Prediction of High Energy Particle Shower Primary Energy and Core Location using Artificial Neural Network (ANN)

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Abstract: Artificial Neural Network (ANN)s can be modeled for High Energy Particle analysis with special emphasis on shower primary energy and core location. The work describes the use of an ANN based system which has been configured to predict primary energy and locations of cores of showers in the range \(10^{10.5}\) to \(10^{20.5}\) eV. The system receives density values as inputs and generates sizes and coordinates of shower events recorded for values captured by 20 core positions and 100 detectors in an area of radius 100 meters. Twenty ANNs are trained for the purpose and the positions of shower events optimized by using cooperative learning. The results derived with variations of input upto 50% show success rates in the range of 90%.

Keywords: EAS, Core, Primary Energy, Location, NKG.

1 Introduction

Study of Extensive Air Shower (EAS) characteristics involve analysis and measurement of the size, position and time extent of the events. Experimental density values maybe used to calculate the shower sizes and location of events which involves tedious theoretical work. Also there are several constraints related to experimental works associated with the measurements involved due to related uncertainties. Some of them are due to inaccurate knowledge on interactions of shower particles and primary energies [1] [2]. Therefore, there always exist a necessity to develop a readily available system which can be used to predict primary energy and locations of showers. Soft-computational tools like Artificial Neural Network (ANN) provide a viable option as these can be trained to adapt to situations and learn the variations taking place. The knowledge developed using apriori references can be utilized for predicting future developments as an aid to expand the knowledge of EAS and can be made a part of physical experiential apparatus to facilitate adaptive orientation of monitoring and analysis of shower events that too in real time. The most preferable aspects of the ANN in these applications are parallelism, adaptive processing, self-organization, universal approximation and ability of tackling highly nonlinear problems. The present work discusses the formulation and working of an ANN based system for prediction of EAS size in the range \(10^{10.5}\) to \(10^{20.5}\) eV. The system uses a Multi Layer Perceptron (MLP) - a class of feed forward ANN trained with error back - propagation algorithm to predict the primary energy of showers. The prediction is made after extensive training with data samples simulated resembling experimental conditions. The work also discusses the formulation and working of another ANN based system for prediction of EAS event location in the given range. Twenty MLPs are trained with error back - propagation algorithm in a cooperative configuration to provide optimized shower event coordinates.

2 Application of ANN for Shower size prediction and Core Location

Artificial Neural Network (ANN)s are non-parametric prediction tools that can be used for a host of pattern classification problems and prediction problems [3]. The application of the ANN considers two aspects. First training the network and then testing it. During training the ANN acquires knowledge and later uses this knowledge to make prediction. Here a MLP is used for the work which consists of several layers of artificial neurons grouped as input, hidden and output stages. The equation for output in a MLP with one hidden layer is given as:

\[
O_x = \sum_{i=1}^{N} \beta_i g[w_i]_i[x] + b_i \tag{1}
\]

where \(\beta_i\) is the weight value between the \(i^{th}\) hidden neuron. Such a set-up maybe depicted as in Figure 1. The process of adjusting the weights and biases of a perceptron
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Figure 1: Multi Layer Perceptron

Figure 2: Conceptual set-up used for simulation of density functions of EAS

or MLP is known as training. Showers were generated according to a modified NKG function [2] with particle content between $10^{10.5}$ to $10^{20.5}$ eV with Moliere radius of 70 m. Their cores were evenly distributed within a circle of radius 50 m centered on the middle of the array. This restriction was adopted to avoid edge effect. A conceptual model of the core and detector locations used for the work are depicted in Figure 2.

The high energy showers between $10^{10.5}$ to $10^{20.5}$ eV are simulated and density values calculated. The required shower sizes are generated from the trained MLP.

While calculating density values core positions and locations of detectors are important. These coordinates are used to simulate the density values. The work considers twenty shower events taking place within a radius of fifty meters. The ANN is designed to accept density values obtained for twenty showers and provide coordinates of the EAS events of which the measurements are made. The density values captured by the detectors and coordinates of the shower events are unique hence require separate ANN predictors for each of the positions. For twenty shower events similar number of ANN are formed and a lay-out akin to the committee machine [3] is formulated. The set-up is essential for accurate prediction and optimization of the results. The training is carried out in a cooperative environment as to minimize the predicted error. The fundamental considerations governing the working and parameter selection of the cooperative ANNs or committee machines can be explained using the analysis given in [3] [4]:

Let a training set of $m$ input-output pairs $(x_1, t_1), (x_2, t_2), ... (x_m, t_m)$ be given and N ANNs are trained using this group of data. For simplicity, let for $n$-dimensional input there be a single output. Let for network functions $f_i$ for a number of networks represented by indices $i = 1, 2, ..., N$, the cooperative or committee network formed generates as output given as

$$f = \frac{1}{N} \sum_{i=1}^{N} f_i$$

(2)

The rationale behind the use of the averaging in the output of the cooperative or committee network as given by (2) is the fact that if one of the constituent networks in the ensemble is biased to some part of the input samples, the ensemble average can scale down the prediction error considerably [4].

3 Experiential Results and Discussion

The application of the MLP for core size and location prediction considers two aspects. First is the choice of the hidden layer and second is the combination of activation functions. A MLP is constituted with one hidden and one each of input and output layers. Trial and error method is used to find the best suitable hidden layer configuration. In the input layer log-sigmoid activation functions are used. In the hidden layer all activation functions are tan-sigmoid while in the output layer log-sigmoid functions are used. The details of governing principles are available in [5], [6]. The experiential arrangement for prediction of shower primary energy is shown in Figure 3. Another arrangement for determining the core locations using a cluster of twenty ANNs is shown in Figure 4. The outcome of the MLP training vary depending upon the number of iterations of the learning cycle and the data used. Mean Square Error (MSE) convergence and prediction precision are used to ascertain the performance of the MLP blocks. Samples used for training includes data samples of density values with several types of noise between 1 to 30 dB. Experimental results to determine the best training method of the MLP is based on the results shown in Table 1. From the Table 1 it is seen that a three layered ANN trained with gradient descent with momentum back propagation carried out using traindm function in Matlab 7.5 Toolbox provides the best success rate within 12000 epochs. There are a few more functions of identical nature like traingd, traingdx and traingda which are also used for training the
Figure 3: Experimental Set-up to determine primary energies

Figure 4: Experimental Set-up to determine core coordinates

Table 1: Results derived during training- ANN trained with traingd, traingdm, traingdx and traingda

<table>
<thead>
<tr>
<th>SL Num</th>
<th>Epochs</th>
<th>Success rate in %</th>
<th>Time in sec.s</th>
</tr>
</thead>
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<td>5000</td>
<td>93.8</td>
<td>25.6</td>
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<tr>
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<td>10000</td>
<td>92.2</td>
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<td></td>
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<td>209.6</td>
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</table>

Figure 5: Expected versus ANN generated results after 20000 epochs

set-up and the results summarized in Table 1. This set-up is taken as the MLP block forming the MLP-Cluster for prediction of shower size and location. Each MLP block receives density values from 80 to 100 detectors with particle content between $10^{10.5}$ to $10^{20.5}$ eV with Moliere radius of 70 m. The results derived by the trained ANN after training it for about 20000 epochs is depicted in Figure 5. A $\chi^2$-distribution between expected and ANN predicted showers sizes with variation of ANN training sessions is shown in Figure 6. The results thus derived establish the usefulness of the ANN in predicting the shower sizes for the range considered for the work.

Each of the twenty units of the ANN cluster is formed by the MLP trained with back-propagation. The average data size for each of the block is fifty sets of $20 \times 100$ where 20 represents the number of shower cores and 100 denotes the density values recorded by the detectors. Noise between
Figure 6: $\chi^2$-distribution between expected and ANN predicted showers sizes with ANN training sessions

-3 dB and 3 dB are mixed to make the ANN cluster robust enough to deal with variations found from experiential works. Figure 7 shows the location of shower events as predicted by the ANN blocks with detector positions and core positions shown. The plot is for one event of which the density values are fed to the trained ANN set-up. The location of all the twenty showers has also been generated using the ANN cluster as a whole. Initially as the training is limited to a few thousand sessions, the event cluster is spread inside and outside the fifty meter radius. The expected results are a grouping inside the fifty meter arc. As training sessions are increased with more number of samples, the predicted results start to cluster inside the intended circle. A unitary ANN block instead of a cluster can also be used for the purpose but prediction results are atleast 5% below than that generated by the cluster. Moreover, the cluster with its optimization capacity provides the best result out of a sample set of twenty applied to it. This is an advantage provided by the cluster. Moreover, as the shower core has its own unique location and density values, a unitary block shows best discrimination capacity only when applied for a single shower core location prediction. After training with fifty sets of data, the plotted values are generated as the average of twenty sets of inputs of which half are with noise variation in the mentioned range. The results show a success rate of around 95%.

4 Conclusion

The work described here provides an account of the application of ANN for shower size prediction. The work is restricted to the range $10^{10.5}$ to $10^{20.5}$ eV using simulated data. Two sets of samples are created: one for training and the other for testing. The testing data considers variations upto 50% of the training data. The success rate derived establishes the ability of the ANN to handle a task like shower size prediction. The work also is an attempt to use ANN based techniques to predict core locations. The experiential work carried out with a ANN cluster is found to be better suited for handling core location prediction and optimization. The system thus developed is a readily available tool which can provide nearly precise location details of shower in the range $10^{10.5}$ to $10^{20.5}$ eV.

References