compressed system. Depending on initial energy of the nuclei the quark-gluon plasma (QGP) is expected to occur . There are many experimental signals for QGP and recently many efforts have been made to analyze experimental data obtained in relativistic heavy ion collisions in order to search for these signals . It is obvious that the properties of the matter formed after collision depend not only on initial energy but also on centrality. This is one of the reasons why the analysis of the experimental data is made in so called centrality bins [1]. Neural networks are widely used for solving many problems in most science problems of linear and non linearcases . Neural network algorithms are always iterative, designed to step by step minimize (targeted minimal error) the difference between the actual output vector of the network and the desired output vector [2].This paper uses an ANN program to model the nonlinear relationship between centrality and particles ratios . The following sections provide introduction to ANN, describe the selected ANN structure, simulation results and discuss the results.

2-Artificial Neural Network (ANN)Model

ANN is a network of highly interconnecting processing elements (neurons) operating in parallel [3-12]. These elements are inspired by biological nervous systems. A neuron has one or more inputs, each of which is individually weighted. A neuron has one or more output that is weighted when connecting to other neurons. The neuron itself includes a function that incorporates its inputs (via summation) then, normalizes its output via a transfer function (see Fig. (1))the connections between neurons largely determine the network function. A subgroup of processing elements is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layers, there may be additional layer(s) of units, called hidden layer(s). Fig. (1) represents the typical neural network. It is possible to train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. The ANN model was trained with different numbers of neurons and chose randomly logsig (Log sigmoid) transfer functions and Trainrp (Resilient back propagation; Rprop) algorithm for hidden layers. The resilient back propagation algorithm is known as one of the fastest and most all round training algorithms for artificial neural networks. The supervised learning used to train the network, is associated with an output pattern, considered as the target or the desired pattern. A teacher is assumed to be present during the learning process such that when a comparison is made between the network's computed output and the correct expected output, to determine the error. Then the error can be used to change network parameters, leading to an improvement in performance.

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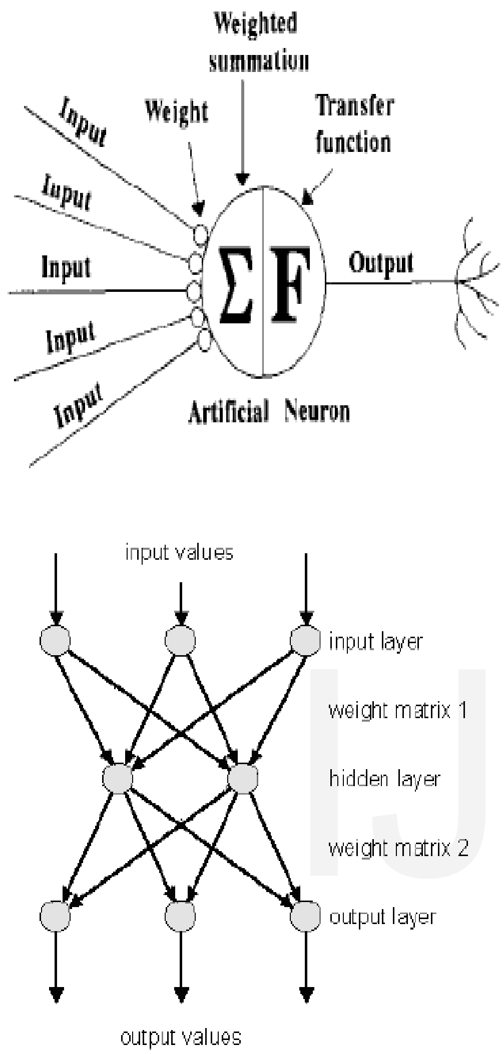

Fig. (1). Architecture of an artificial neuron and a typical neural network.

3 ANN model for centrality

Neural networks were trained simultaneously using experimental data of centrality at different energies. The proposed ANN model of centrality is given as two inputs- and one output. The inputs are energies($\sqrt{S_{NN}}$ =39 ,11.5GeV and 7.7GeV) and centrality(0-5 , 20-30 and 40-60 %). The output is the particle ratios. As the nature of the inputs (different centrality) is completely different from each other, authors choose our individual neural networks trained separately using experimental data. Author used three networks with the same hidden layer , neurons in each hidden layer and performance. A simplification of the proposed ANN models is shown in Fig. (2).

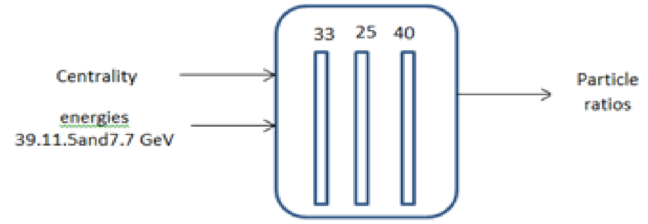

Fig. (2) Block diagram for particle ratios based ANN model.

4 Results

The centrality is estimated using ANN. ANN simulate the values of particle ratios as a function of centrality(0-5 , 20-30 and 40-60%) and energies ($\sqrt{S_{NN}}$ =39 , 11.5 and 7.7 GeV). The first network was configured to have centrality (0-5%) and energies ($\sqrt{S_{NN}}$=39 , 11.5 and 7.7 GeV), The second network was configured to have centrality (20-30%) and energies ($\sqrt{S_{NN}}$=39 , 11.5 and 7.7 GeV) and third network have centrality (40-60%) and energies ($\sqrt{S_{NN}}$=39 , 11.5 and 7.7 GeV), Using this input-output arrangement, different networks configurations were tried to achieve good mean square error (MSE) and good performance for the networks. First , second and third ANN having three hidden layers of 33, 25and40neurons. The transfer functions of these hidden layers were chosen to be logsig, while the output is to be pureline. Network performance was evaluated by plotting the ANN model output against the experimental data and analyzing the percentage error between the predicted and the experimental data Figs. (3). It reveals that the training sum of squared errors is always reduced during the training procedure. The best mean square error for each network was reached after 202 epochs .The simulation results from the obtained function which is given in appendix are best fitting with the experimental data as shown in Figs.(4 , 5 and 6).

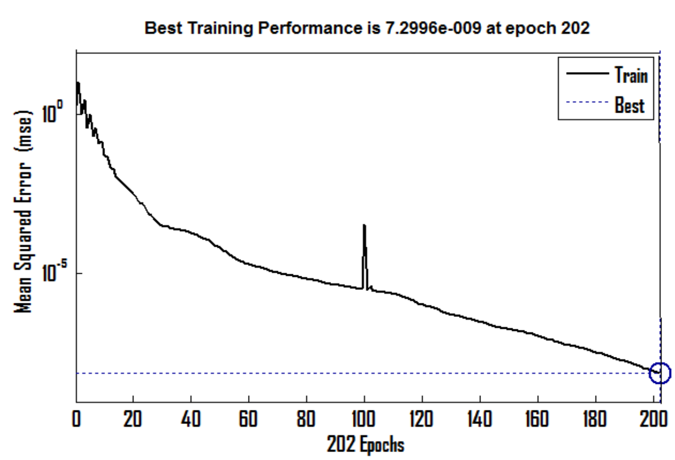

Fig. 3 Performance for particle ratios using ANN, where epochs are the numbers of training.

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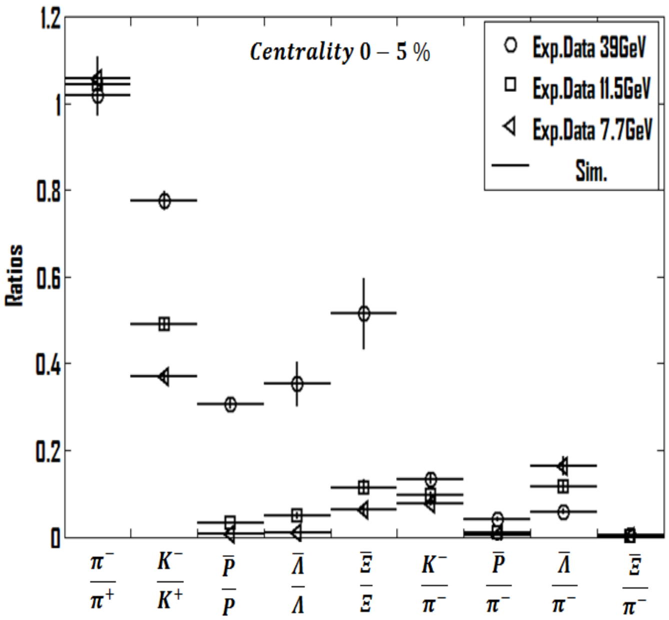


Fig.4 ANN model for particles ratios at centrality (0-5%) and energies ($\sqrt{S_{NN}}$=39,11.5 and 7.7 GeV) [13-15].

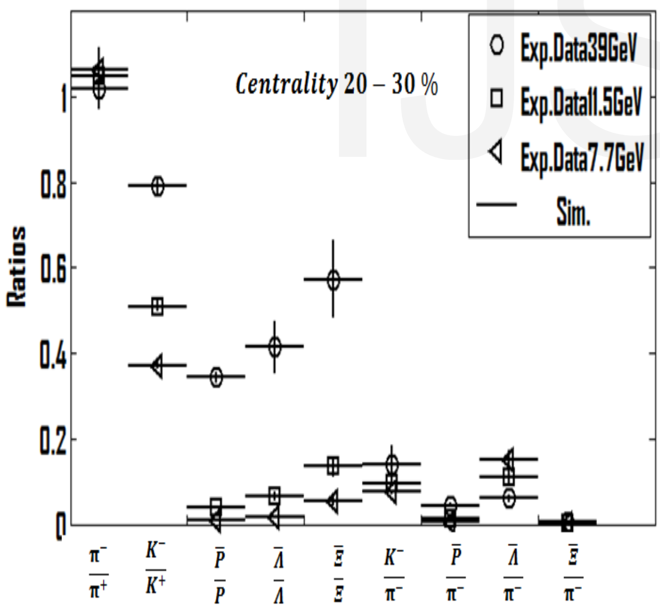


Fig.5 Simulation results of Particles ratios at different energies ($\sqrt{S_{NN}}$ =39,11.5 and 7.7 GeV) and centrality (20-30%)[13-15].

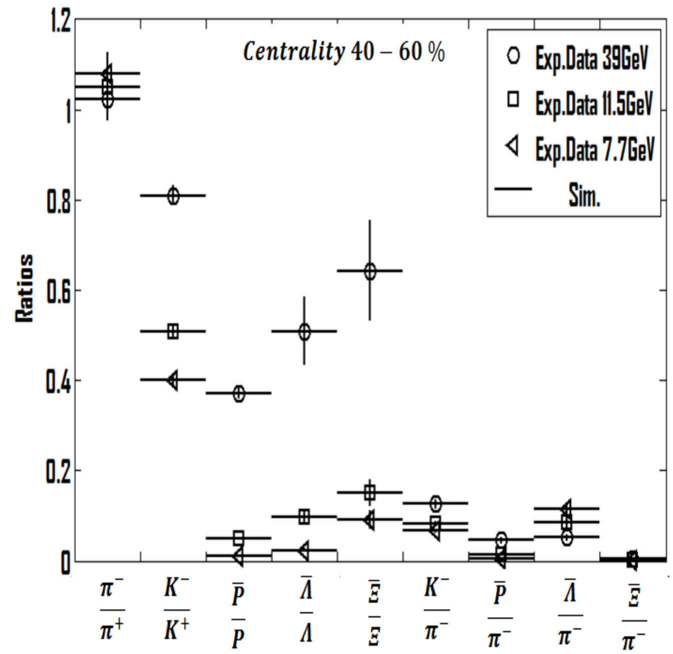


Fig.6 Particles ratios simulation at different energies ($\sqrt{S_{NN}}$ =39,11.5and7.7GeV)and centrality (40-60%)[13-15]

5 Conclusion

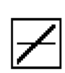
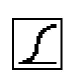
In this paper, a method was proposed to model experimental particles ratios for Au-Au collisions at different centrality (0-5 , 20-30 and 40-60 %) and different energies ($\sqrt{S_{NN}}$ =39 , 11.5 and 7.7 GeV) using ANN. The trained ANN shows excellent results matched with the experimental data. The designed ANN introduce a powerful model and shows a good match to the experimental.then, the capability of the ANN techiques to simulate the experimental data with almost exact accuracy recommends the ANN to dominate the modeling techniques in physics of Au – Au collisions.

Appendix

The equation which describes particles ratios isgiven by:

pureline [net. LW{4,3} logsig(net. LW{3,2} logsig(net. LW{2,1} logsig(net. IW{1,1}T+net. B{1})+net. B{2})+net. B{3})+ net. B{4}],

where

Pureline ,  logsig 

T: the input (centrality and energies),

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net. IW{1,1}: linked weights between the input layer and firsthidden layer,
net. LW{2,1}: linked weights between the first hidden layerand the second hidden layer,
net. LW{3,2}: linked weights between the second hidden layerand third layer,
net. LW{4,3}: linked weights between the third hidden layerand output layer,
net. B{1}: the bias of the first hidden layer,
net. B{2}: the bias of the second hidden layer,
net. B{3}: the bias of the third hidden layer, and
net. B{4}: the bias of the output layer.

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