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Artificial Neural Network Modeling in Hadrons Collisions

[1, 2] Moaaz A. Moussa
[1] Ain Shams University, Faculty of Education, Physics Department, Roxi, Cairo, Egypt.
[2] Buraydah Colleges, Physics Department, Al-Qassim, Buraydah, King Abdulazziz Road, East Qassim University, P.O.Box 31717, KSA.
moaaz2030@yahoo.com

[1] Mahmoud Y. El-Bakry
Tabuk University, Faculty of Sciences, Physics Department, Tabuk, KSA.

[3, 4] A. Radi, [3, 5] E. El-dahshan, [1] M. Tantawy
[3] Ain Shams University, Faculty of Sciences, Physics Department, Abbassia, Cairo, Egypt.
[4] The British University in Egypt (BUE).
[5] Egyptian E-Learning University- 33 El-mesah St., El-Dokki- Giza- Postal Code 12611, Egypt.

Abstract— Evolutions in artificial intelligence (AI) techniques and their applications to physics have made it feasible to develop and implement new modeling techniques for high-energy interactions. In particular, AI techniques of artificial neural network (NN) implement more effective models. The neural network (NN) model and parton two fireball model (PTFM) have been used to study the charged particles multiplicity distributions for antipro ton-neutron ($\bar{p}-n$) and proton-neutron ($p-n$) collisions at different lab momenta. The neural network model performance was also tested at non-trained space (predicted) and matched them effectively. The trained NN shows a better fitting with experimental data than the PTFM calcula tions. The NN simulation results prove a strong presence modeling in hadrons collisions.

Index Terms— Neural Network Model; Parton Model; Multiparticle Production.

1 Introduction

The validity of the mathematical treatment and assumptions comes from the agreement between the theoretical results and corresponding outcomes from experimental measurements. The closest is this agreement the successful is a certain modeling. Models are provided for the hadron structure [1-3]. These include the quark model [4], three fireball model [5], fragmentation model [6, 7], and many others. The theories and ideas concerning multiparticle production go back to the late of 1930s with a significant interlude at Fermi's statistical theory of particle production [8]. Multiparticle production can be also modeled and described efficiently by studying the multiplicity distribution [9]. Several methods exist which investigate the multiplicity distribution of particles at high energy [10-13]. Among these are the multiplicity scaling [10, 11], the statistical boot strap model [12], the two sources model [14], the negative binomial distribution [15], fireballs [16], strings [17], quark gluon plasma [18, 19] and many others.

Parallel to the theoretical approach based on different views, development in the artificial intelligence (AI) field has given the neural networks a strong presence in high-energy physics [20-22]. Neural networks are composed of simple interconnected computational elements operating in parallel. These artificial neural networks (ANNs) are trained, so that a particular input leads to a specific target output. The objective of this paper is to extract the multiplicity distribution of charged particles for $\bar{p}-n$ and $p-n$ collisions at different lab momenta using PTFM and NNM. Section 2 presents parton two fireball model PTFM at high energies. Section 3 provides the multiparticle production in proton-neutron and antiproton-neutron collisions using PTFM. The NN model is described in Sections 4, 5. The results and conclusion of both models are explained in Section 6.

2 Parton Two Fireball Model (PTFM)

According to the parton two fireball model [23-25], $\bar{p}-n$ and $p-n$ interaction will be characterized by the impact parameter and the corresponding overlapping volume. Let us assume that the two interacting hadrons at rest are spheres each of radius (R). Therefore, the two colliding particles can interact strongly when the impact parameter is in the region from $0 \rightarrow 2R$. Therefore, the statistical probability of any impact parameter (b) within an interval (db) is given by

$$P(b)db = \frac{bdb}{2R^2} \tag{1}$$

Let us use a dimensionless impact parameter, X defined as, $X = b/2R$. Then, Eq. (1) can be rewritten as

$$P(X)\ dX = 2X\ dX \tag{2}$$

Where $0 \le X \le 1$

Now we employ the overlapping volume, $V(b)$ as a clean cut [26] as

$$V(b) = V_0 (1 - \frac{3b}{8R} - \frac{3b^2}{8R^2} + \frac{5b^3}{32R^3}) \tag{3}$$

In terms of the dimensionless impact parameter (X), the overlapping volume $V(X)$ can be given by

$$V(X) = V_0 (1 - 0.75X - 1.5X^2 + 1.25X^3). \tag{4}$$

Then the fraction of partons, $Z(X)$participating in the interaction may be written as,

$$Z(X) = \frac{V(X)}{V_0} = (1 - 0.75X - 1.5X^2 + 1.25X^3). \tag{5}$$

According to Eq. (2) and Eq. (5), the Z-function distribution can be given by,

$$P(Z)\, dZ = 2X\, dX\, (-2.4375 X - 0.75 X^{-1} + 7.125 X + 0.75 X^2 - 9.375 X^3 + 4.687 X^4)^{-1} \tag{6}$$

where, $0 \le Z \le 1$

From Eqs. (2, 5) and using least square fitting technique (LSFT), Z-function distribution can be written in the following form,

$$P(Z)dZ = \sum_{k=-1}^{k=3} C_k Z^k dZ \tag{7}$$

Where, C_k (k = -1, 0, 1, 2, 3) are free parameters to be calculated to produce a fitting between Eq. (6) and the curve drawn from Eq. (7). From such fitting procedure the obtained values for C_k are,

$C_{-1} = 0.089, C_0 = 1.21, C_1 = -2.65, C_2 = 3.228$ and $C_3 = -1.823$.

3 Multiparticle Production in $\bar{p}-n$ and $p-n$ Collisions

After the collision takes place, the partons within the overlapping volume stop in the center of mass system (CMS); their kinetic energy (K.E.) will be changed into excitation energy to produce two intermediate states (fireballs). The produced fireballs will radiate the excitation energy into a number of newly created particles, which are mostly pions. We assume that each fireball will decay in its own rest frame into a number of pions with an isotropic angular distribution. The number of created pions will be defined by the fireball rest mass (M_f) and the mean energy consumed in the creation of each pion (ε).

The energy available for the creation of pions from each fireball will be,

$$M_f - m = T_\circ Z(X) \tag{8}$$

Where, T_0 is the kinetic energy of the incident proton in CMS and given by, $T_0 = \frac{Q}{2}$, Q is the total available kinetic energy in CMS.

The number of created pions (N_0) from each fireball will be given by,

$$n_o(Z) = \frac{Z(X)T_0}{\varepsilon} = \frac{Z(X)Q}{2\varepsilon} \tag{9}$$

It is clear that Eq. (9) gives the total number of created particles (charged and neutral) as a function of the dimensionless impact parameter.

To get the charged particles multiplicity distribution, we have to assume some distribution for the charged particles (n_{ch}) in the final state of the interaction at any impact parameter out from the total created particles (n_0). We considered the new created particles from each fireball can be divided into a number of pairs. Each pair will be either charged or neutral to satisfy the charge conservation.

From equations (7) and (9), the total number of created particles distribution, $P(n_o)$ can be calculated from the following equation,

$$P(n_o) = \sum_{k=0}^{3} (\frac{1}{Q})^{k+1} c_k \left[\frac{\left[2a(n_o+1)^2 + 2b(n_o+1)\right]^{k+1} - (2an_o^2 + 2bn_o)^{k+1}}{k+1} \right] + c_{-1} \ln\left[\frac{2a(n_o+1)^2 + 2b(n_o+1)}{2an_o^2 + 2bn_o} \right] \tag{10}$$

We assume a binomial and Poisson distributions for the probability distribution for the creation of charged pion pairs from one fireball of the forms,

1) Binomial Distribution of the form,

$$\psi(n_2) = \frac{N!}{n_2!(N - n_2)!} p^{n_2} q^{(N-n_2)} \tag{11}$$

2) Poisson Distribution of the form,

$$\psi(n_2) = \frac{N^{n_2}}{n_2!} p^{n_2} e^{-NP} \tag{12}$$

where, N is the number of pairs of created particles from one fireball ($N=n_0/2$), n_2 the number of pairs of charged pions , p the probability that the pair of pions is charged, q the probability that the pair of pions is neutral.

Therefore, the charged particles distribution from one fireball will be given by,

$$\phi(n) = \sum_{n_0} \psi(n_2) P(n_0) \tag{13}$$

Then, the charged particles multiplicity distribution from the two fireballs will be,

$$P(n_{ch}) = \sum_{n=1}^{nch} \varphi(n)\varphi(n_{ch}-n)\ ; \quad n_{ch} = 2,4,6,........Q/\varepsilon \tag{14}$$

We assume that ε increases with the multiplicity size, (n_0), as, $\varepsilon = an_0 + b$

where, a and b are free parameters which can be taken to be, a= 0.01, b = 0.35 for $\bar{p}-n$ and a = 0.01, b = 0.44 for $p-n$.

Charged particles multiplicity distributions have been calculated at P_L=50, 80 GeV/c for $\bar{p}-n$ and P_L=100, 200, 400 GeV/c for $p-n$ which are represented in fig 1. a, b, c, d and e along with the corresponding experimental data [27-30].

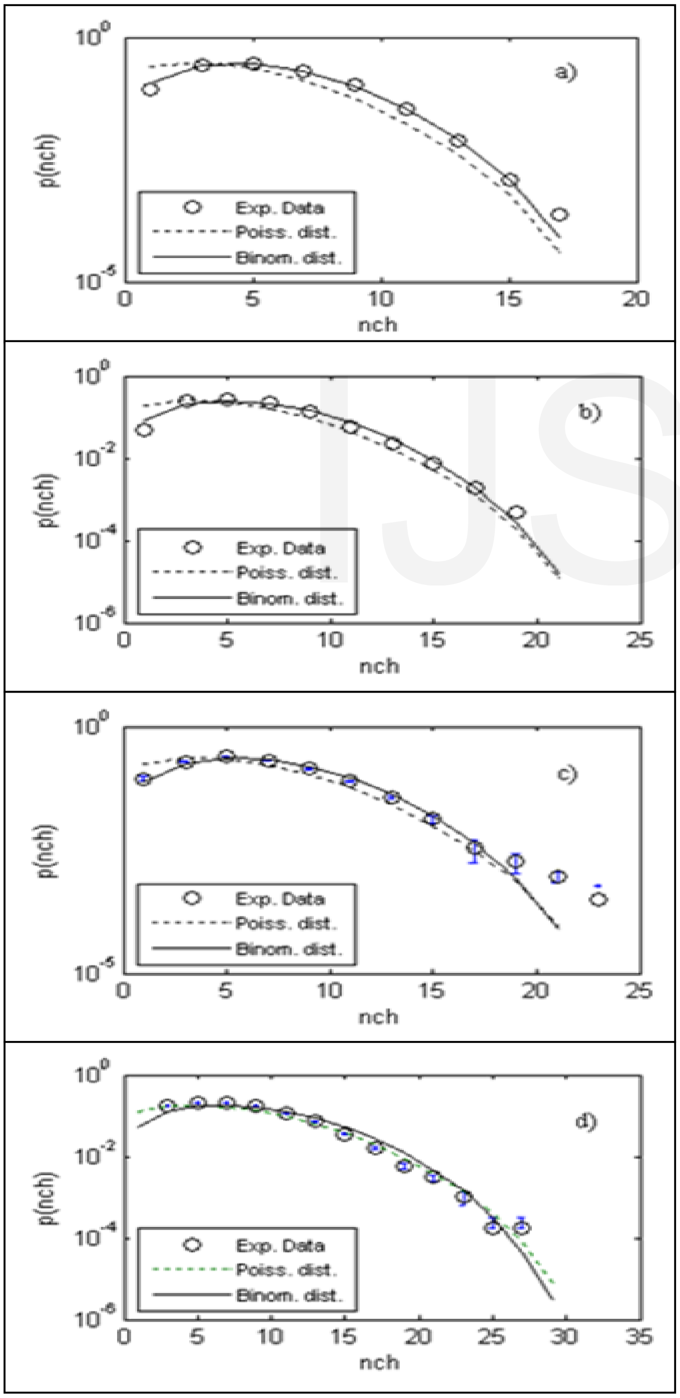
4 Artificial Neural Networks (ANNs)

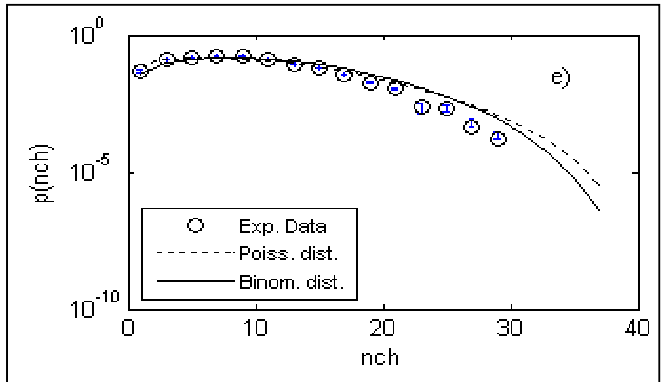
An ANN is made up of a number of simple and highly interconnected computational elements. There are many types of ANNs, but all of them have three things in common: individual neurons (processing elements), connections (topology), and a learning algorithm. The processing element calculates the neuron transfer function of the summation of weighted inputs. A simple neuron structure is shown in the fig 2. The neuron transfer function, f , is typically step or sigmoid function that produces a scalar output (n) as in Eq. (15).

$$n = f \sum_i w_i I_i + b \tag{15}$$

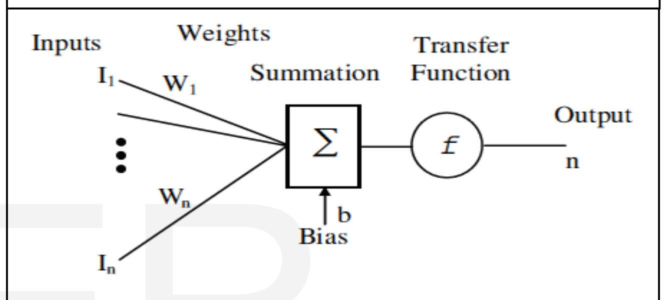
where I_i , w_i , b are the i th input, the i th weight and b the bias respectively.

A network consists of one or more layers of neurons. A layer of neurons is a number of parallel neurons. These layers are configured in a highly interconnected topology.





"Figure 1. Normalized multiplicity distribution of charged particles n_{ch} for $\overline{p}-n$ and $p-n$ collisions calculated according to the parton two fireball model as parameterized by Poisson and binomial distribution using Eq.(14) in comparison with the corresponding experimental data at a) 50, b) 80, c) 100, d) 200 and e) 400 GeV/c"



"Figure 2. Neuron model"

5 Training of the h-h-ANN

Neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Training in simple is to make a particular input leads to a specific target output. The weights are adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

The proposed ANNs in this paper was trained using Levenberg–Marquardt optimization technique. This optimization technique is more powerful than the conventional gradient descent techniques [31-35].

The Levenberg–Marquardt updates the network weights using the following rule:

$$\Delta W = (J^T J + \mu I)^{-1} J^T e$$

where J is the Jacobian matrix of derivatives of each error with respect to each weight, μ is a scalar, changed adaptively by the algorithm and e is an error vector.

The only requirement for this method is a considerably large memory for large problems. The initial training weights were also chosen using the Nguyen–Widrow random generator in order to speed up the training process [31-35].

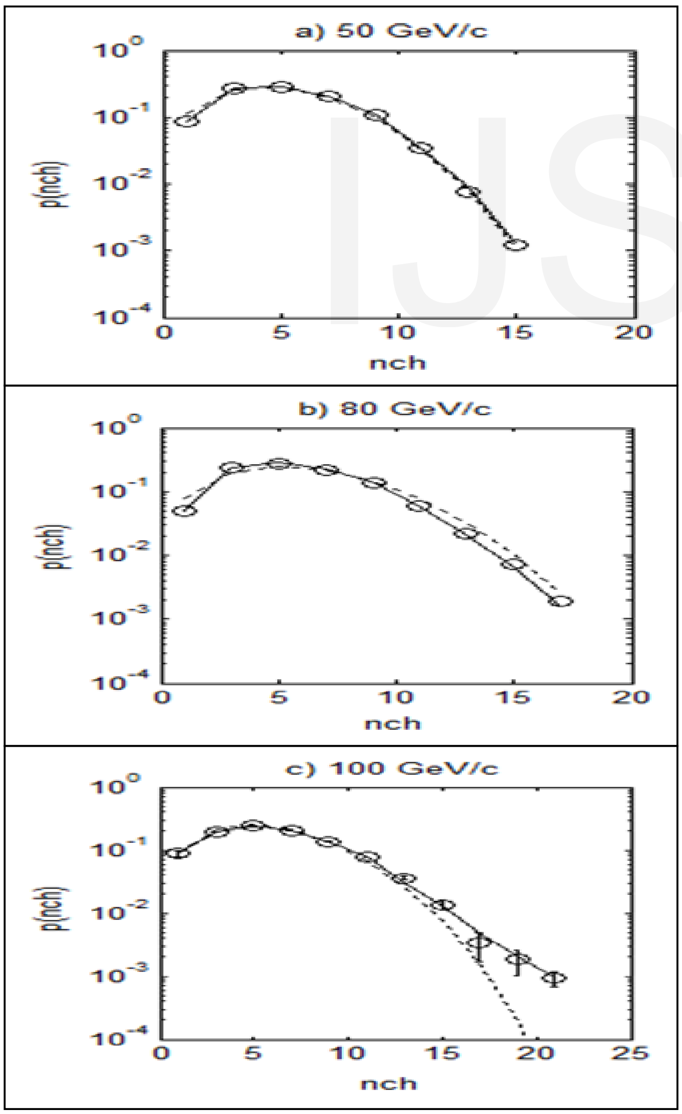
6 Results and Conclusion

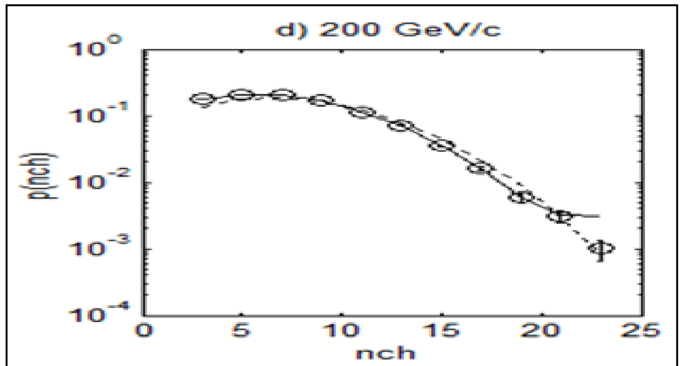
The charged particles multiplicity distributions using PTFM, Eq. (14), are calculated for $\overline{\mathrm{p}}-\mathrm{n}$ and $\mathrm{p}-\mathrm{n}$ assuming ε given by:

$$\varepsilon = an_0 + b$$

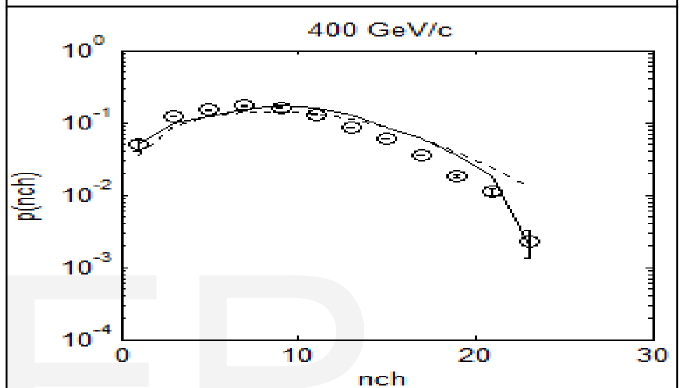
where, a = 0.01, b = 0.35 for $\overline{\mathrm{p}}-\mathrm{n}$ and a = 0.01, b = 0.44 for $\mathrm{p}-\mathrm{n}$. The results of these calculations are represented in fig 1. a, b, c, d and e along with the experimental data [27-30] which show fair agreement with the corresponding experimental data. It can be seen from fig 1. that the emission of secondary particles is assumed to follow a binomial distribution.

We have also modified our calculations using ANN model and these calculations are represented in fig 3. a, b, c, d and e along with the same experimental data [27-30]. We have also found some considerably variations in comparison with fig 1. Using the input-output arrangement, different network configurations were tried to achieve good mean squared error (MSE) and good performance for the network. It consists of an input layer (P_{Lab}, n_{ch}), one hidden layers of 10 neurons, respectively, and an output layer consisting of one neuron P (n_{ch}).





"Figure 3. Comparison between the experimental and simulated multiplicity distribution of pions $P(n_{ch})$ for $\overline{\mathrm{p}}-\mathrm{n}$ collisions at a) 50, b) 80 GeV/c and $\mathrm{p}-\mathrm{n}$ collisions at, c) 100, d) 200 GeV/c: (—) NN model, (……) PTFM model, (O) experimental data".



"Figure 4. Comparison between the experimental and predicted multiplicity distribution of pions $P(n_{ch})$ for $\mathrm{p}-\mathrm{n}$ collisions at 400 GeV/c: (—) NN model, (……) PTFM model, (O) experimental data".

The transfer functions were chosen to be a tansigmoid function for the hidden layer and a pureline function for the output layer, the trained NN model shows almost exact fitting. It is worth mentioning that the NN training data did not include the experimental data at PL =400 GeV/c. This means that the NN model, not only simulated the trained observations (fig 3) but also predicted the multiplicity distribution of charged pions for untrained observations as shown in fig 4. Then, the ANN technique is able to exactly model for multiplicity distribution at lab momenta for different beams in hadrons collisions.

Appendix

Where net is 2-10-1 (input-i-j-k-output) and the equation is

[(net: LWi (tansigmoid (pureline (net: I A + net: bi) + net: b))))]

Where, A is the input consists of two elements
net: I : linked weights bet. the input layer and 1st hidden layer,
net: LW: linked weights bet. 3rd input layer and output layer,
net: bi: biases for the hidden layer,
net: b : biases for output layer.

I(input, hidden)(2, 10) =

$$\begin{Bmatrix} 4.7630 & 3.4592 & -3.6549 & -2.5606 & 4.0100 & -2.9577 & -0.1847 & 2.3966 & 3.3804 & 4.0002 \\ -0.4856 & -1.8749 & 3.8754 & -1.7683 & 1.9219 & -3.8578 & -4.8338 & 0.6290 & 1.9331 & 0.0420 \end{Bmatrix}$$

LW (hidden, ouput)(10,1) =

$$\begin{Bmatrix} 0.4117 \\ 0.2625 \\ 0.1937 \\ 0.5731 \\ -0.0846 \\ 0.0104 \\ -0.2503 \\ -2.6346 \\ 0.8085 \\ -2.4237 \end{Bmatrix}$$

b (10,1) =

$$\begin{Bmatrix} -3.9147 \\ -3.5424 \\ 1.9821 \\ 3.0480 \\ -0.2501 \\ -1.0340 \\ 0.2278 \\ 1.7418 \\ 2.5888 \\ -3.7691 \end{Bmatrix}$$

bi (output) = -1.2991

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