International Journal of Engineering Research in Africa Vol. 4 (2011) pp 75-85
Online available since 2011/May/16 at www.scientific.net

doi:10.4028/www.scientific.net/JERA.4.75

Neuro-Fuzzy Based Modeling of Electrostatic Fields for Harmattan Season in Zaria

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[Date received: 20 May 2010. Date accepted: 30 April 2011]

Key words: Fuzzy logic, Neural network, Neuro-fuzzy modeling, Electrostatic field.

Abstract: This paper presents a Neuro-Fuzzy based modeling of electrostatic fields for harmattan season in Zaria, Nigeria based on online based data capturing mechanism, which involved the use of a data acquisition system interfaced with a digital electrostatic field strength meter (model 257D) and a computer system. The acquired electric field data were captured by the computer using the Microsoft Office Excel Program for twenty-four months (February 2007 – February 2009). The focus of the analysis is determining the effect of environmental factors such as temperature, pressure and relative humidity on the static electric field during the harmattan season. The plots of the electrostatic field against the variation of the environmental factors were used as the qualitative analytical tools and yielded a non-linear relationship. The data was analyzed using Neuro-Fuzzy technique, which is a hybrid intelligent system combining the benefits of computational techniques of Fuzzy Logic and Artificial Neural Networks. The result of the analyses yielded good neural statistical values of Root Mean Square (RMS) of 0.32, Average Absolute Error of 0.18, and Pearson R value of 0.96 for the harmattan scenario, which are reflections of a good model. The result was further buttressed by the 3D plot of the Neuro-Fuzzy based modeling of the experimental parameters. With the insignificant values of the RMS and Average Absolute value, the empirical model gave a fairly good prediction which could be relied upon to predict the electrostatic fields during harmattan in Zaria, Nigeria.

Nomenclature

b= bias; a bias value allows for shifting the activation function to the left or right, which may be critical for successful learning
d = desired output of the neural network
DoS= degree of support
f = activation function of a node which defines the output of that node given an input or set of inputs
f'= activation function of first order
i = initial value of given training data
j = final value of training data
L = layers of synaptic weights of the neural network
W = synaptic weights of the connections between hidden and input layer
x^0 = input vector, that is, the input layer where data are presented to the network through an input buffer
x^L= output vector, that is, the output layer with a buffer that holds the output response to a given input
μ= Learning Rate: a real number constant, usually 0.2 for output layer neurons and 0.15 for hidden layer neurons
δ= change in correction rate, that is, a gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron
η= Neuro-Fuzzy learning rate

Introduction

Neuro-Fuzzy Logic is a hybrid intelligent system that combines Neural Network with a Fuzzy system. They are natural complementary tools in building intelligent systems which can reason like human beings [1]. While Neural Network is good at recognizing patterns, it is not good at explaining how they reach their decisions. It is called a black box model because it hides the relationship between inputs and outputs in the weights of the neuron behind its hidden layers, which makes it difficult to interpret these weights due to their complex nature. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions (restricted domain applications) but they cannot automatically acquire the rules they use to make those decisions [2, 3]. While Fuzzy Logic provides an inference mechanism under cognitive uncertainty, computational Neural Networks offer exciting advantages, such as learning, adaptation, fault-tolerance, parallelism and generalization, but accused of being a black box. This makes it difficult to interpret these weights due to their complex nature. It also suffers from slow convergence, local minima, and low understandability. The limitations of the individual systems have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques [2,3,4]. Thus, one may incorporate the concept of Fuzzy Logic into the Neural Networks. The resulting hybrid system is Neuro-Fuzzy Logic. This enables the system to deal with cognitive uncertainties in a manner more like humans, The works of Mohamed [5], Rotshtein et al [6], Edwards [7] and Mu'azu [8] exemplify the use of Neuro-Fuzzy Logic to model various complex systems including physical phenomena such as harmattan, thunderstorm, water management and so on.

Electrostatic field is a phenomenon which describes the charge distribution function. It is of significance to the power and telecommunication industries where effective protection is highly needed against earthing fault of their equipment, which could develop as a result of extreme dryness of the harmattan season, leading to the breakdown of electrical insulation properties for materials, used in power, telecommunication, and avionics (as in the aerodrome). With subsequent prevalence of static electricity effect, bodies that become electrically charged may retain their charge for a long period. The presence of much dust in the atmosphere during this period leads to a substantial effect on the electric field production, which could induce excessive voltage into the equipment and damage them [9, 10].

Similarly, electrostatics during harmattan plays a vital role, where an increased value above 200V/cm could lead to damage of automobile electronic devices and Complementary Metal Oxide Semiconductor (CMOS) based devices such as the computer. The National Telecommunication and Information Administration (NTIA) [11] in the USA established the effect of electrostatic field on automobile electronic devices and concluded that an increase in the value of the field above 200V/cm constitutes danger to such devices.

Zaria is located within the co-ordinate position of latitude 11ºN and Longitude 8ºE and 655 meters above sea level. This falls within the Sahara zone, where harmattan activities exist due to the operation of the North-East tradewind. Harmattan is a natural phenomenon which describes the very dry dust – laden atmosphere, which rises in the Sahara desert and is carried south by winds from that area within the West-African region periodically from October of one year to March of the next year. This is common to the dry season of the Savannah region [10], hence the need for an online capturing of electrostatic field for harmattan season in Zaria that has a number of aviation industry institutions and facilities.

Harris [12] worked on the electrical effects of the Harmattan dust storms in Zaria. In the work, measurement of electric field strength using analog devices was carried out over a period of 24 hours during the severe harmattan time (February 1967) in Zaria. He discovered that there was a positive electric field perpendicular to the surface at any position on the ground during the fair weather of the day, because the upper conducting layers of the atmosphere are at a positive potential with respect to the ground. The limitation of Harris' work is such that the measurement was carried out over 40 years ago and was for only 24hrs with analogue devices. Recently, Akinsanmi et al [9, 10] have carried out electric field measurements in Zaria which was accomplished in two years using modern techniques of on-line capturing mechanism which gives a larger and more reliable data for good modeling mechanism, covering both harmattan and non-harmattan periods. In this paper, the modeling of electrostatic fields during the harmattan season in Zaria is presented.

On-line capturing of electrostatic field becomes essential for effective monitoring of:

(a) electrostatic field towards effective earthing of power, telecommunication and aerodrome devices.
(b) electrostatic field against the effect of high static charges on automobile, electronic and computer CMOS devices, and
(c) weather condition for the control of agricultural losses of some crops and products that are negatively affected during the harmattan season.

Since the phenomenon under consideration is characterized by chaotic and non-linear nature, which could be better modeled by a non-linear soft-computing technique, there was the need therefore to use the Neuro-Fuzzy approach for modeling the electrostatic field system during the harmattan season in Zaria.

Materials and Methods

Measurement of Electric Field in Zaria: Modern techniques of using Data Acquisition system (DAQ), interfaced with the modern electrostatic field meter was utilized. The study was conducted between February 2007-February 2009 at the Thermodynamics Laboratory of the Department of Mechanical Engineering, Ahmadu Bello University, Zaria, Nigeria, where room for adequate consideration of the electrodynamic properties of the fields under consideration could be explored. The electrostatic field meter has a very sensitive sensor to detect the presence of electric field in an environment in kV/cm. An analogue to digital converter (ADC) was used to convert the analogue output from the field meter to digital for the DAQ system to handle. With the DAQ system, the measured electric field strength could be monitored on the computer system alongside with the time measurement, and the corresponding collected data logged and later exported to Microsoft Excel for onward graphical analysis of the recorded data.

Using the probe to surface separation as a calibration factor, the electrostatic meter was also used to measure surface voltage. The probe was suspended by a tripod stand at 2 meters above the ground to capture the electrostatic field through the data acquisition device which was connected to a computer system. The instrument utilizes all solid-state components including modern integrated and hybrid circuits. The system provides an output signal proportional to the surface charge accumulation, while making no physical contact with the material being monitored. The co-environmental factors to harmattan-temperature, pressure and relative humidity were also measured with a thermometer, barometer and hygrometer (dry and wet) respectively.

Multilayer perceptrons: These are Neuro-Fuzzy systems which are based on the interpretation of weights and activation of neuron functions. Although the back-propagation algorithm can be used very generally to train Neural Networks, it is most famous for applications to layered feed-forward networks, or multilayer perceptrons. Simple perceptrons are very limited in their representational capabilities. For example, they cannot represent the XOR function. However, it is easy to see that XOR can be represented by a multilayer perceptron. This is because the XOR can be written in terms of the basic functions AND, OR, and NOT, all of which can be represented by a simple perceptron.

In between the input layer and the output layer are the hidden layers of the network. We will consider multilayer perceptrons with L layers of synaptic connections and L + 1 layers of neurons. This is sometimes called an L+1 layer network. A network with a single layer can approximate any function, if the hidden layer is large enough. This has been proved by a number of people, generally using the Stone-Weierstrass theorem [8]. So, the multilayer perceptron algorithm has been established as a powerful engineering tool for the Neural Networking system [8, 9, 10].

The algorithm: The algorithm of the network is mathematically expressed as [13]:

$$x^{0^{W^1}b^1} \rightarrow x^{1^{W^2}b^2} \rightarrow \ldots . \rightarrow x^{L^{W^{L+1}}b^{L+1}} \tag{1}$$

where $x^L \in R^{nL}$ for all L= 0…,L and W^L is an n_L by n_{L-1} matrix for all L = 1…,L.

There are L+1 layers of neurons, and L layers of synaptic weights. We will like to change the weights W and biases b so that the actual output x^L becomes closer to the desired output d.

The back-propagation algorithm consists of the following steps.

1. Forward pass. The input vector x^0 is transformed into the output vector x^L, by evaluating the equation [15].

$$x_i^l = f(\mu_i^l) = f\left(\sum_{j=1}^{n_{l-1}} W_{ij}^l x_j^{l-1} + b_i^l\right) \tag{2}$$

for l = 1 to L.

2. Error computation. The difference between the desired output d and actual output x^L is computed.

$$\delta_i^L = f'(\mu_i^L)(d_i - x_i^L) \tag{3}$$

3. Backward pass. The error signal at the output units is propagated backwards through the entire network, by evaluating

$$\delta_j^{l-1} = f^{'(\mu_j^{l-1})} = f\left(\sum_{i=1}^{n_l} \delta_i^l W_{ij}^l\right) \tag{4}$$

from i = L to 1

4. Learning updates. The synaptic weights and biases are updated using the results of the forward and backward passes,

$$\Delta W_{ij}^l = \eta \delta_i^l x_j^{l-1} \tag{5}$$

$$\Delta b_i^l = \eta \delta_i^l \tag{6}$$

These are evaluated for l = 1 to L. The order of evaluation does not matter.

Neural Net Learning: The Error Back Propagation: The problem of learning in neural networks is that of finding a set of connection strengths (weights) that allow the network to carry out the desired computation. The network is provided with a training set and its role is to modify its connections in order to approximate the function from which the training set was drawn. The network is then tested for ability to generalize [13]. The Fuzzy Tech 5.5 software tool was used in this case.

If the hidden layer is non-linear, an error back propagation (EBP) neural net is able to approximate its function [8, 14]. The error back propagation algorithm has a way to compute these weights and this involves four steps:

(1) The network is initialized by assigning random values to synaptic weights;
(2) A training pattern is fed and propagated forward through the network to compute an output for each output node;
(3) The computed outputs are compared with the expected (target) outputs and a match is computed;
(4) A backward pass through the network is performed, changing the synaptic weights to some of its connections on the basis of the observed output errors, if the output differs from the target. If, however, the output and target match, no change is made to the net [14].

Steps (1) to (4) are iterated for each pattern in a training set. The network performance is then checked (usually on the basis of a mean squared error) and a new set of training patterns is submitted to the network (i.e. a new epoch is started) if it needs further optimization [8, 14].

Results and Discussion

Table 1 shows the results of the experimental measurements of electrostatic field. The co-related climatic parameters of harmattan such as temperature, pressure and relative humidity were also measured and analyzed relative to the measured electric field in Zaria. The Fuzzy rules were used to yield the Electrostatic Field Forecast Model that relates electric field with the co-environmental membership functions, shown in Figure 1.

Table 1 Experimental Measurements of the Electrostatic Field and the Co-environmental factor Measurements during Harmattan Months in Zaria

Day	Relative Humidity H (%)	Temperature T (^{o}C)	Pressure P (mmHg)	Electrostatic Field E (kV/cm)
01/10/2007	77.0	29.0	709.0	-2.49249
04/10/2007	73.0	29.0	708.0	-2.42755
07/10/2007	93.0	29.0	709.0	-2.36212
10/10/2007	98.0	28.0	707.0	-2.33386
13/10/2007	57.0	29.0	706.0	-2.23775
16/10/2007	57.0	30.0	708.0	-2.22014
19/10/2007	60.0	30.0	708.0	-2.28918
22/10/2007	93.0	29.5	708.0	-2.18877
25/10/2007	42.0	29.0	707.0	-2.16277
28/10/2007	40.0	30.0	707.0	-1.95034
01/11/2007	44.0	30.0	708.0	-2.23775
04/11/2007	95.0	30.0	709.0	-2.2397
07/11/2007	70.0	30.5	710.0	-2.22014
10/11/2007	30.0	30.0	706.0	-2.09727
13/11/2007	40.0	28.5	706.0	-2.18877
16/11/2007	69.0	29.0	709.0	-2.16277
19/11/2007	23.0	29.5	708.0	-1.95034

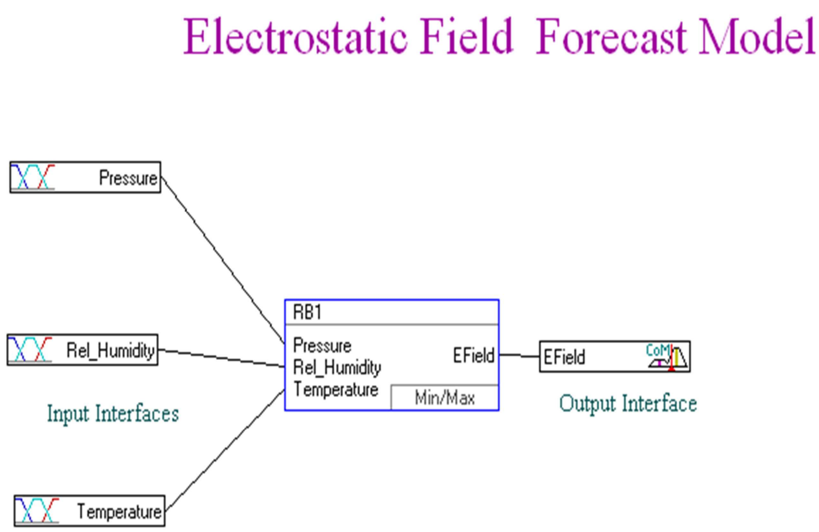

Figure 1 Electrostatic field forecast model using Fuzzy Logic system

The electrostatic field forecast model, after optimization, had forty rules which were the IF THEN rule based control mechanism for the model. The parameters rule block (RB1) is as shown in Table 2. Part of the rule base is shown in Table 3.

Table 2 Parameter Table of the Neuro-Fuzzy based Electrostatic Field Forecast Model Rule Block

Aggregation:	MINMAX
Parameter:	0.00
Result Aggregation:	MAX
Number of Inputs:	3
Number of Outputs:	1
Number of Rules:	40

Table 3 Rule base of the electrostatic field forecast model

IF			THEN	
Pressure	Rel. Humidity	Temperature	DoS	E. Field
Low	Low	Low	0.10	very_low
Low	Low	Low	0.36	Low
Low	Low	Low	0.56	Medium
Low	Low	Low	0.38	High
Low	Low	Low	0.46	very_high
Medium	Low	Medium	0.65	very_low
Medium	Low	Medium	0.29	Low
Medium	Low	Medium	0.77	Medium
Medium	Low	Medium	0.59	High
Medium	Low	Medium	0.22	very_high

3.3 3D Plots of the Experimental Parameters

The three dimensional (3D) plots of the Neuro-Fuzzy based modeling of the experimental parameters are shown in Figures 2 - 4. The non-linear relationship between the electrostatic field and the co-environmental factors can be seen from the three-dimensional plots.

Figure 2 is the 3D plot of Humidity, Temperature and Electrostatic Field.
The 3D plot of Electrostatic Field, Humidity and Pressure is shown in Figure 3.
Figure 4 is the 3D plot of Pressure, Temperature and Electrostatic Field.

Analysis Using Neural Network: 140 data points were used for the analysis: 97 were used for training while 43 were used for testing as shown in Table 4

The results of the Neuro-Fuzzy analysis yielded the time series plot of the electrostatic field during harmattan as shown in Figure 5, which is a dynamic non-linear one. The time series yielded the summary in Table 4.

Observations Based on Neuro-Fuzzy Modelling Technique: From Table 4, the following observations could be made with respect to the harmattan scenario: The Pearson R (train) = 0. 941235 for the train data while the R (test) = 0. 95976 for the test data. The closeness suggests that the model generalizes well and can make accurate prediction when it processes new data (data not obtained from the train or test data). Root Mean Square (RMS) error was RMS (train) = 0. 352986 and RMS (test) = 0.315679 for the train and test data respectively. The average absolute error Avg Abs (train) = 0. 200102 and Avg Abs (test) = 0. 180009.

Table 5 shows the comparison of experimentally measured and predicted electrostatic fields for some days of the harmattan season. The results show that the predicted electrostatic fields compare fairly well with measured values giving a maximum deviation of about 14% as shown. This shows that the neuro-fuzzy logic model could be used to predict electrostatic fields.

Table 4 Summary Statistics

Electrostatic Field (kV/cm)	R	Net-R	Avg. Abs.	Max. Abs.	RMS	Accuracy (20%)	Conf. Interval (95%)	Records
All	0.946544	-0.9325	0.193931	1.799462	0.341961	0.935714	0.671726	140
Train	0.941235	-0.92052	0.200102	1.799462	0.352986	0.927835	0.696628	97
Test	0.95976	-0.96091	0.180009	1.574052	0.315679	0.953488	0.635061	43

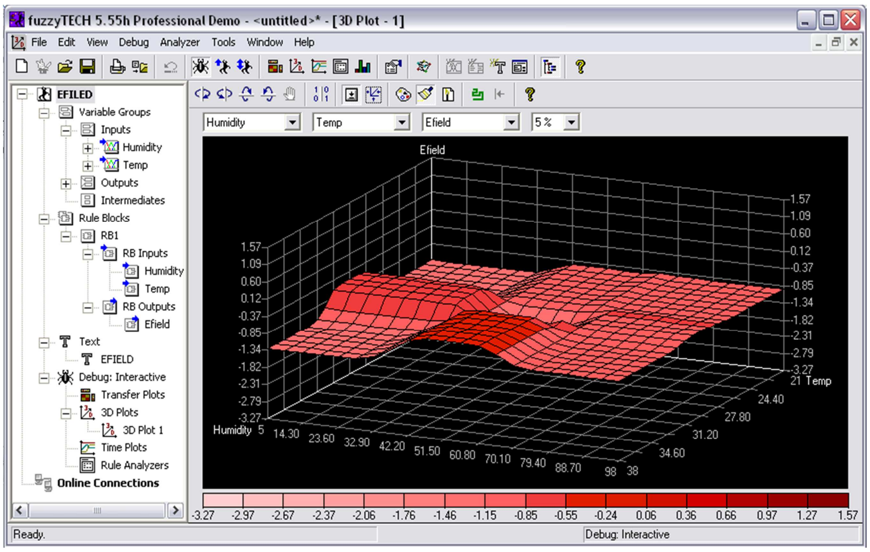

Figure 2 3D plot of humidity, temperature and electrostatic field

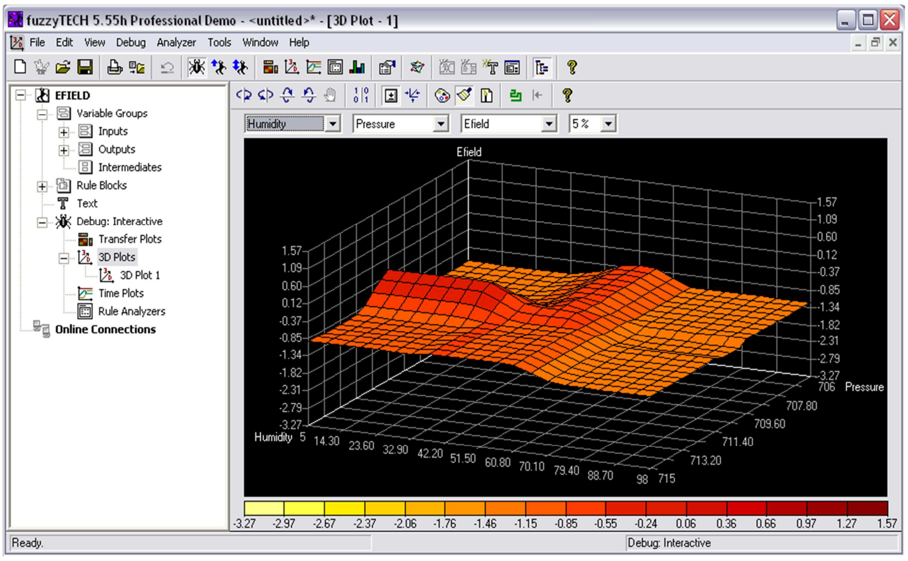

Figure 3 3D plot of pressure, humidity and electrostatic field

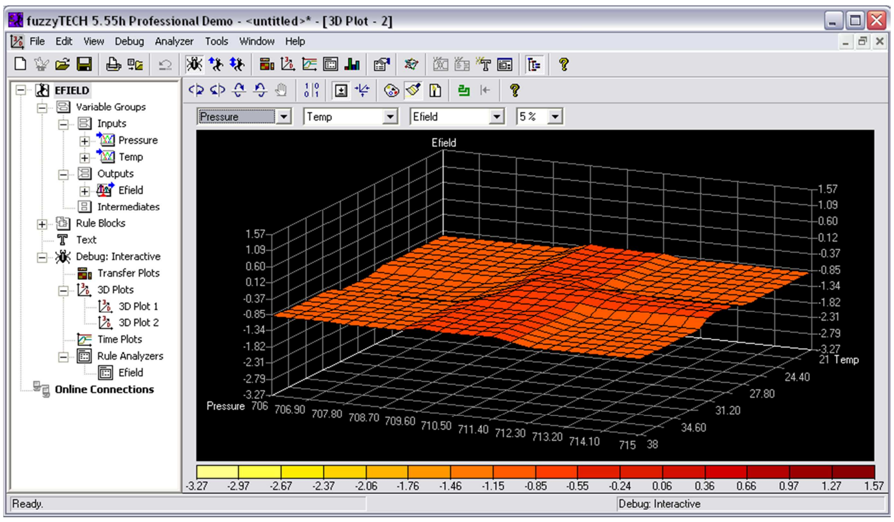

Figure 4 3D plot of pressure, temperature and electrostatic field

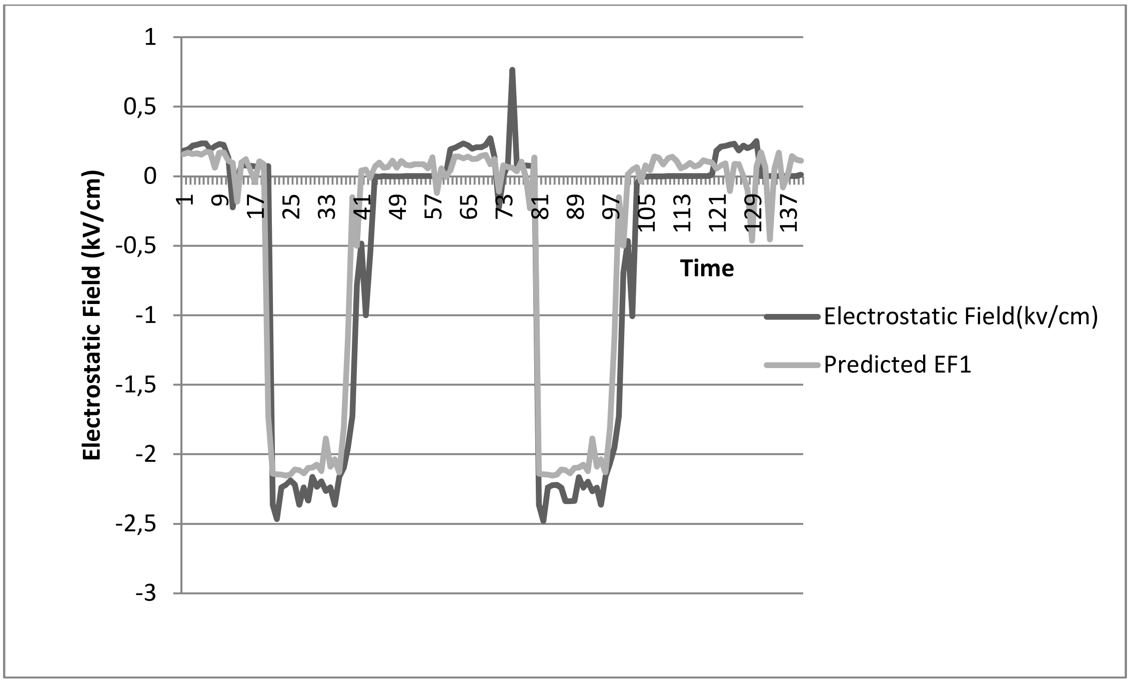

Figure 5 Time series plot of electrostatic field for harmattan season

Table 5 Results of Neuro-Fuzzy model prediction for harmattan season in Zaria

Day	Relative Humidity X1 (%)	Temperature X2 (^{o}C)	Pressure X3 (mmHg)	Electrostatic Field, EF(kV/cm)	Predicted EF1 (kV/cm)	% Deviation (EF – EF1)/EF
01/10/07	77.0	29.0	709.0	-2.36212	-2.1397	9.4
04/10/07	73.0	29.0	708.0	-2.46683	-2.14455	13.1
07/10/07	93.0	29.0	709.0	-2.23775	-2.14767	4.0
10/10/07	98.0	28.0	707.0	-2.22014	-2.15403	2.98
13/10/07	57.0	29.0	706.0	-2.18877	-2.14623	1.9
16/10/07	57.0	30.0	708.0	-2.2169	-2.11055	4.8
19/10/07	60.0	30.0	708.0	-2.36212	-2.11519	10.5
22/10/07	93.0	29.5	708.0	-2.2397	-2.13765	4.6
25/10/07	42.0	29.0	707.0	-2.33386	-2.09895	10.1
28/10/07	40.0	30.0	707.0	-2.16277	-2.09596	3.1
01/11/07	44.0	30.0	708.0	-2.23317	-2.07541	7.0
04/11/07	95.0	30.0	709.0	-2.19513	-2.12154	3-4
07/11/07	70.0	30.5	710.0	-2.26299	-1.88547	16.7
10/11/07	30.0	30.0	706.0	-2.2397	-2.08831	6-8
13/11/07	40.0	28.5	706.0	-2.36212	-2.03629	13-8
16/11/07	69.0	29.0	709.0	-2.16277	-2.12972	1-5
19/11/07	23.0	29.5	708.0	-2.09727	-1.8108	13.7

Conclusion

A neuro-fuzzy based model for predicting electrostatic fields in harmattan season in Zaria, Nigeria has been developed. The model is able to predict electrostatic fields fairly accurately. It could be used for effective monitoring of devices against high static charges in the power, communications and aviation industries amongst others.

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International Journal of Engineering Research in Africa Vol. 4
10.4028/www.scientific.net/JERA.4

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