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Development of surface meteorological data-based models for prediction of vertical profile of radioclimatic parameters

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ABSTRACT:*This study presents development of surface meteorological data-based models for prediction of vertical profile of radioclimatic parameters. To achieve this, suitable models were developed on Artificial Neural Network (ANN) and Adaptive-Neuro Fuzzy Inference System (ANFIS) using data obtained from previous research that was conducted by launching both radiosounde and collecting data from fixed mast. The two results obtained from ANFIS and ANN were compared to see which will achieve a greater accuracy. Primary and secondary radioclimatic parameters are essential for computing values of different parameters used in the design of wireless networks. The secondary radio parameter are determined from the primary radioclimatic parameters namely; atmospheric pressure, relative humidity and temperature. The results revealed that prediction obtained by ANFIS has a greater accuracy and the result can actually be used for prediction. This research shows that data acquired using ANN and ANFIS models are cost effective and can be used in place of launching radiosonde equipment in order to capture the vertical profile of the radioclimatic parameters. The result of the research will go a long way in solving the problem encountered during the launch of radiosounde equipment. Also, the need to visit sites whenever data collation is needed will be to a great extent reduced. The loss of radiosounde equipment, which often happens at site, will also be completely eliminated.*

KEYWORDS*:Artificial Neural Network, Adaptive-Neuro Fuzzy Inference System, Radioclimatic Parameters, Vertical Profile*

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I. INTRODUCTION

Over the years, wireless communication networks have grown to become the dominant communication technology across the globe. In the design and planning of wireless communication networks, the vertical profile of some radioclimatic parameters is required. Among such parameters is the radio refractive index at the lower part of the atmosphere. Refractive index is defined as a ratio of the radio wave propagation velocity in free space to its velocity in a specified medium. Radio–wave propagation is determined by changes in the refractive index of air in the troposphere. Changes in the value of the troposphere radio refractive index can curve the path of the propagating radio wave. At standard atmosphere conditions near the earth surface, the radio refractive index is equal to approximately 1.0003[1]. As the conditions of propagation in the atmosphere vary from the standard ones, the anomalous radio-wave propagation is observed. Such anomalies are incident with some meteorological conditions (inversion of temperature, high evaporation and humidity, passing of the cold air over the warm surface and conversely) [2].

Analytically, the atmosphere radio refractive index depends on primary radioclimatic parameters, namely; air temperature, humidity, atmospheric pressure and water vapour pressure. Furthermore, air temperature, pressure and humidity depend on the height (altitude) at a point above the ground surface. Even small changes in any of these variables can make a significant influence on radio- wave propagation, because radio signals can be refracted over whole signal path [3]. In a well–mixed atmosphere, pressure, temperature and humidity decrease exponentially as a function of height, h [4]. The value of radio refractive index is very close to the unit and the changes in this value are very small in time and space. With the aim of making them more visible, the term of refractivity, N, is used.

Another important characteristic of the atmosphere is the vertical gradient of the refractive index. Profiles of refractive index values in the 1 km interval above ground are important for the estimation of super–refraction and ducting phenomena and their effects on radar observations and VHF field strength at points beyond the horizon. The vertical gradient of the refractive index is responsible for bending of propagation direction of the electromagnetic wave [5].

Given the relevance of vertical profile of radioclimatic parameters in wireless network design and their dependence on altitude, data of the lower and upper atmosphere are regularly collected using radiosonde equipment which is launched from ground level into the atmosphere using whether balloon or any other means of lifting the radiosonde equipment. The main aim of this research is to develop a model that can effectively generate the vertical profile of the primary and hence, calculate the secondary radioclimatic parameters based on surface meteorological data captured at ground level. This will eliminate the need to launch the radiosonde into the atmosphere.

II. MATERIALS AND METHODS

In this study, analytical and simulation research methods were used. In the analytical method, mathematical expressions along with ANN algorithms and ANFIS rule base are derived for prediction of the vertical profile of various radioclimatic parameters of interest. The simulation part entails the simulation of the ANN and ANFIS models using Mathlab/Simulink and the primary radioclimatic data obtained from the study area. The primary radioclimatic data is the data set of clear air (in the absence of rain, fog or snow) radiosonde data for Calabar which was obtained from the Nigerian Meteorological Agency (NIMET). Particularly, the vertical profile of air temperature, atmospheric pressure and relative humidity as well as refractivity index were considered. The prediction performance of ANN and ANFIS model for the vertical profile for a height of 0 m (surface) to 1000 m were considered and compared. The results of the analysis were verified and validated in comparison with existing models.

2.1 Study area

The study area for this work is a location in Cross River state in the South-South region of Nigeria. Cross River state is located at 4°57'north in latitude and 8°19' east in longitude. The southern part of Nigeria experiences heavy and abundant rainfall. The storms are usually conventional in nature due to the regions proximity to the equatorial belt. The annual rainfall received in this region is very high, usually above the 2000mm (78.7in) rainfall totals applicable to tropical rainforest climate worldwide. 2.2 Data collection

In this research, radiosonde data from Nigerian Meteorological Agency (NIMET) for Cross River state was used. Twelve (12) months data for the year 2013 was used. The data contains the monthly data of temperature, pressure and relative humidity for various altitudes above sea level for the 12 months in the year 2013. The radiosonde sounding data was obtained in word pad format and had to be exported to Microsoft Excel platform for easy manipulation. When the data was successfully exported to Excel, clear air parameters (temperature, pressure and humidity) were carefully sorted out at different altitudes.

Particularly, the data used for this study is a radio sounde data from 0 m altitude to about 1000 m altitude with atmospheric parameters comprising of temperature, pressure and relative humidity for different months. Sample data for the month of January and February are given in Table Iand TableII respectively. 2.3

Vertical profile of radioclimatic parameters based on surface data

Artificial neural network (ANN) was used to predict the atmospheric parameters with altitude and surface data as input. Particularly, multilayer perceptron MLPartificial neural network was used. The ANN includes three layers, named input layer, middle or hidden layer and output layer. In the ANN architectural, there are four input (altitude, surface temperature, surface pressure and surface relative humidity), five hidden neurons in the hidden layer and three outputs (atmospheric parameters in the orders of pressure, temperature and relative humidity).

The number of neurons in the middle layer has to be optimized during the network design. In this study, the sigmoid function was selected as the transfer functions. Specifically, the hyperbolic tangent sigmoid was selected for the middle layer and the linear transfer function for the output layer. Also, the radiosounde dataset were partitioned into 70% for training the ANN model, 15 % for validation and 15 % for testing.There are 20 data sets for each month, selecting 70% for training, 15% for test and 15% for validation means 14 data sets were used for training, 3 data sets were used for validation and 3 data sets used for test respectively. The program was done in such a way that first to fourteenth data sets were used for training, fifteenth to seventeenth dataset were used for validation and the rest were used for test respectively as shown in Table III, Table IV and Table Vfor the month of January. The same was applied for the other months.Table VI shows ANN prediction of pressure in Januaryand Table VII shows the ANFIS prediction of pressure in January**.** The maximum number of neurons in a layer can be calculated from the Equation 2.1[6]:

$n \le \frac{k(n_i+n_o)-n_o}{n_i+n_o+1}$ Equation 2.1

Where, k = number of samples, n_i = number of inputs and n_o is the number of outputs. Based on the available data k =14, $n_i = 4$ and n_o = 3. According to calculations, the maximum number of neurons for the training data is about 11.875 neurons.

Accordingly, at first, the number of neurons was set at 12 in the multi-layer perceptron (MLP) neural network to find the optimal number of neurons in the hidden layer. The optimizing criterion was minimizing the Mean Squared Error of the model predictions in comparison to the test data. The number of neurons was reduced gradually. Eventually the optimal value was five. Hence, five (5) neurons were used in the ANN model. In addition, the LewenbergMarquard algorithm was used as the training function.

After determining the number of optimal neurons, the weights and biases of the input and hidden layers were calculated. The weights and biases were used in making the prediction for any given input data.2.4Determination of the vertical profile of atmospheric radio refractivity index

Atmospheric radio refractivity is estimated from the radiosonde data. The data used are the primary clear-air radioclimatic parameters, namely; temperature, pressure and relative humidity. Also, for any given altitude, the ANN predicted temperature, pressure and relative humidity were used to determine the refractivity index at that altitude. The refractivity is computed according to the ITU-R P.453-9 model given as [7] [8]:

N =Ndry + Nwet $=\frac{77.6}{T}\ (P+4810\frac{e}{T})$ Equation 2.2

The dry term of the radio refractivity is given as [7] [8]:

Ndry $=\frac{77.6\ P}{T}$ Equation 2.3

The wet term of the radio refractivity is given as [7] [8]:

Nwet $=\frac{77.6}{T}\ (4810\frac{e}{T})\ = 3.73256(10^5)\frac{e}{T^2}$ Equation 2.4

Where, T = atmospheric temperature in kelvin, P = total atmospheric pressure in hpa, e = water vapour pressure in hpa.

The water vapour pressure is determined with the expression [7] [8]:

$e = \frac{6.112H}{100}\exp(\frac{17.5t}{t+240.9})$ Equation 2.5

where, H = relative humidity, t = atmospheric temperature in Kelvin

Altitude was used as the input and three outputs; namely, the temperature, pressure and relative humidity at the altitude of interest. The input data are converted to degrees of memberships and membership values in a process called fuzzification. The triangular membership function was used for the four inputs as well as the output. Each of the four inputs was divided into three triangular membership functions. Also, the outputs were divided into three triangular membership functions. The input variables (explanatory variables) and the output variables were imported to the ANFIS environment via the workspace key after clicking on load data. Fuzzification process was performed in the MATLAB FIS editor.

The performance measures used to evaluate the developed model are regression coefficient or coefficient of determination (R2), root means square error (RMSE) and sum of square errors (SSE). The root mean square error (RMSE) is given in Equations 2.6 and Equation 2.7.

Also, for any given altitude, the ANFIS predicted temperature, pressure and relative humidity were used to determine the refractivity index at that altitude. The refractivity index was computed using the Equation 2.2 to Equation 2.5.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_t - \hat{Y}_t\right)^2$$

Equation 2.6

Where, Yt = actual industrial electricity consumption and $\hat{Y}$ t = predicted value from the model. The Root Means Square Error (RMSE) is given as;

RMSE $= \sqrt{MSE}$ Equation 2.7

The formula for the sum of square error (SSE) is given as;

$$SSE = \sum_{i=1}^{n}\left(Y_t - \hat{Y}_t\right)^2$$

Equation 2.8

III. RESULTS AND DISCUSSION

Table I shows the ANN Predicted radio sounde data for January from ground level (0 m) to 1050 m. The atmospheric parameters predicted are the Pressure, temperature and relative humidity.Figure 1 shows the comparison between the predicted value using ANN model and the actual value used in the building of the ANN model.Figure 2 shows the comparison between the predicted value using ANFIS model and the actual value used in the building of the ANFIS model. From Table II, R-square for ANN = 85.518 while R-square for ANFIS = 91.227. Figure 3shows thecomparisonbetween Actual, ANN and ANFIS models for January when compared side by side.

IV. CONCLUSION

Radiosounde data equipment was used to obtain the radioclimatic data of altitude ranging from 0m (ground level) to 1000m. Two artificial intelligence models namely; ANN and ANFIS were used to predict the atmospheric parameters. A statistical performance model was implored to obtain the best model for prediction and further implementation. It was observed that ANFIS had a better prediction performance greater than 91% accuracy in all cases over ANN which has values around 85% accuracy in some cases.

Figures and Tables

Table I: Radiosounde data for January

S/N	Altitude (m)	Pressure (pa)	Temperature (°C)	Relative Humidity (%)
1	0	1013.1	31.5	66
2	44.3	1006.7	30.3	84
3	107.4	1000.4	29.6	79.7
4	169.6	994.2	28.9	75.3
5	225.8	988.3	28.2	70.9
6	277.1	982.4	27.7	70.9
7	328.4	976.1	27.2	72
8	379.8	969.5	26.7	73.2
9	445.4	962.8	26.2	74.4
10	512.8	956.3	25.7	75.6
11	577.8	950.1	25.2	77
12	635.7	944.2	24.6	78.4
13	689.5	937.7	24.1	79.9
14	740.7	932.3	23.5	81.4
15	790.2	927.1	23	82.9
16	837.3	921.8	22.7	83.2
17	886.5	916.6	22.4	83.3
18	937.6	911.4	22.1	83.4
19	991.9	905.8	21.4	83.4
20	1047.6	900.1	20.9	82

Table II: Radiosounde data for February

S/N	Altitude (m)	Pressure (pa)	Temperature (°C)	Relative Humidity (%)
1	0	1014.2	31.9	58
2	44.3	1009	30.2	61
3	107.4	1003.9	29.7	64
4	169.6	998.8	29.2	66.4
5	225.8	993.8	28.8	67.1
6	277.1	988.8	28.3	67.7
7	328.4	984.1	28	68.4
8	379.8	979.6	27.6	69.4
9	445.4	975.2	27.2	70.5
10	512.8	970.8	26.8	71.5
11	577.8	966.4	26.4	72.5
12	635.7	961.8	26	73.6
13	689.5	956.8	25.5	75.2
14	740.7	951.5	25.1	76.8
15	790.2	946.2	24.6	78.3
16	837.3	940.9	24.1	79.9
17	886.5	935.6	23.7	81.4
18	937.6	930.1	23.2	82.5
19	991.9	924.7	22.7	83.6
20	1047.6	919.2	22.2	84.7

Table III: Training data for the month of January

S/N	Altitude (m)	Pressure (pa)	Temperature (oC)	Relative Humidity (%)
1	0	1013.1	31.5	66
2	44.3	1006.7	30.3	84
3	107.4	1000.4	29.6	79.7
4	169.6	994.2	28.9	75.3
5	225.8	988.3	28.2	70.9
6	277.1	982.4	27.7	70.9
7	328.4	976.1	27.2	72
8	379.8	969.5	26.7	73.2
9	445.4	962.8	26.2	74.4
10	512.8	956.3	25.7	75.6
11	577.8	950.1	25.2	77
12	635.7	944.2	24.6	78.4
13	689.5	937.7	24.1	79.9
14	740.7	932.3	23.5	81.4

Table IV: Validation data for the month of January

S/N	Altitude (m)	Pressure (pa)	Temperature (^{o}C)	Relative Humidity (%)
15	790.2	927.1	23	82.9
16	837.3	921.8	22.7	83.2
17	886.5	916.6	22.4	83.3

Table V: Test data for the month of January

S/N	Altitude (m)	Pressure (pa)	Temperature (^{o}C)	Relative Humidity (%)
18	937.6	911.4	22.1	83.4
19	991.9	905.8	21.4	83.4
20	1047.6	900.1	20.9	82

Table VI: ANN prediction of pressure in January

S/N	Altitude (m)	Actual	Predicted	e	e^2	|e%|
1	0	1013.1	1012.1	1.0420	1.0857	0.0010
2	44.3	1006.7	1007.3	-0.6497	0.4221	0.0006
3	107.4	1000.4	1000.4	0.0056	0.0000	0.0000
4	169.6	994.2	993.99	0.2099	0.0441	0.0002
5	225.8	988.3	988.15	0.1549	0.0240	0.0002
6	277.1	982.4	982.57	-0.1713	0.0293	0.0002
7	328.4	976.1	976.75	-0.6516	0.4246	0.0007
8	379.8	969.5	970.7	-1.2043	1.4502	0.0012
9	445.4	962.8	962.76	0.0446	0.0020	0.0000
10	512.8	956.3	954.48	1.8155	3.2961	0.0019
11	577.8	950.1	946.8	3.2955	10.8604	0.0035
12	635.7	944.2	941.78	2.4163	5.8385	0.0026
13	689.5	937.7	937.96	-0.2640	0.0697	0.0003
14	740.7	932.3	932.49	-0.1852	0.0343	0.0002
15	790.2	927.1	926.92	0.1780	0.0317	0.0002
16	837.3	921.8	921.78	0.0196	0.0004	0.0000
17	886.5	916.6	916.61	-0.0078	0.0001	0.0000
18	937.6	911.4	911.39	0.0134	0.0002	0.0000
19	991.9	905.8	905.84	-0.0369	0.0014	0.0000
20	1047.6	900.1	900.09	0.0124	0.0002	0.0000

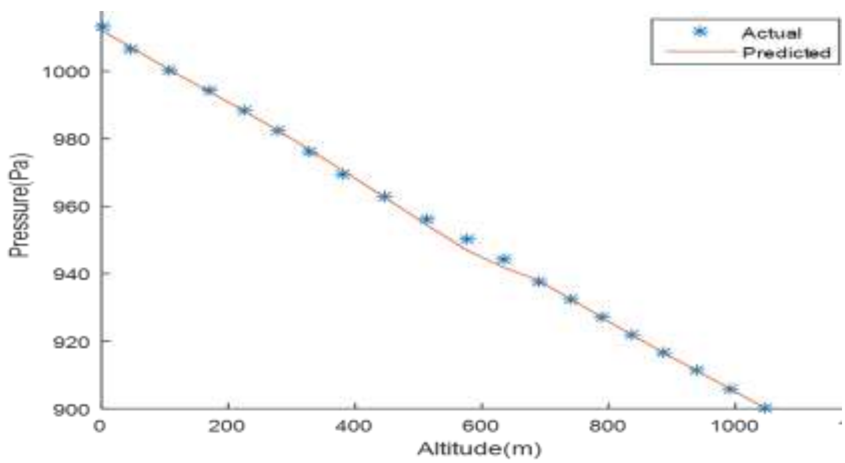

Figure 1: Plot showing the prediction of Pressure with ANN for January

Table VII: ANFIS Prediction of Pressure in January

S/N	Altitude (m)	Actual	Predicted	e	e^2	|e%| 1.0e-03
1	0	1013.1	1012.9	0.1596	0.0255	0.1575
2	44.3	1006.7	1007	-0.3444	0.1186	0.3421
3	107.4	1000.4	1000.1	0.3182	0.1013	0.3181
4	169.6	994.2	994.33	-0.1343	0.0180	0.1351
5	225.8	988.3	988.37	-0.0709	0.0050	0.0717
6	277.1	982.4	982.34	0.0605	0.0037	0.0616
7	328.4	976.1	976.04	0.0619	0.0038	0.0634
8	379.8	969.5	969.57	-0.0748	0.0056	0.0771
9	445.4	962.8	962.78	0.0154	0.0002	0.0160
10	512.8	956.3	956.26	0.0375	0.0014	0.0392
11	577.8	950.1	950.12	-0.0152	0.0002	0.0160
12	635.7	944.2	944.2	0.0014	0.0000	0.0015
13	689.5	937.7	937.75	-0.0539	0.0029	0.0575
14	740.7	932.3	932.23	0.0716	0.0051	0.0768
15	790.2	927.1	927.07	0.0283	0.0008	0.0305
16	837.3	921.8	921.92	-0.1194	0.0143	0.1295
17	886.5	916.6	916.53	0.0708	0.0050	0.0773
18	937.6	911.4	911.36	0.0359	0.0013	0.0394
19	991.9	905.8	905.86	-0.0637	0.0041	0.0704
20	1047.6	900.1	900.08	0.0205	0.0004	0.0227

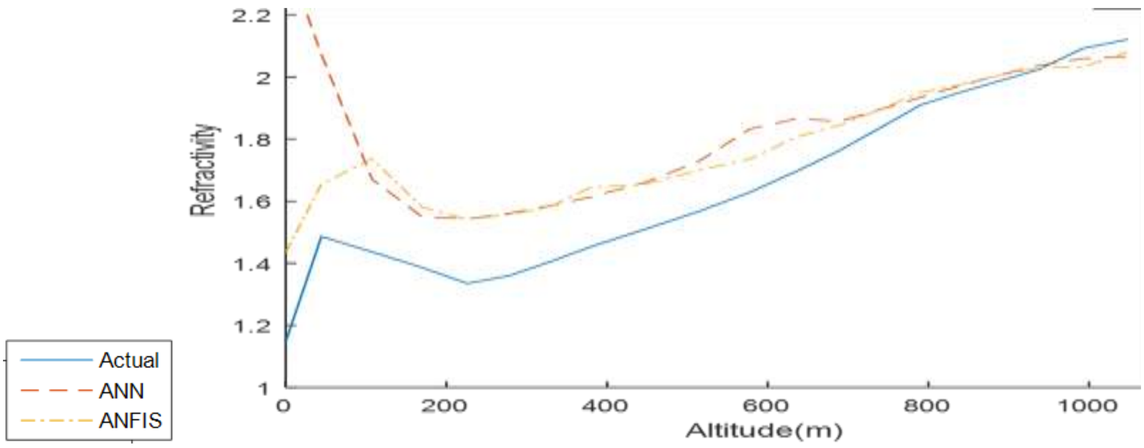

Figure 2: Refractivity Prediction with ANN and ANFIS models for January

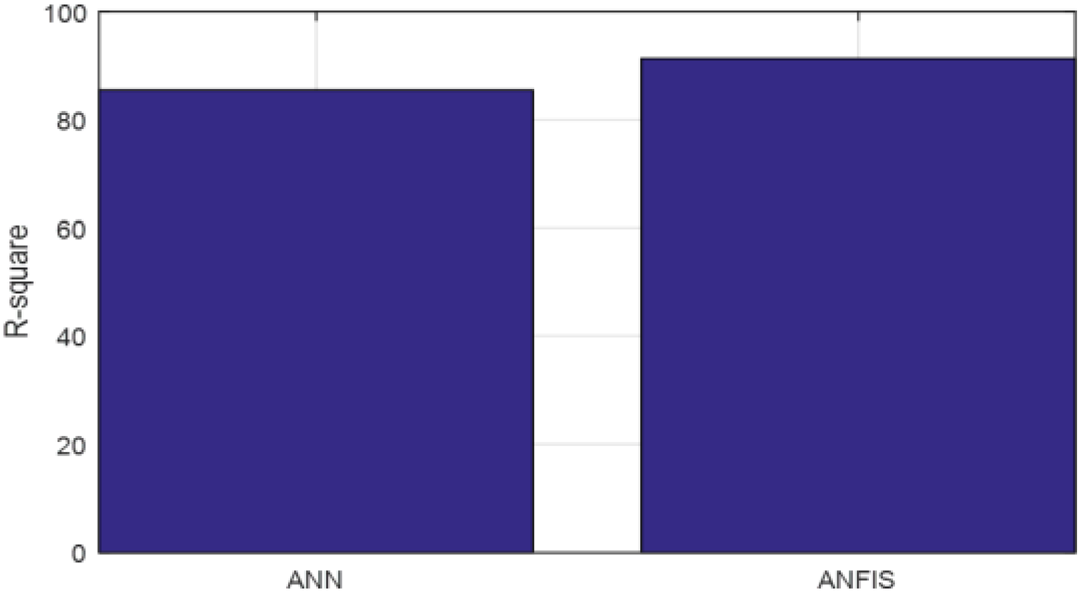

Figure 3: Bar chart of the R-square value for ANN and ANFIS for January

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