RECEIVED SIGNAL STRENGTH COMPUTATION FOR BROADCAST SERVICES USING ARTIFICIAL NEURAL NETWORK

K. C. Igwe*,
O. D. Oyedum
Dept of Physics, FUT Minna
Niger State, Nigeria
*k.igwe@futminna.edu.ng

M. O. Ajewole
Dept of Physics, FUT Akure
Ondo State, Nigeria
A. M. Aibinu
Dept of Mechatronics Engr. FUT Minna
Niger State, Nigeria

***Abstract*—**This paper investigates the influence of weather parameters on very high frequency (VHF) radio signals. Received signal strength (RSS) data were obtained from four broadcast stations in Niger State, transmitting at 91.2 MHz, 92.3 MHz, 100.5 MHz and 210.25 MHz while atmospheric parameters of temperature, pressure, relative humidity and wind speed data were obtained from the Tropospheric Data Acquisition Network (TRODAN) situated at the Federal University of Technology, Bosso Campus, Minna, Nigeria. The measurements were carried out for six months (January - July). An artificial neural network (ANN) model was designed to compute received signal strength using the measured atmospheric parameters. The training of the network was performed using Levenberg-Marquardt feed-forward backpropagation algorithm. The training process was performed by the evaluation of different effects of activation functions at the hidden and output layers, number of neurons in the hidden layer and data normalisation. The results obtained showed that the ANN model performed satisfactorily for the four broadcast stations as the computed signal strength values from the ANN model were reasonably close to the measured signal strength values with minimal errors. Also, the model performed well when tested on different data sets not used for the ANN training.

Keywords*—*Artificial neural network, received signal strength, VHF

I. INTRODUCTION

Successful propagation of radiowaves at very high frequency (VHF) and higher frequencies through the troposphere is largely dependent on the weather, which is very variable in most climates. Generally, a statistical approach is adopted in practice for prediction of propagation effects. For effective and reliable communication between a transmitter and a receiver, knowledge of the spatial and temporal variability of field strength is required. Where a high quality signal is desired, especially in broadcast applications, this assumes greater significance. Also, the efficiency of any communication system depends on the models utilised in calculating the coverage area and interference problems [1, 2].

In the VHF and UHF (ultra high frequency) bands, field strength prediction takes account of the effects of the refractive nature of the atmosphere and the terrain in the vicinity of the transmitter and receiver. Allowance is also made for location variability for prediction of land area coverage, with account taken of local clutter surrounding the receiver [3]. Moreover, the diurnal and seasonal variations between actual values of field strength and the predicted values may be caused by variations in atmospheric conditions. Such variations can result in marked increase (or decrease) in field strength for several hours or even several days. More permanent changes can arise when the radio refractivity gradient of the atmosphere varies markedly from the normal values to which the propagation curve relates [4].

Propagation conditions of radio frequency energy at the earth's surface often vary considerably from month to month, and this monthly variability can change largely from year to year. These statistics of signal variability are required for predicting the performance of radio systems and for spectrum planning. Therefore, in this context it is important to know, for example, the signal level exceeded for large percentages of time or location [5].

Some broadcast signals, especially TV (television) at VHF may experience interference from co-channel transhorizon signals caused by ducting. It is therefore very important to have an accurate means of estimating the RSS values.

II. RELEVANT THEORY

A. Atmospheric parameters and radio refractivity

Radio signals at VHF and higher frequency bands are greatly influenced by radio refractivity. Particularly, surface refractivity correlates positively with radio field strength, and knowledge of its temporal variability is imperative in predicting the performance of terrestrial radio

978-1-5386-2501-9/17/$31.00 ©2017 IEEE

networks, especially at VHF and microwave frequencies. Also, knowledge of the variability of the atmospheric parameters from which radio refractivity depends is likewise important for radio propagation [6].

The radio refractive index *n*, of a parcel of air is defined as the ratio of the propagation velocity of an electromagnetic radiation in vacuum to that in air. The radio refractivity is defined by [7] as:

$$N = (n - 1)\, X\, 10^6 \quad (1)$$

N is the refractivity, which is the difference between refractive index of air and vacuum scaled up to parts per thousand. It is related to temperature, pressure and water vapour pressure by:

$$N = \frac{77.6}{T}\left(P + \frac{4810e}{T}\right) \quad (2)$$

where *P* is the atmospheric pressure in millibars (mb), *e* is the water vapour pressure in mb and T is the absolute temperature in Kelvin.
The vapour pressure, *e* is calculated from [1]:

$$e = (RH\ x\ e_s)/100 \quad (3)$$

where RH is the relative humidity and e_s is the saturated vapour pressure. e_s is calculated from:

$$e_s = 6.11 \exp\left[(19.7t)/(t + 273)\right] \quad (4)$$

t is the air temperature in ^{o}C.

The existence of correlation between RSS and atmospheric parameters and between RSS and refractivity has been reported by earlier researchers [8,9,10,11,12]. Reference [13] have also shown that wind speed and wind direction affect signal propagation. It is therefore on this premise that atmospheric parameters of temperature, pressure, relative humidity and wind speed were used as input data to the ANN to compute the RSS.

B. Overview of Artificial Neural Network

The artificial neural network (ANN) mimics the human biological neural network. The ANN comprises of partially or completely interconnected simple processing units called neurons. The neuron is a nonlinear unit that gets input signals from other units or from the environment, giving an output. The received signals by a neuron are modulated by real numbers called synaptic weights (or just weights). By modifying the weights through a training process, NNs can learn underlying connections from a given set of typical examples to solve a particular problem instead of following a predefined set of rules. In feed forward networks, the neurons are normally arranged in layers [14]. These are the input and output layers, which interact with the environment, and another layer (or layers) of hidden neurons, which do not interact with the environment. The neurons undergo a definite order of evaluation: the system receives the input signals, processes them through an activation or transfer function, and returns the signals to the environment through the output neurons [14].

Forecasting is one major area of ANN application [15]. Different types of ANN models exist. The multi-layer perceptron (MLP) is one of the most popular models. The MLP is a feedforward ANN model whose general structure comprises of three layers: the input layer, the hidden layer and the output layer. The MLP uses a supervised learning technique called backpropagation (BP) for training the network [16]. An important parameter that determines the relationship between the inputs and output of a node and a network is called the activation function or the transfer function. Types of activation functions are: Logistic sigmoid (also known as logsig) activation function, hyperbolic tangent sigmoid (also known as tansig) activation function and the linear (also known as purelin) activation function.
The logsig activation function is written mathematically as

$$f(u) = \frac{1}{1 + e^{-u}} \quad (5)$$

the tansig activation function is mathematically given as

$$f(u) = \frac{2}{1 + e^{-2u}} - 1 \quad (6)$$

while the purelin activation function is expressed as

$$f(u) = u \quad (7)$$

Data normalisation is also a very important preprocessing step in the use of ANN. It is a scaling technique that standardises the values of all variables from dynamic range to specific range. There are different types of normalisation techniques such as Min-Max, Z-Score, Decimal Scaling and Unitary. Application of the relevant normalisation technique can enhance the neural network training.
The Decimal Scaling normalisation standardises the given data by moving the decimal points of values of feature *A*. The number of decimal points moved depends on the maximum absolute value of *A*. A value *x* of *A* is normalised to x' by the expression:

$$x' = \frac{x}{10^m} \quad (8)$$

where *A* = values of the measured data set
x = data value to be normalised
x' = normalised value
and *m* is the smallest integer such that $\max|x'| < 1$

III. METHODOLOGY

The RSS were measured from four broadcast stations located in different parts of Niger State, Nigeria. These are Crystal FM transmitting at 91.2 MHz, Search FM transmitting at 92.3 MHz, Power FM transmitting at 100.5

MHz and NTA (Nigerian Television Authority) Minna transmitting at a frequency of 210.25 MHz. The measurements were carried out for three dry months (January-Mar) and three wet months (May-July). Table I gives details of the measurement parameters for the four VHF links.

TABLE I: MEASUREMENT PARAMETERS FOR THE VHF LINKS

Frequency (MHz)	91.2	92.3	100.5	200.25
Tx[a] height (m)	450.00	180.00	540.00	150.00
Rx[b] height (m)	3.20	3.20	3.20	3.20
Path distance (km)	7.15	15.00	83.19	5.77
Tx Power (kW)	15.00	0.30	8.50	10.00

[a]Tx = Transmitter, [b]Rx = Receiver

The instrument used for the signal strength measurement is the Geberit digital signal level meter, GE-5499 covering the signal range of 30-120 dBμV.
The atmospheric parameters comprising surface air temperature, pressure, relative humidity and wind speed were measured at the Tropospheric Data Acquisition Network (TRODAN) station situated at the Federal University of Technology, Bosso Campus, Minna. The instrument used for this measurement was the Campbell CR-1000 data logger. The CR-1000 was powered by a nominal 12 V DC source. Suitable sensors that measure these atmospheric parameters were attached to the CR-1000.

C. *Model development*

The measured weather parameters namely: temperature, pressure, relative humidity and wind speed were used as input data to the ANN. The training of the network was performed using Levenberg-Marquardt (LM) feed-forward backpropagation algorithm.

The proposed MLP network with variable neurons in the hidden layer is shown in Fig. 1.

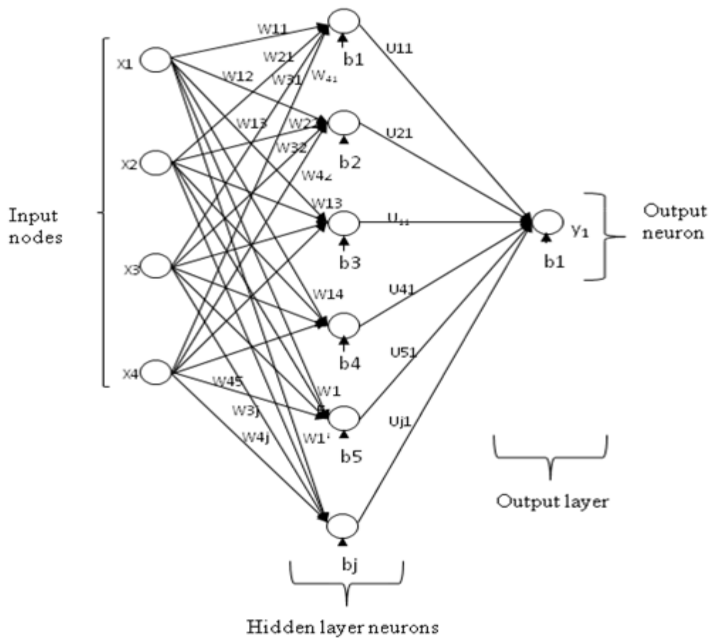

Fig. 1: The proposed MLP structure

x_i for $1 \leq i \leq 4$ are the set of input nodes; w_{ij} and u_{jk} are the sets of adjustable weight values where w_{ij} connects the *ith* input node to the *jth* neuron in the hidden layer, while u_{jk} connects the *jth* output in the hidden layer to the *kth* node in the output layer; y_k (k = 1) is the output layer. The neuron and the output node are each linked to adjustable bias values: b_j (j = number of neurons) is linked with the *jth* neuron in network layer 1, b_k (k = 1) is linked with the node in network layer 2. Within each network layer are the weights w, the multiplication and summing operations, the bias b, and the activation function [17,18].

IV. RESULTS AND DISCUSSION

Performance analysis of the signal strength model was carried out. For optimal network performance, different sets of activation functions at the hidden and output layers were used. These are: the logistic sigmoid (logsig); the hyperbolic tangent sigmoid (tansig); and the linear (purelin) activation functions. The training was also performed using different numbers of hidden layer neurons. The parameters evaluated in this training process are the effects of activation functions at the hidden and output layers, number of neurons in the hidden layer and data normalisation. The accuracy of the system is greatly influenced by these parameters. The output result is the mean and variance of ten different attempted iterations.

In evaluating the effect of activation function, the number of neurons in the hidden layer and the activation function at the output layer were held constant while the activation function in the hidden layer was varied. Afterwards, the number of neuron in the hidden layer and the activation function in the hidden layer were held constant while the activation function at the output layer was varied. Mean square error (MSE) was calculated for the ANN simulated output model of each of the trained networks, hence the network having the least MSE was chosen. The result obtained for this trial is shown in Table II.

TABLE II: EFFECT OF ACTIVATION FUNCTION

Hidden Layer	Output Layer	Mean	Variance
Tansig	Tansig	1.2E+02	3.6E+01
Logsig	Tansig	1.1E+02	2.6E+02
Purelin	Tansig	1.1E+02	1.3E+02
Tansig	Logsig	1.1E+02	1.1E+02
Logsig	Logsig	1.1E+02	6.1E+01
Purelin	Logsig	1.1E+02	2.5E+02
Tansig	Purelin	9.1E+01	1.9E+02
Logsig	Purelin	1.1E+02	9.7E+02
Purelin	Purelin	1.1E+02	1.5E+01

As observed in Table II, the accuracy obtained using the hyperbolic tangent sigmoid activation function in the hidden layer and the linear activation function in the output layer is better than those obtained using the other set of activation functions. Therefore, the combination of tansig activation function in the hidden layer and purelin activation function in the output layer is recommended for the proposed model.

In order to also explore the effect of number of neurons in the hidden layer, the number of neurons was varied from 1 to 10 at every step size of 1, while tansig activation function in the hidden layer and purelin activation function in the output layer were held constant. Fig. 2 shows the effect of number of neurons on the ANN.

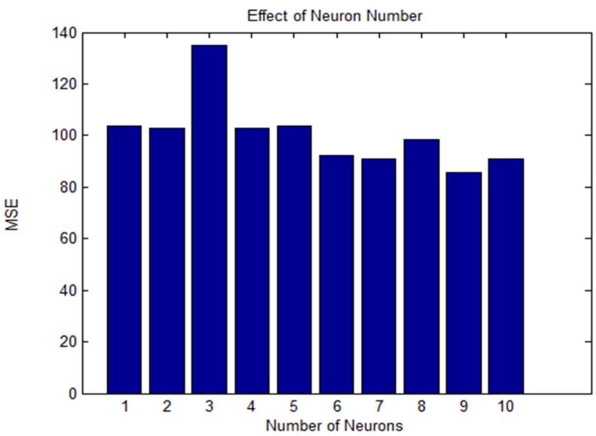

Fig. 2: Effect of Number of Neurons

It is visible from the results obtained that increasing the number of neurons beyond 9 in the hidden layer has no significant effect on the accuracy of the model. Therefore, the optimal number of neurons in the hidden layer was chosen to be 9.

The next step taken was to validate the network by analysing the regression plot created for each of the number of neurons used in the training. Of the 10 number of neurons used, the best plot was that created for neuron number 9 and the result is presented in Fig. 3.

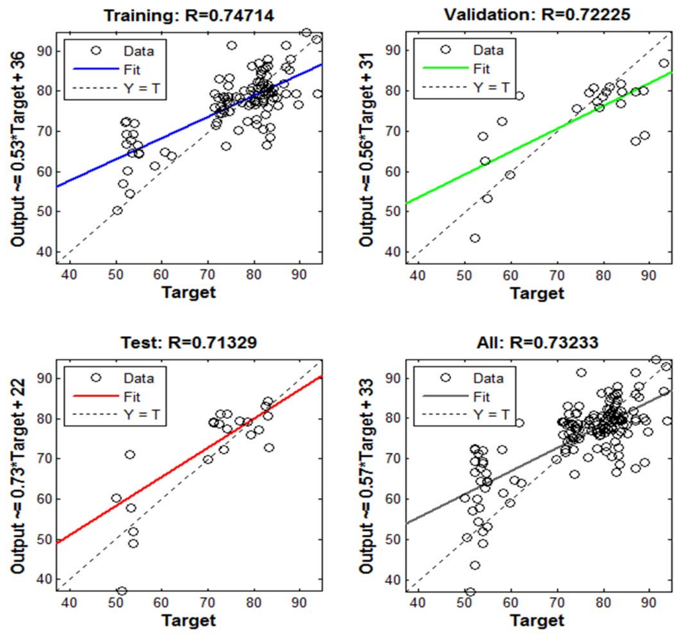

Fig. 3: Regression analysis for Neuron Number 9

Fig. 3 shows the relationship between the output of the measured data (target) and the modeled output from the ANN. The three axes represent the training, validation, testing and the overall data performance. The solid line in each axes represents the best fit linear regression line between the modeled output and the target, while the R value is the coefficient of correlation. The correlation coefficient values for this network indicate that there is a linear relationship between the modeled output and the target. Correlation coefficients of 0.74, 0.72 and 0.71 obtained for the training, validation and testing results respectively indicate a good fit.

Normalisation preprocessing technique was further applied so as to obtain an optimal network with minimal errors. The data was standardised using Decimal Scaling. This effect is presented in Fig. 4.

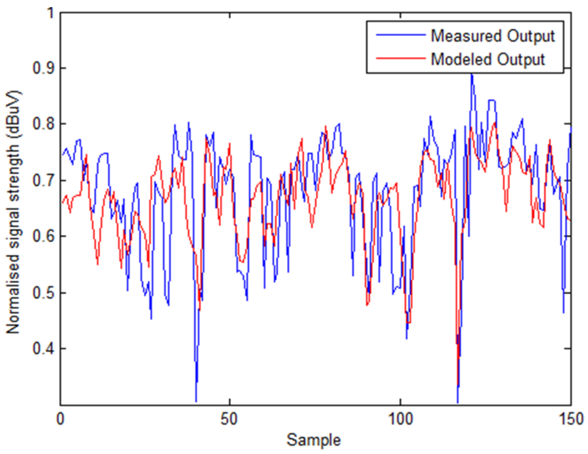

Fig. 4: Effect of Normalisation

It is clear that with the Decimal Scaling normalisation, increasing the number of neurons in the hidden layer increases the accuracy of the system as neuron number 9 produced the optimal result.

The proposed model network was then trained using tansig activation function in the hidden layer and purelin activation function in the output layer, neuron number 9 in the hidden layer and the application of Decimal Scaling normalisation to the data.

These combined parameters greatly enhanced the overall performance of the system. The measured data from Crystal FM link were used in the initial ANN training.

In investigating how accurate the network was, measured data from NTA was further trained using the same parameters derived from the training of Crystal FM data.

D. *Testing of the developed model*

The developed ANN model from NTA data was tested on different data sets measured from Search FM, Power FM and Crystal FM links. The results obtained are presented in Figs. 5-8. These results show the variation of the measured signal strength with the ANN modeled signal strength output and the corresponding MSE in the modeled output.

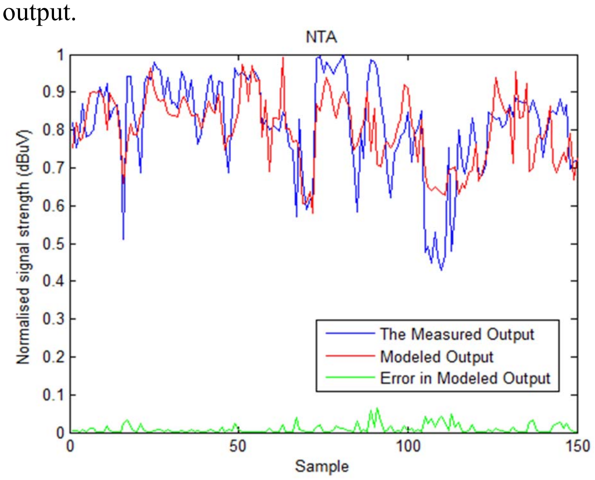

Fig. 5: Measured and ANN modeled signal strength with MSE for NTA link

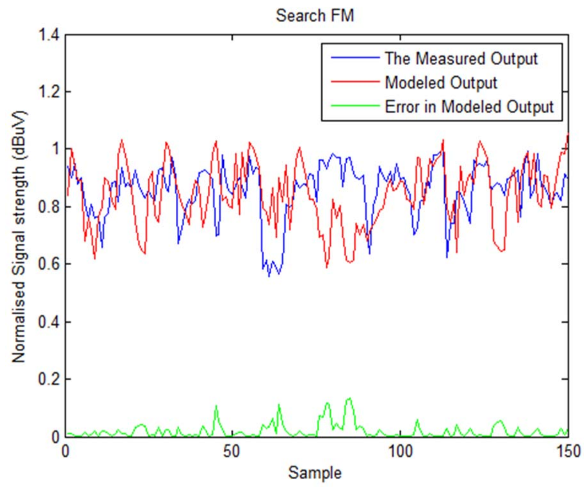

Fig. 6: Measured and ANN modeled signal strength with MSE for Search FM link

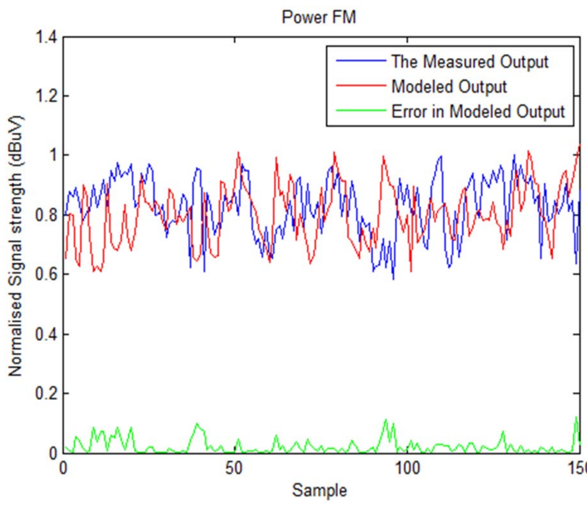

Fig. 7: Measured and ANN modeled signal strength with MSE for Power FM link

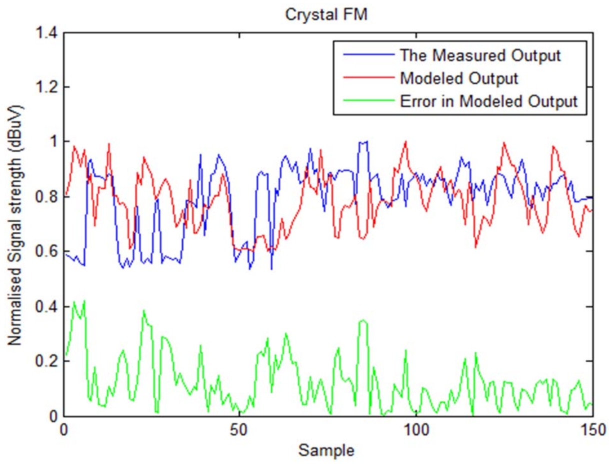

Fig. 8: Measured and ANN modeled signal strength with MSE for Crystal FM link

It is observed from Figures 5-8 that the models performed well for the four VHF links as modeled signal strength values were reasonably close to the measured signal strength values and the computed errors from the modeled output were significantly low.

CONCLUSION

An artificial neural network model that computes received signal strength (RSS) at VHF band, using atmospheric parameters has been developed. The parameters evaluated in the training process were effects of activation functions at the hidden and output layers, number of neurons in the hidden layer and data normalisation. Results obtained have shown that the accuracy and overall performance of the ANN model was greatly influenced by the combinations of tansig activation function in the hidden layer and purelin activation function in the output layer, neuron number 9 in the hidden layer and Decimal Scaling normalisation. Also, for the four VHF broadcast links considered, the models performed satisfactorily as computed signal strength values were adequately close to the measured signal strength values; and the computed errors from the modeled output were sufficiently low. It can therefore be concluded that the developed ANN model can sufficiently compute received VHF signal strength using measured atmospheric parameters in Minna and environs. It is recommended that other preprocessing techniques be applied to obtain better accuracy for future work.

REFERENCES

[1] M.P.M. Hall, "Effects of the troposphere on radio communication", Peter Peregrinus Ltd., U.K. and U.S, 1979, pp. 180- 181.

[2] M.V.S.N. Prasad, R.T. Rao, I. Ahmad, and K.M. Paul, "Investigation of VHF signals in bands I and II in southern India and model comparisons", Indian Journ. of Radio and Space Physics, vol. 35, 2006, pp. 198-205.

[3] R. Grosskopf, "ITU field-strength prediction methods for terrestrial point-to-area services", Proceed. of WFMN07, Chemnitz, Germany, B3 ed., vol. II, 2007, pp. 63-67.

[4] Australian Broadcasting Planning Handbook, "Technical planning parameters and methods for terrestrial broadcasting", Australian broadcasting authority, Canberra, 2004, pp. 10.

[5] O.A. Aboaba, "Tropospheric VHF radiowave propagation measurements in a tropical location in Nigeria", U.N.E.S.C.O. and Int. Atomic Energy Agency, The Abdus Salam Int. Centre for Theoretical Physics, Triestie, 2006, Retrieved from http://www.ictp.it/pub_off on 11th July, 2013.

[6] O.D. Oyedum, J.A. Ezenwora, K.C. Igwe, J.O. Eichie, and A.S. Moses, "Diurnal and annual cycles of surface refractivity and related atmospheric parameters in Minna, Nigeria", The Nig. Journ. of Space Research (NJSR), vol. 10, 2011, pp. 141-156.

[7] E.K. Smith, and S. Weintraub, "The constants in the equation for atmospheric refractive index at radio frequencies", Proceed. IRE, vol. 41, 1953, pp. 1035-1037.

[8] O.D. Oyedum, and G.K. Gambo, "Surface radio refractivity in Northern Nigeria", Nig. Journ. of Physics, vol. 6, 1994, pp. 36-41.

[9] O.A. Aboaba, and O.O. Jegede, "Correlation studies of VHF radiowave propagation and radiometeorological conditions", Proceed. of the 11th Int. Conf. on Antennas and Propagation, ICAP2001, IEEE Conf., 480th ed., vol.1, UMIST, Manchester, UK, 2001, 170-171.

[10] S.D. Gunashekar, D.R. Siddle, and E.M. Warrington, "The effect of weather conditions on transhorizon propagation of UHF radio waves in the British Channel Islands", Proceed. of the Loughborough Antennas and Propagation Conf., 2005, ISBN 0947974334.

[11] D.R. Siddle, E.M. Warrington, and S.D. Gunashekar, "Signal strength variations at 2 GHz for three sea paths in the British Channel Islands: Observations and statistical analysis", Radio Science, vol. 42, 2007, pp. 1-15.

[12] F.J. Oluwole, and O.M. Olayinka, "A test of the relationship between refractivity and radio signal propagation for dry particulates", Research Desk, 4th ed., vol. 2, 2013, pp. 334-338.

[13] D.E. Barrick, "Theory of HF and VHF propagation across the rough sea (1 and 2)", Radio Science, 5th ed., vol. 6, 1971, pp. 517-533.

[14] J.C.F. Pujol, and J.M.A. Pinto, "A neural network approach to fatigue life prediction. Int. Journ. of Fatigue", Elsevier Journs., vol. 33, 2011, pp. 313-322.

[15] R. Sharda, "Neural networks for the MS/OR analyst: An application bibliography", Interfaces, 2nd ed., vol. 24, 1994, pp. 116-130.

[16] G. Zhang, B.E. Patuwo, and M.Y. Hu, "Forecasting with artificial neural networks: The state of the art", Int. Journ. of forecasting, Elsevier Journs., vol. 14, 1998, pp. 35-62.

[17] M.H. Beale, M.T. Hagan, and B.D. Howard, "Neural network toolbox™ 7", User Guide, 2011.

[18] A.M. Aibinu, A.A. Shafie, and M.J.E. Salami, "Performance analysis of ANN based YCbCr skin detection algorithm", Procedia Engineering, vol. 41, 2012, pp. 1183-1189.