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Estimation of Tropospheric Refractivity with Artificial Neural Network at Minna, Nigeria

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Abstract - The study of refractivity and its effect at the tropospheric region is very important as the parameters help in planning for communication links. This study is aimed at calculating and estimation of refractivity at the tropospheric region with tropospheric parameters of relative humidity, absolute temperature and atmospheric pressure of January and October at Minna, Nigeria. The ITU-R, model and artificial neural network model were used. Validation results are thus, January, absolute temperature = 0.4313 K, relative humidity = 0.9989 %, pressure = 0.0201 (hpa) and October, absolute temperature = -0.3146 K, relative humidity = 0.9597 % and pressure = 0.1962 respectively. The validation of the correlation coefficient results show that all the tropospheric parameters has effects on refractivity, but relative humidity has more effect and is merely on October which was attributed to the large quantity of moisture at the tropospheric region during the rainy season which is between April to October as stated by Adadiji. From Table 1 and 2 and figure 1 to 6, it clear that ANN has the capacity of estimating refractivity since the estimated values has close agreement with the calculated values.

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Strictly as per the compliance and regulations of :

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Abstract - The study of refractivity and its effect at the tropospheric region is very important as the parameters help in planning for communication links. This study is aimed at calculating and estimation of refractivity at the tropospheric region with tropospheric parameters of relative humidity, absolute temperature and atmospheric pressure of January and October at Minna, Nigeria. The ITU-R, model and artificial neural network model were used. Validation results are thus, January, absolute temperature = 0.4313 K, relative humidity = 0.9989 %, pressure = 0.0201 (hpa) and October, absolute temperature = -0.3146 K, relative humidity = 0.9597 % and pressure = 0.1962 respectively. The validation of the correlation coefficient results show that all the tropospheric parameters has effects on refractivity, but relative humidity has more effect and is merely on October which was attributed to the large quantity of moisture at the tropospheric region during the rainy season which is between April to October as stated by Adadiji. From Table 1 and 2 and figure 1 to 6, it clear that ANN has the capacity of estimating refractivity since the estimated values has close agreement with the calculated values.

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I. Introduction

The structure of the radio refractive index, *n*, at the lower part of the atmosphere is a very important parameter in planning of the communication links. The atmosphere which is the propagation medium for radio transmission is characterized by different refractive indices at different levels (Oyedum and Gambo 1994). These varying indices significantly affect radio wave propagation.

Multipath effects arise due to large scale variations in atmospheric radio refractive index, such as horizontal layers with very different refractivity (Grabner, and Kvicera, 2003). This effect becomes noticeable, when the same signal takes different paths to its target and the rays arriving at different times thereby interfering with each other during propagation through the troposphere. The consequence of this large scale variation in the tropoospheric refractive index is that radio waves propagating through the atmosphere become progressively curved towards the earth. Thus, the range of the radio waves is determined by the height dependence of the refractivity. Therefore, the refractivity of the atmosphere will not only affect the curvature of the ray path but will also provide some insight into the fading of radio waves through the troposphere. These have led to the interest of looking at the possibilities of using a model to estimate refractivity with tropospheric parameters. Artificial neural network (ANN) model is a computer software program that behaves the same way as the human brain. The network usually consists of an input layer, some hidden layers and an output layer.

This work aims at using artificial neural network (ANN) model with meteorological parameters of absolute temperature, pressure, and relative humidity as input data to predict refractivity at Minna, Nigeria.

II. Materials and Procedures

a) Source of Data

The meteorological data of relative humidity, temperature and pressure were obtained from the Centre for Basic Space Science (CBSS), University of Nigeria Nsukka. Equations (2) and (3) given below were used to compute the values for refractivity and water vapour pressure (e). The geographical location of the area Minna is as shown in table 1.

Table 1 : Geographical location of the station

Station	latitude	longitude	Attitude (m)
Minna	9.37^0 N	6.30^0 E	256

b) Theory of Refractivity

Radio –wave is determined by changes in the refractive index of air in the troposphere. Because it is close to unity (about 1.0003), the refractive index of air is measured by a quantity called the radio refractivity, N which is related to refractive index, n as (ITU-R, 2003):

$$N = 1+N \times 10^6 \quad (1)$$

In terms of measured meteorological quantities, the refractivity N can be expressed as:

$$N = 77.6\frac{p}{T} + 3.73 \times 10^5\left(\frac{e}{T^2}\right) \quad (2)$$

Where : p = atmospheric pressure (hpa), e = water vapour pressure and T = absolute temperature (K).

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The water vapour pressure e is usually calculated from the relative humidity with the following equation:

$$e = \frac{RH}{100} \, a \exp\left(\frac{b\,t}{t + c}\right) \qquad (3)$$

Where the temperature is given in ℃ and the coefficients a, b and c take the following values: a = 6.1121, b = 17.502, and c = 240.97.

Therefore,

$$e = \frac{RH}{100} \, 6.1121 \exp\left(\frac{17.502\,t}{t + 240.97}\right)$$

Where : RH = relative humidity (%), t = temperature in degree Celsius ℃.

c) Procedure of Artificial Neural Network Estimation

For the estimation of tropospheric refractivity, 3-2-1 multilayer peceptron (MLP) neural networks were used, which includes the input layer, a linear output layer and a sigmoid hidden function. In order to predict the tropospheric refractivity, a classifier were developed, which merely associates the ground values of pressure, absolute temperature and relative humidity and predicts the tropospheric refractivity at Minna for the specific observatory period. The selection of sigmoid transfer function is because it allows any relation between the system predictors and the output.

The network predictors consist of 3 X N matrix, where each row represent the ground pressure, absolute temperature and relative humidity respectively for total of N observatory period, while each colum stands for the days used, which can be derived from equation (4). In order to validate the refractivity results and investigate for any further improvement and recommendation of the model, regression analyses were carried out.

d) Theory of Artificial Neural Network Model

The neurons act like parallel processing units. An artificial neuron is a unit that performs a simple mathematical operation on its inputs and imitates the functions of biological neurons and their unique process of learning (Ibeh et al, 2012). From Fig. 1 we have that weighed sum of the inputs

$$\boldsymbol{v_k} = \sum_{j=1}^{N} \mathrm{x_j}\, w_{kj} + b_k \qquad (4)$$

is calculated at kth hidden node.

w_{kj} is the weight on connection from the jth to the kth node; $\mathrm{x_j}$ is an input data from input node; N is the total number of input (N = 31); and b_k denotes a bias on the kth hidden node. Each hidden node then uses a sigmoid transfer function to generate an output

$$z_k = [1+e^{(-v_k)}]^{-1} = f(v_k) \qquad (5)$$

between -1 and 1.

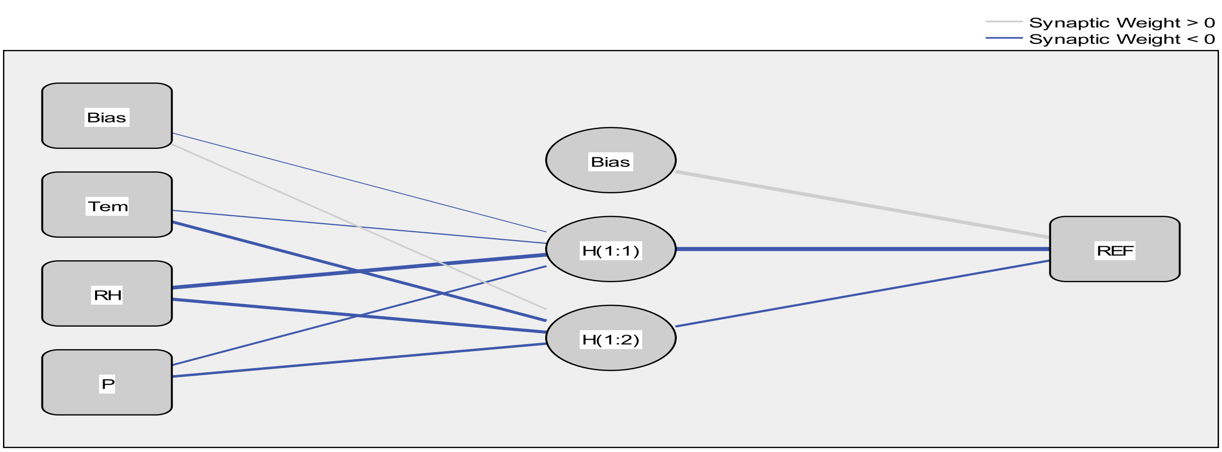
We then set the output from each of the hidden nodes, along with the bias b_0 on the output node, to the output node and again calculate a weighted sum,

$$y_k = \sum_{k=1}^{N} \mathrm{v_k}\, z_k + b_k \qquad (6)$$

Where N is the total number of hidden nodes; and v_k is the weight from the kth hidden node to the sigmoid transfer function of the output node.

III. Results and Discussion

Table 2 is the estimation of refractivity of meteorological data of absolute temperature, relative humidity, atmospheric pressure, calculated refractivity and artificial neural network estimation of refractivity at Minna of January and October, 2009 respectively. Figure 1 is the network diagram. Result obtained for the daily calculated and estimation of tropospheric refractivity at Minna for January and October is presented in Table 2 respectively.



Hidden layer activation function: Sigmoid

Output layer activation function: Sigmoid

Figure 1: Network Diagram

In Table 2 a large difference between the values of refractivity in January and October is highly observed. The refractivity value is higher in October. This could be attributed to high values of relative humidity.

The high refractivity value confirmed the statement of Adadiji, (2008) that refractivity values are observed to be generally high during the rainy season (April – October). He further stated in his work that the high values are due to high air humidity (very close to 100%).

The validation analysis of correlation coefficient on the effect of tropospheric parameters on refractivity show that relative humidity has close to 100% effect.

The correlations analysis of refractivity with all the atmospheric parameters shows that the correlation coefficient of refractivity with each of temperature, relative humidity and pressure at Minna for January are o.43, 1.0 and 0.02 respectively. In October the correlation coefficients are respectively -0.31, 0.96 and 0.20. From the result in January, refractivity is completely influenced by relative humidity. In October, the influence is a little bit less than that in January. The overall result indicates that relative humidity has greater influence on refractivity with the two different months or season considered. Temperature and pressure has little or no effect on refractivity under the period of study hence their low correlation coefficient with refractivity.

From Table 2 and figure 2 to 7, it is clear that ANN can be use to estimate tropospheric refractivity of Minna, since both the calculated and estimated values has close agreement.

From table 2 to 7, ANNref represent refractivity estimation of artificial neural network, Tem. represent absolute temperature, RH represent relative humidity, Ref represent refractivity respectively.

IV. Conclusion

The study of refractivity and its effect at the tropopsheric region of Minna in Nigeria is a very important as the parameters help in planning the communication links. The validation of the correlation coefficient results show that all the tropospheric parameters have effects on refractivity, but relative humidity has more effect and is merely on October which was attributed to the large quantity of moisture at the troposphere during the rainy season which is between April to October as state by Adadiji. From Table 2 and figure 2 to 7, it is clear that ANN has the capacity of estimating refractivity.

Acknowledgement

Authors wish to express their profound gratitude to the management and staff of the Centre for Basic Space Science (CBSS), University of Nigeria, Nsukka for supplying the data for the tropospheric parameters of this work.

References Références Referencias

1. Adediji A.T and Ajewole M.O, (2008) Vertical profile of radio refractivity gradient in Akure, south-west, Nigeria, Progress In Electromagnetics Research C, Vol. 4, 157–168, 2008
2. Grabner, M. and V. Kvicera, "Clear-air propagation modeling using parabolic equation method," Radio Engineering, Vol. 12, No. 4, 50–54, 2003.
3. Ibeh G. F, Agbo G. A and Rabia, S, (2012), Application of artificial neural network and Angstrom-Prescott models in prediction of global solar radiation of Uyo City, Nigeria with atmospheric parameters. Advances in Applied Science Research, 2012, 3 (1):619-624
4. ITU-R, " Effect of Temporal Variations of Refraction on Radio wave Propagation" Rec P881, ITU, Geneva, 131-138, 1982.
5. Oyedum, O.D. and Gambo, G.K. (1994): Surface Radio Refractivity Norther Nigeria. Nig. J. Phys, Vol.6, 36-41.

Table 2 : Minna Meteorological Data For January October, 2009

	Atmospheric parameters estimation in January		Atmospheric parameters estimation in October	
Date	Refractivity, N-units	ANN_{REF} N-units	Refractivity, N-units	ANN_{REF} N-units
1/1/2009	271.0544525	274.60	356.5481052	357.08
2/1/2009	275.3722889	274.90	355.9020258	356.21
3/1/2009	275.3163324	274.99	349.5771302	349.66
4/1/2009	279.6008402	276.31	346.5879717	346.35
5/1/2009	274.8514794	275.76	345.5941351	345.41
6/1/2009	273.0597755	274.86	343.1590852	343.35
7/1/2009	292.986399	290.92	361.7624981	359.94
8/1/2009	268.3168988	274.19	357.799226	358.17
9/1/2009	338.6648802	328.01	357.4811448	357.48
10/1/2009	322.5500852	325.63	353.762127	354.26
11/1/2009	328.5559534	327.62	347.6803539	347.69
12/1/2009	333.8285224	328.01	355.1351964	355.40
13/1/2009	270.2412859	272.80	352.5858326	352.50
14/1/2009	273.1603293	274.14	344.4727377	344.55
15/1/2009	278.9883037	278.07	357.6435149	357.72
16/1/2009	307.3309620	315.62	355.2199322	356.02
17/1/2009	316.8938847	324.33	351.2342304	351.28
18/1/2009	328.7936466	327.59	354.5881569	354.40
19/1/2009	312.2606525	325.48	353.7259292	353.54
20/1/2009	283.8785572	274.93	349.906618	349.72
21/1/2009	275.6875823	273.40	349.6676148	350.00
22/1/2009	270.6980512	274.48	351.1906812	350.66
23/1/2009	272.9680961	275.28	344.2962555	343.84
24/1/2009	275.3075448	275.98	348.6706128	348.50
25/1/2009	277.3180941	274.51	349.0745612	348.93
26/1/2009	295.2679312	292.11	344.3451933	344.78
27/1/2009	291.2213452	289.20	341.6831885	342.37
28/1/2009	283.4740147	280.91	347.5362109	346.96
29/1/2009	332.5238012	327.59	349.6991945	349.24
30/1/2009	278.7621149	277.08	352.0536456	351.30
31/1/2009	314.2687866	323.95	337.1522459	340.67

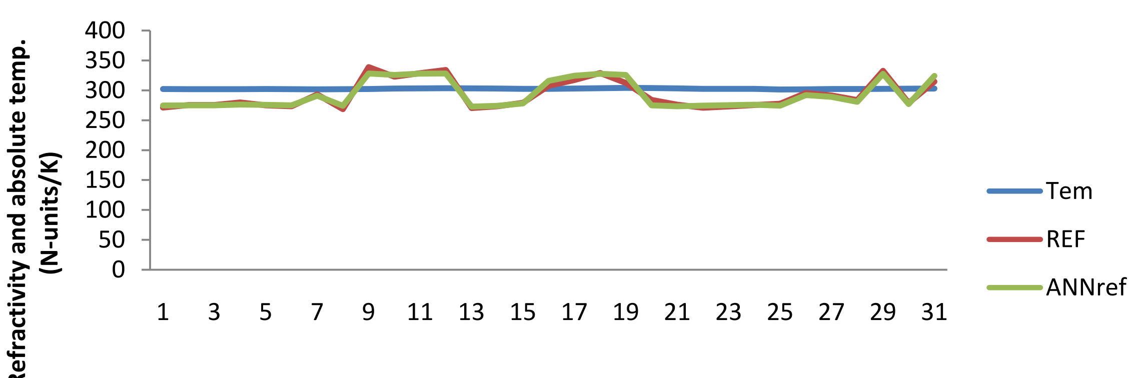


Figure 2: Graph of absolute temperature, refractivity and ANN refractivity Estimation for January at Minna

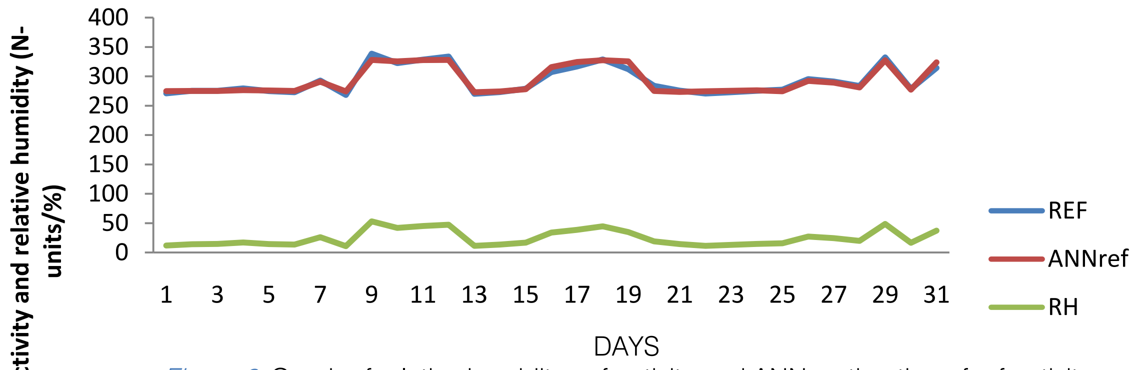


Figure 3: Graph of relative humidity, refractivity and ANN estimation of refractivity for January at Minna

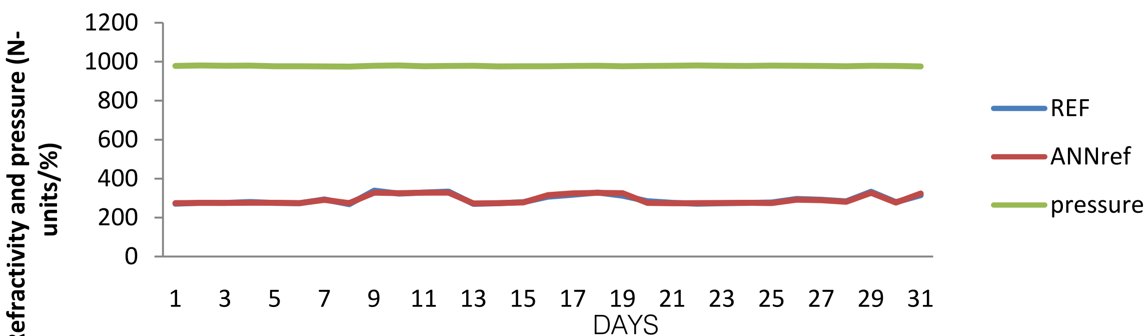


Figure 4: Graph of pressure, refractivity and estimation of ANN refractivity for January at Minna

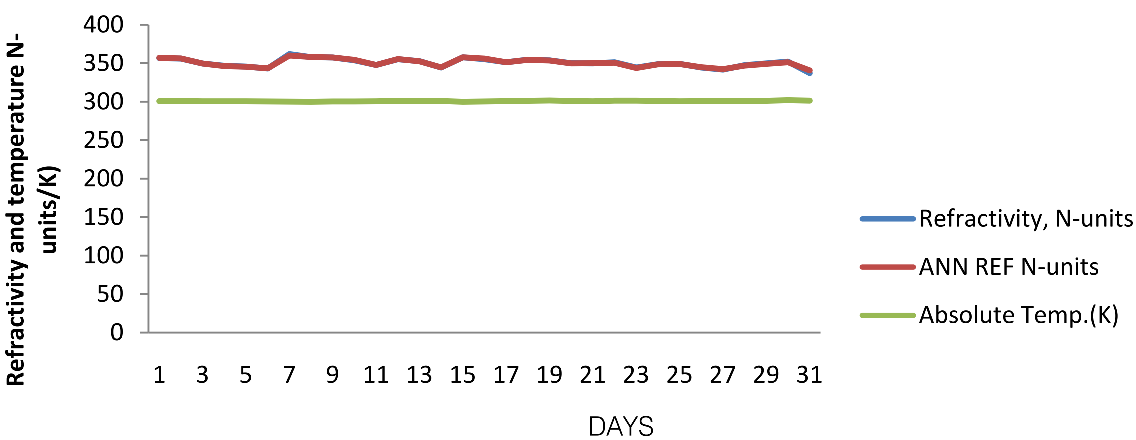


Figure 5: Graph of absolute temperature, refractivity and estimation of refractivity of October at Minna

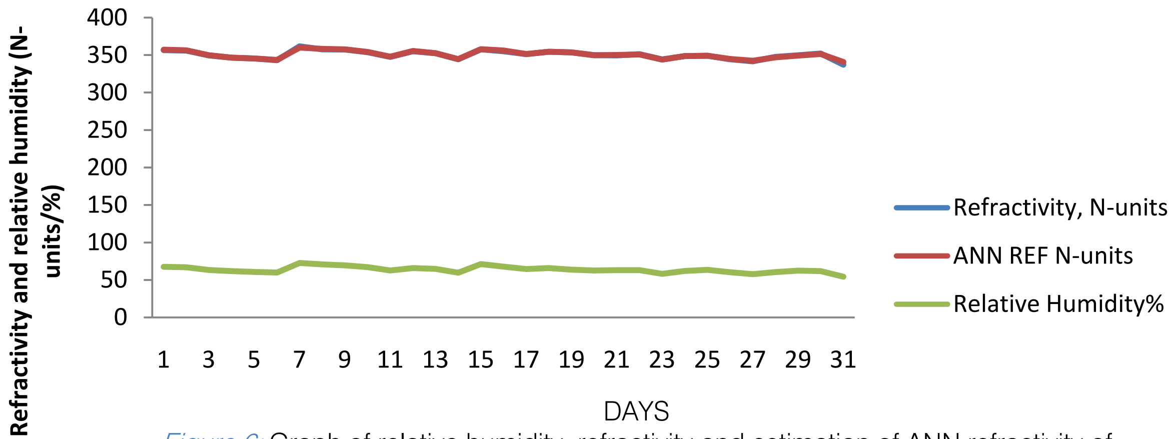


Figure 6: Graph of relative humidity, refractivity and estimation of ANN refractivity of October at Minna

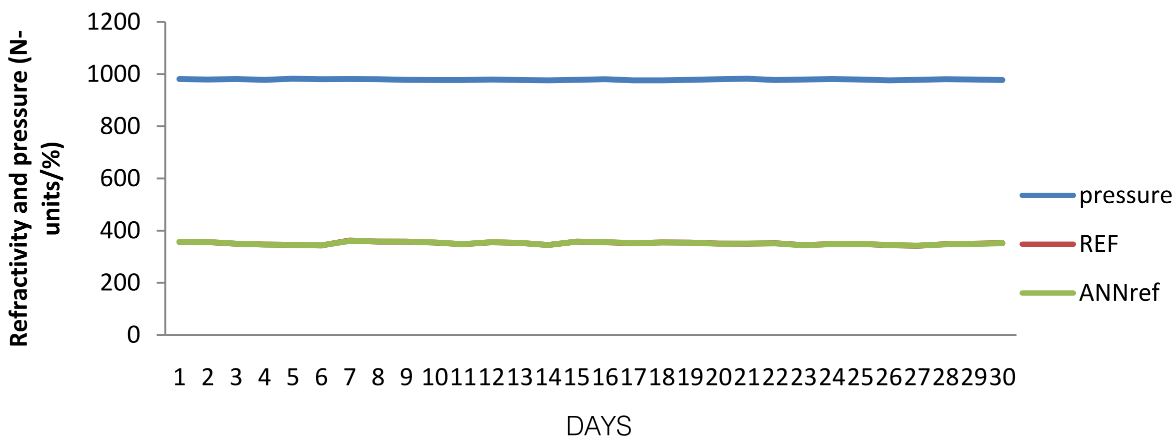


Figure 7: Graph of pressure, refractivity and estimation of ANN refractivity of October at Minna