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

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Abstract
This paper presents a Neuro-Fuzzy based modeling of electrostatic fields during non-harmattan season in Zaria, Nigeria based on the on-line 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 are captured by the computer using the Microsoft Office Excel Program for twenty-four months (2007 - 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 non-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 0.35, Average Absolute Error of 0.23, and Pearson R value of 0.94 for the non-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 good prediction which could be relied upon to predict the electrostatic fields during non-harmattan in Zaria, Nigeria.

Keywords: fuzzy logic, neural network, neuro-fuzzy modeling, electrostatic field

INTRODUCTION

Zaria is located within the co-ordinate position of latitude 11ºN and Longitude 8ºE above sea level. This falls within the Sahara zone, where harmattan activities exist due to the operation of the North- East trade wind. Harmattan is a natural phenomenon which describe the very dry dust – laden atmosphere, which rises in the Sahara desert and is carried south by winds from that area within the West-Africa region periodically from October – March of every year. This is common to the dry season of the Savannah region (Akinsanmi *et al*., 2007 and 2009). The non-harmattan season is a period characterized by high relative humidity and low temperature (Ati, 2002). The period experiences rainfall and extends from April to September each year.

Electric Field: It is usual and useful to introduce the concept of the electric field at this point. Electric field is a vector field. Given, a vector function of x. It is written as E(x) and is defined as the force that would be experienced by a charge q at x, divided by q^3. Thus, for a distribution of charges q_i at
x_i, i = l,2,...,n, E(x) =

$$\sum_{i=1}^{n} \frac{q_1(x - x_i)}{|x - x_i|^3} \tag{1}$$

The electric field has the property of being independent of the 'test'
Charge q; it is a function of the change distribution which gives rise to the force on the test charge, and, of course, of the test charge's position. This object has dimension Q/L^2 or $M^{1//2}/L^1/^2T$.

Using electrostatics, it can be seen that the charge density ρ(x) of a collection of point charges can be written as a sum of delta functions:

$$\rho(x) = \sum_{1=i}^{n} q_i \delta(x - x_i) \tag{2}$$

Subjecting equation (1) to further analysis yields

$$E(X) = \int d^3x' \rho(x')(x - x')/|x - x'|^3$$

$$= \sum_{i=1}^{n} q_i (x - x_i)/|x - x_i|^3 \tag{3}$$

$$\oint D.ds = Qens \tag{4}$$

(Carpenter, 1989, 1993a, 1993b; Coulomb, 2000).

Neuro-Fuzzy Logic is a hybrid intelligent system that combines neural network with a fuzzy system. Fuzzy logic and neural networks are natural complementary tools in building intelligent systems (Nath, 2007). While neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. 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 (Fuller, 2001; Qiu, 2008). 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, which hides the relation between inputs and outputs in the weights of the neurons behind its hidden layers. This makes it difficult to interpret these weights due to their complex nature. It also suffers from slow convergence, local minima, and low understandability. To enable a system to deal with cognitive uncertainties in a manner more like humans, one may incorporate the concept of fuzzy logic into the neural networks. The resulting hybrid system is Neuro-Fuzzy logic. These limitations have been a central driving force behind the creation of intelligent hybrid systems- Neuro-Fuzzy logic system where two or more techniques are combined in a manner that overcomes the limitations of individual techniques (Fuller, 2001; Mohamed, out 2005; Qiu, 2008).

Neural network is an aspect of Neuro-Fuzzy logic that is used to carry mathematical modeling of physical phenomenon by handling complex input and output relationships (Arisariwong, 2001). From a mathematical point of view, Neural Net is a complex non-linear function with many parameters that can be adjusted (calibrated or trained) in such a way that the output becomes similar to the measured output on a known data (Ihe, 2000). This means that the Neural Net is able to generalize relevant output for a set of previously unseen input data (Abraham and Philip, 2001). In essence, it can be considered as universal approximators of non-linear dependencies trained by experimental data (Rotshtein et al., 2003). Neural Nets can, therefore, be trained to approximate any continuous function to any desired accuracy, without a need to specify its type. They can also be applied to incomplete or corrupted data and still yield acceptable results because the Neural Nets are relatively fault-tolerant having many processing nodes (Edwards, 1998; Purvis et al., 1999; Mu'azu, 2006).

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 2007 – 2009 at the Thermodynamic Laboratory of the Department of Mechanical Engineering, Ahmadu Bello University, Zaria, Nigeria, where room for adequate consideration of the electrodynamics 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 along side with the time the measurement was made and the corresponding collected data logged and later exported to Microsoft Excel for onward graphical analysis of the recorded data (Mason, 2002; Akinsanmi et al 2008; Akinsanmi et al, 2009).

The meter measures electric field strength in kilovolts per centimeter. Using the probe to surface separation as a calibration factor, it may also be used to measure surface voltage. The instrument utilizes all solid-state components including modern integrated and hybrid circuits. It may be operated from its internal re-chargeable battery system or optionally from AC power lines. The system provides an output signal proportional to the surface charge accumulation, while making no physical contact to the material being monitored. The measurement was done during the non-harmattan months in and outside an enclosed place. The chosen enclosed place was the Thermodynamic laboratory of the Department of Mechanical Engineering, Ahmadu Bello University, Zaria, because of the available facilities which gives room for adequate consideration of the electrodynamics properties of the fields. (Akinsanmi, et al., 2008, Akinsanmi et al., 2009). The co-variant environmental factors to the non-harmattan period – Temperature, Atmospheric Pressure, Relative Humidity measurement devices are located around the test point. The Thermometer was used for the Temperature, and the Barometer was used the Pressure, whereas dry and wet hygrometer was used for the Relative Humidity.

Multilayer Perceptrons: Although the backpropagation algorithm can be used very generally to train neural networks, it is most famous for applications to layered feedforward 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-layer network, and sometimes 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. So multilayer perceptrons algorithm is a powerful tool. (Seung, 2002).

The Algorithm: The algorithm of the network is mathematically expressed as:

$$x^0 \xrightarrow{W^1 b^1} x^1 \xrightarrow{W^2 b^2} \ldots \xrightarrow{W^L b^L} x^L \qquad (5)$$

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'd like to change the weights W and biases b so that the actual output x^L becomes closer to the desired output d.

The backprop 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

$$x_i^l = f(u_i^l) = f\left(\sum_{j=1}^{n_{l-1}} W_{ij}^l x_j^{l-1} + b_i^l\right) \qquad (6)$$

for l = 1 to L.

2. Error computation. The difference between the desired output d and actual output xL is computed.

$$\delta_i^L = f'(u_i^L)(d_i - x_i^L) \qquad (7)$$

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

$$\delta_j^{l-1} = f'^{\left(u_j^{l-1}\right)} = f\left(\sum_{i=1}^{n_l} \delta_i^l W_{ij}^l\right) \qquad (8)$$

from l = L to 1

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

$$\Delta W_{ij}^l \; - \eta \delta_i^l x_j^{l-1} \qquad (9)$$

$$\Delta b_i^l = \eta \delta_i^l \qquad (10)$$

These are evaluated for l = 1 to L. The order of evaluation doesn't matter (Seung, 2002).

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 (Mukherjee, 2003). If the hidden layer is non-linear, an error back propagation (EBP) neural net is able to approximate its function (Scardi, 1999; Mu'azu, 2006). 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 (Scardi, 1999; Mukherjee, 2003).

Steps (1) through (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 (Scardi, 1999, Mu'azu, 2006).

RESULTS AND DISCUSSION

The measurement was done between February 2007 and February 2009 in and outside the Thermodynamic Laboratory of the Department of Mechanical Engineering, Ahmadu Bello University, Zaria, Nigeria. Some of the results of the experimental measurements of electrostatic field are shown in Table 1. The co-related climatic parameters to the non-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 Fig. 1.

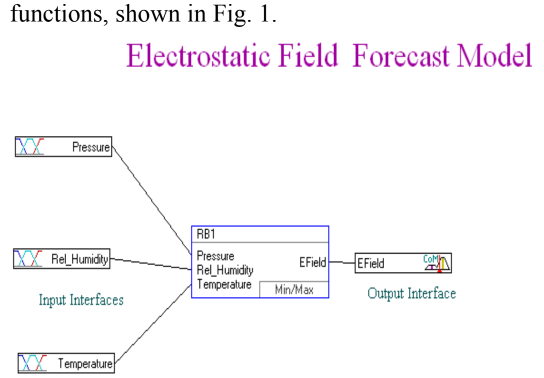

Fig. 1: Electrostatic Field Forecast Model Fuzzy Logic System

The Electrostatic Field Forecast Model, after optimization, has forty rules. The parameters rule block (RB1) is as shown in Table 2. The rule base is shown in Table 3.

Table 1: Experimental Results of the Electrostatic Field and the Co-environmental factors Measurements during Non-harmattan Months

Day	Relative Humidity X1 (%)	Temperature X2 (^{o}C)	Pressure X3 (mmHg)	Experimental Electrostatic Field (KV/cm)
01/04/07	96.0	38.8	714.0	0.09011
04/04/07	97.2	37.8	713.8	0.07741
07/04/07	96.6	38.0	714.0	0.0693
10/04/07	90.0	36.9	712.9	0.05335
13/04/07	92.0	37.5	712.8	0.05067
16/04/07	94.0	38.5	713.0	0.05274
19/04/07	95.0	40.0	712.9	0.05417
22/04/07	94.8	40.2	714.2	0.05145
25/04/07	95.5	40.1	713.8	0.05512
28/04/07	93.5	40.0	714.0	0.05316
01/05/07	92.4	31.0	714.0	0.02849
04/05/07	94.0	30.5	714.0	0.02437
07/05/07	93.0	31.0	712.0	0.01115
10/05/07	96.3	31.9	713.8	0.01951
13/05/07	93.8	32.0	712.9	0.00584
16/05/07	90.0	34.0	711.0	0.00322
19/05/07	92.0	33.0	714.0	0.00354
22/05/07	94.0	34.0	713.9	0.00584
25/05/07	93.0	34.7	715.0	0.00456
28/05/07	93.9	37.0	715.0	0.00617

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

3D Plots of the Experimental Parameters

The three dimensional (3D) plots of the Neuro-Fuzzy based modeling of the experimental parameters are shown in Fig.2-4. The non-linear relationship between the electrostatic field and the co-environmental factors could be seen from the three-dimensional plots. Fig. 2 is the 3D plot of humidity, temperature and electrostatic field. The 3D plot of electrostatic field, humidity and pressure is shown in Fig.3. Fig. 4 is the 3D plot of pressure, temperature and electrostatic field.

Analysis Using Neural Network

140 data points were used for the Neuro-Fuzzy analysis: 97 were used for training while 43 were used for testing (Table 4). The results of the Neuro-Fuzzy analysis yielded the time series plot of the electrostatic field during non-harmattan in Fig. 5. 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 non-harmattan season: The Pearson R (train) = 0. 959045 for the train data while the R (test) = 0. 940514 for the test data. The

Table 3: Rule Base of the Electrostatic Field Forecast Model

IF			**THEN**	
Pressure	**REL_HUMIDITY**	**Temperature**	**DoS**	**EField**
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
high	Low	high	0.70	very_low
high	Low	high	0.83	Low
high	Low	high	0.30	medium
high	Low	high	0.15	High
high	Low	high	0.96	very_high
low	Medium	low	0.62	very_low
low	Medium	low	0.37	Low
low	Medium	low	0.43	medium
low	Medium	low	0.29	High
low	Medium	low	0.17	very_high
medium	Medium	medium	0.96	very_low
medium	Medium	medium	0.35	Low
medium	Medium	medium	0.12	medium
medium	Medium	medium	0.82	High
medium	Medium	medium	0.69	very_high
high	High	high	0.11	very_low
high	High	high	0.34	Low
high	High	high	0.22	medium
high	High	high	0.22	High
high	High	high	0.78	very_high
low	High	low	0.45	very_low
low	High	low	0.70	Low
low	High	low	0.58	medium
low	High	low	0.07	High
low	High	low	0.45	very_high
medium	High	medium	0.68	very_low
medium	High	medium	0.63	Low
medium	High	medium	0.08	medium
medium	High	medium	0.80	High
medium	High	medium	0.13	very_high

Table 4: Summary Statistics

Electrostatic Field (KV/cm)	R	Net-R	Avg. Abs.	Max. Abs.	RMS	Accuracy (20%)	Conf. Interval (95%)	Records
All	0.950312	-0.89563	0.195643	1.255145	0.313867	0.8928571	0.6165409	140
Train	0.959045	-0.90469	0.178701	1.255145	0.297489	0.9072165	0.5871029	97
Test	0.940514	-0.87751	0.233859	1.118516	0.347994	0.8604651	0.7000691	43

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. 297489 and RMS (test) = 0. 347994 for the train and test data respectively. The average absolute error Avg Abs (train) = 0. 178701 and Avg Abs (test) = 0. 233859. These values show good modeling which was tested on all the non-harmattan period data and some of the results, compared with the empirical data as shown in table 5

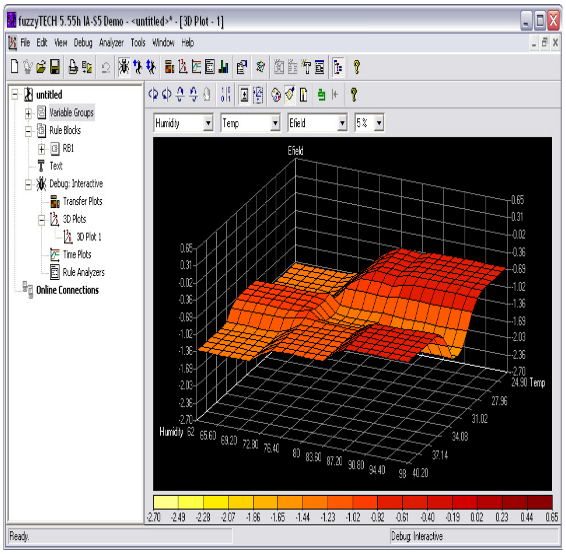

Fig. 2: 3D plot of humidity, temperature and electrostatic field Authors survey, 2010)

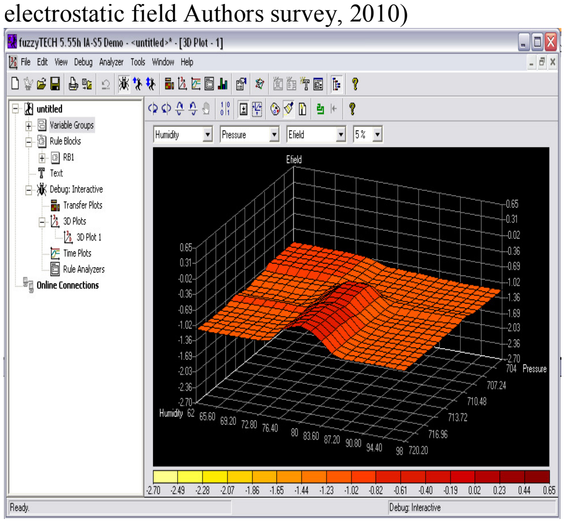

Fig. 3: 3D plot of pressure, humidity and electrostatic field (Authors survey, 2010)

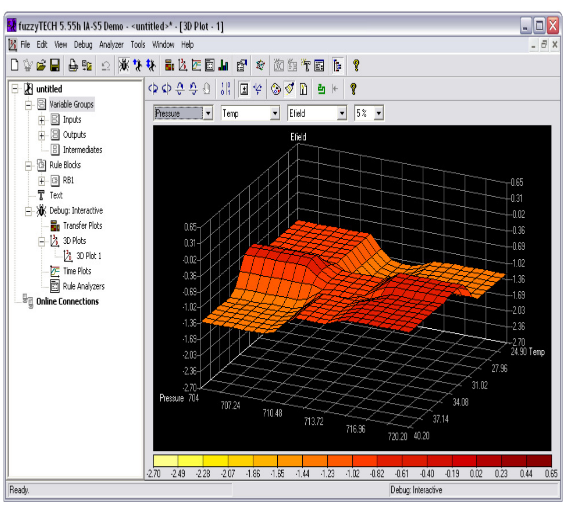

Fig. 4: 3D plot of pressure, temperature and electrostatic field (Authors survey, 2010)

Table 5: Results of Neuro-Fuzzy Model Prediction for Non-harmattan Season (Authors survey, 2010)

Day	Relative Humidity X1 (%)	Temperature X2 (°C)	Pressure X3 (mmHg)	Electrostatic Field(kv/cm)	Predicted EF1
01/04/07	96.0	38.8	714.0	0.09011	0.047057
04/04/07	97.2	37.8	713.8	0.07741	0.028751
07/04/07	96.6	38.0	714.0	0.0693	0.037489
10/04/07	90.0	36.9	712.9	0.05335	0.038648
13/04/07	92.0	37.5	712.8	0.05067	0.042051
16/04/07	94.0	38.5	713.0	0.05274	0.044985
19/04/07	95.0	40.0	712.9	0.05417	0.048987
22/04/07	94.8	40.2	714.2	0.05145	0.060941
25/04/07	95.5	40.1	713.8	0.05512	0.055384
28/04/07	93.5	40.0	714.0	0.05316	0.061177
01/05/07	92.4	31.0	714.0	0.02849	0.012493
04/05/07	94.0	30.5	714.0	0.02437	-0.03662
07/05/07	93.0	31.0	712.0	0.01115	-0.03466
10/05/07	96.3	31.9	713.8	0.01951	-0.03866
13/05/07	93.8	32.0	712.9	0.00584	0.005218
16/05/07	90.0	34.0	711.0	0.00322	0.038481
19/05/07	92.0	33.0	714.0	0.00354	0.030428
22/05/07	94.0	34.0	713.9	0.00584	0.025712
25/05/07	93.0	34.7	715.0	0.00456	0.032349
28/05/07	93.9	37.0	715.0	0.00617	0.048018

CONCLUSION

The result of the analyses yielded good neural statistical values of Root Mean Square (RMS) of 0.35, Average Absolute Error of 0.23, and Pearson R value of 0.94 for the non-harmattan scenario, which are reflections of a good model, hence it could be deduced that electrostatic field during non-harmattan in Zaria is dependent on the co-environmental factors i.e temperature, pressure, and humidity. With the insignificant value of the RMS and the Average Absolute Error values, the Neuro-Fuzzy technique could be relied upon to predict electrostatic field in Zaria, Nigeria.

REFERENCES

Abraham, A. and Philip, N.S., (2001). "Soft computing models for weather forecasting" http://meghnad.iucaa.ernet.in/~nspp/scs.pdf

Akinsanmi, O. Bajoga B. G., Dajab D. D., (2008) . "Comparison analysis of electric field measurement in Zaria" Proceedings of the international conference of Engineering Research and Development, University of Benin, Benin city.

Akinsanmi, O., B.G. Bajoga and D.D. Dajab, (2009). “Comparative analysis of electric field measurement in Zaria”. J. Adv. Mater. Res., 62-64: pp: 141-146.

Akinsanmi O. Bajoga B. G, Farayola, K. S, Adegboye B. A., Mu’azu M. B.(2007). “Measurement and analysis of electric field in Zaria” J.Appl Sci. Res, pp 1377 – 1382.

Arisariwong, S. and Cahroenseang, S. (2001). “Reducing steady state error of a direct drive robot using Neuro-Fuzzy control:, Proceedings of Second Asian Symposium on Industrial Automation and Robotics, Bangkok, Thailand.

Ati, O. F. (2002). Understanding Basic Climatological Terms. Zaria: Pisteuo Publishers. Pp 58 and 98.

Carpenter .C.J. (1989). “Electromagnetic energy and power in terms of charges and potential instead of field” IEEE Proc. A, Vol. 136 (2) pp 55 – 65.

Carpenter. C.J., (1993a). “A circuit approach to field computation” IEEE transactions on Electromagnetics, Vol. 29, No2.

Carpenter.C.J.,(1993b).“Teaching Electromagnetism in terms of the potentials instead of the “Maxwell’s equation” IEEE Trans. Edu., Vol. 36, No 2.

Dixon B., (2000). “Application of neuro-fuzzy techniques to predict ground water Vulnerability” University of South Florida St. Petersburg, Florida 33701, USA.

Edwards, V.,(1998). “Artificial neural networks”, http://aspac.web.unsw.edu.au/Media%20Room/week 4.pdf

Fuller R., (2001). “Neuro-Fuzzy methods for modeling and fault diagnosis”, E”otv”os Lor’and university, Budapest Vacation School, Lisbon, Aug. 31 and September 1, 2002, pp 1-22.

Ihe D.,(2000). “Use of artificial neural network and fuzzy logic for Integrated Water Management: Review of Applications”, Project Report, pp3-5.

Kutsurelis, J.E.,(1998). “Forecasting financial markets using neural networks: An analysis of methods and accuracy”, M.SC Thesis, Naval Post Graduate School, Monterey, pp2 – 17.

Mason, G A, (2002). “Handheld data acquisition system for use in an undergraduate data acquisition course”. IEEE Transaction on Education, 45(4), 388-393. NI (National Instruments) Retrieved December 28th 2004, from the world wide web: http://www.ni.com/

Mohamed F. A. H. M.,(2005). “A new approach for extracting fuzzy rules using artificial neural networks”, Master Thesis in Computer Science, Department of Computer and Information Science. Institute of Statistical Studies and Research, Cairo University.

Mu’azu M.B.,(2006). “Forecasting and modeling statistical phenomena using neurofuzzy logic: A case study of rainfall forecasting for Zaria”, Unpublished PhD Dissertation, Department of Electrical Engineering, A B U, Zaria.

Mukherjee, A.,(2003). Advances in battery mangaement using neural networks and fuzzy logic”, Departemntal seminar (ENGRC350), School of Electrical and Computer Engineering, Cornell University, ppA.3A.7, www.engineering.cornell.edu/engrc350/ingenuity/Muhkrejee_A_issue_1.pdf

Nath B., (2007). “Evolutionary and neural computation”, bnath@csse.unimelb.edu.au, The University of Melbourne, Computer Science and Software Engineering, Semester 2, 2007, pp. 433-679.

Ojala T., (1995). “Neuro-Fuzzy systems in control” Master of Science thesis, Tampere University of Technology, Department of Electrical Engineering

Purvis, M., Kaasabov, N., Benwell, G., Zhou, G., and

Zhang, F., (1999). Neuro-Fuzzy methods for environmental modeling”, Journal of Systems Research and Information Systems, Vol. 8, pp 221 – 239.

Qiu F., (2008). “Neuro-Fuzzy based analysis of hyper spectral Imagery”, Photogrammetric Engineering & Remote Sensing, Vol. 74, No. 10, October 2008, pp. 1235–1247.

Rotshtein, A., Posner, M., and Rakytyanska, H., (2003). “Prediction of the results of football games based on fuzzy model with genetic and neuro tuning”, Eastern European Journal of Enterprise Technologies, pp10 – 15.

Scardi, M., (1999) . “An Introduction to Error Back Propagation Neural Networks.” www.mare-net.com/mscardi/work/nnintro.htm

Seung, S., (2002). 9.641 Lecture: Multilayer perceptrons and backpropagation learning.

Xia W., Ho D., Capretz L. F., 2008. “A Neuro-Fuzzy model for function point calibration”, WSEAS Transactions on Information Science & Applications Issue 1, Volume 5, January 2008 pp 22-39.