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PREDICTION OF TROPOSPHERIC SURFACE DUCTING IN ABUJA USING ARTIFICIAL NEURAL NETWORK (ANN)

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Abstract

Meteorological forecasting is an ever-challenging area of investigation for scientists. Multipath fading is considered to arise from irregularities of the atmospheric refractive index, called radio ducts. By these irregularities, radio waves propagations over this medium are adversely impaired. In this paper, Artificial Neural Network is developed for the purposes of modelling meteorological conditions of Abuja – Federal Capital Territory. The work uses meteorological parameters like temperature, pressure and relative humidity for the purpose of predicting duct presence in Abuja over different periods of the year. The approach applied here uses feed forward artificial neural networks (ANNs) with back propagation for supervised learning using the data recorded at this locality. The trained ANN was used to predict the duct presence in the designated site. The results obtained are very encouraging and it is found that the ANN model can make predictions with high degree of accuracy (over 90%). Our results showed that duct occurrence is not prevalent but adequately visible in the Federal Capital Territory of Nigeria and duct occurrences have tendencies to be season dependent.

Keyword: Meteorological, Refractivity, Communication, Backpropagation, Ducting, Prediction

INTRODUCTION

The climate of a particular geographical location is constantly changing and does not dependent on the climate of other locations in Nigeria. Climate forecasting for the future is therefore needed to inform telecom operators and computer networks with wireless backbones as well as other industries that largely depend on the weather conditions for use of what to expect and how to maximise resources and system payloads to achieving better operations and service delivery to their clients. Weather condition is a very complex system and nonlinear (De and Debnath, 2009) and Artificial Neural Network (ANN) is highly suitable for the situations where the underlying processes exhibit chaotic features (Londhe and Deo, 2004).

The concept of ANN is originated from the attempt to develop a mathematical model capable of recognizing complex patterns on the same line as biological neuron work. These models can handle a large number of data, predict the contribution of these in the outcome and provide prompt and adequate predictions (Mónica and Mónica, 2010). It is useful in the situations where underlying processes or relationships display chaotic properties. ANN does not require any prior knowledge of the system under consideration and are well suited to model dynamical systems on a real-time basis. It is, therefore, possible to set up systems so that they would adapt to the events which are observed and for this, it is useful in real time analyses, for instance, in weather forecasting and other different fields of predictions; therefore, the basis for its usefulness in this research work will be because of its suitability to troubleshooting the chaotic nature of the troposphere, our choice study focus.

Vertical gradients of refractivity are traditionally used to classify meteorological anomalous propagation (AP) conditions as sub-refractive (worse than normal) and super-refractive (better than normal). A sub-refractive layer leads the radio beam to refract away from the earth surface. In super-refractive conditions the radio beam height increases at a lower rate than the assumed normal average propagation. In the worst case of AP, known as ducting, radio waves are trapped and may travel within duct layers just like in a waveguide. In extreme cases, this effect may extend the radio horizon in an order of magnitude. In terms of vertical of the refractivity gradient, sub-refractive layers are characterized by values greater than 0 km^{-1}. Ducting occur when *dN/dz* is equal or less than – 157 km^{-1}. The refractivity gradient for normal refraction conditions ranges between 0 and –78.7 km^{-1} (Bech et al, 1998).

The problem of generating predictions of meteorological events is more complex than that of generating predictions of planetary orbits. This is because the atmosphere is unstable and the systems responsible for the events are the culmination of the instabilities and involve nonlinear interaction between different spatial scales from kilometres to hundreds of kilometres. The presence of tropospheric ducts leads to various effects on the radio-wave propagation, such as trapping, deep slow fading, strong signal enhancement and multipath fading. The knowledge of the presence of such phenomena is important in communication engineering and related disciplines, since it can lead to frequency, transmission angle and power adjustments in order to achieve optimum propagation and detection respectively (Isaakidis, *et al.*, 2007). In this work, pattern recognition algorithm such as ANN is used in order to predict the presence or absence of tropospheric duct using only the surface values of Pressure, Humidity and Temperature.

In this study, Meteorological data are used to evaluate the occurrence of AP at the particular in-land terrains of Nigeria. Pressure, temperature and humidity profiles were used to calculate refractivity gradients and, in particular, to estimate the existence of ducting layers.

Multipath fading is considered to arise from irregularities of the atmospheric refractive index, called radio ducts. By these irregularities, radio propagating waves over this medium are adversely impaired (Sasaki and Akiyama, 1982). Therefore, it is important to clarify radio duct occurrence probabilities and radio duct properties themselves in order to evaluate the multipath parameters, which are necessary for radio system design in computer networks and communication purposes.

The aim of this work is to develop neural network and use it to predict duct occurrences from commonly observed meteorological data and compare the overall effects on radio signals in the Abuja locality of Nigeria. In so doing, we will be able to gain insights into the extents of the processes controlling the present impairment on wireless communication signals in computer and communication networks operating in the locality.

LITERATURE REVIEW

Adeyemi (2006) established the relationships between radio refractivity aloft and surface water vapour density, in g/m^3 over three radiosonde stations in Nigeria using an analysis of variance (ANOVA) technique on upper air climatological data spanning over a decade (1975 – 1990). Falodun and Ajewole (2006) had stated that the structure of the radio refractive index in altitudes of first 100 m of the troposphere is important for the planning and design of microwave communication links. The results obtained also show that the values of the refractivity gradient at the 100 m altitude were high in the morning and late evening/night hours while they show minima during the afternoon hours for Akure locality. Thus, the worst propagation condition obtained for Akure was observed in the afternoon within the time window from 15:00 to 18:00 local time (LT) during the dry months and from roughly 17:00 to 19:00 LT during the rainy season.

Okereke and Abdullahi (2006) studied the effects of tropospheric refractivity variations on GSM signals in Bauchi metropolis using meteorological data obtained from Bauchi air strip over a five-year period (1995 – 1999) determined at a height of 608.3m above sea level. They recommended that the problem of GSM signal outages stemming from fluctuations of the tropospheric refractivity could be addressed by employing, at the base stations, adaptive or smart antennas instead of sectorized antennas as the practice has been in Nigeria and multilevel adaptive modulation schemes instead of a fixed level modulation.

Adediji *et al.* (2007) established that during the clear sky conditions, atmospheric refractive index is the important parameter that influenced the propagation of radio wave. In a follow-up to this work and their earlier work Falodun and Ajewole (2006) and Adediji and Ajewole (2008) further reconfigured the experimental settings using five different height levels beginning from the ground surface and at intervals of 50 m from the ground to a height of 200m (0, 50, 100, 150 and 200 m) on a 220 m Nigeria Television Authority TV tower at Iju in Akure North Local Government Area of Ondo State. And their results showed that the propagation conditions had varying degree of occurrence with sub-refraction conditions dominant between January – July while Super-refraction and Ducting conditions were prevalent between August – December. Similarly, in the works of Falade *et al.* (2014), they showed that surface radio refraction generally has a higher value during the raining season than dry season, which partly coincides with the harmattan season.

Lenouo (2012) showed the annual average of the duct percentage occurrence to be about 39.20 % over Douala, Cameroon. Kaissassou *et al*. (2015) using ECMWF model determined ducting conditions over West Africa and the computation of statistical distributions of the vertical gradient of refractivity determined from 2 years of radiosonde data over, Douala and Niamey. They found that duct presence often results in spurious returned echoes and misinterpretation of radar images such as erroneous precipitation detection. They also obtained show that the local climate has an appreciable influence on the vertical profile of refractivity, and that most of ducts occur in the night, morning (0000, 0600 UTC) and late afternoon (1800 UTC).

METHODOLOGY

Meteorological Data

Statistical analysis of tropospheric ducting requires meteorological data over a long period in the same or different climate locations over the region. The data to be used for the current study is obtained from the Nigeria Meteorological Agency (NiMet) and these are the temperature, relative humidity and pressure, measured at the Meteorological station in Abuja (Lat. 7^0 N and Lat 12^0 N; Long 2.8^0 and Long 10^0 E). The data set covers the periods from January 2009 to December 2013.

Refractive Model and Methods

According to ITU-R recommendation P453-9, refractivity equation is defined as

$$N = \frac{77.6P}{T} - \frac{5.6e}{T} + \frac{3.75x10^5 \cdot e}{T^2} \quad \text{--------} \ (3.1)$$

Where N is the radio refractivity, P is the atmospheric pressure (hPa), e is the water vapour pressure (hPa), n is the refractive index and T is the absolute temperature (Kelvin degrees). Equation 3.1 is simplified and expressed as:

$$N = \frac{77.6}{T}\left(P + \frac{4810e}{T}\right) \quad \text{----} \ (3.2)$$

Given the relative Humidity, the water vapour pressure can be computed using the following ITU equations;

$$e = \frac{RH}{1000} a e^{\frac{bt}{t+c}} \quad \text{---------- (3.3)}$$

Where t is given in ^0C and the coefficient b and c. Defining the refractive conditions in the troposphere (that is, sub-refractive, super-refractive, ducting e.t.c.) the modified refractivity (or refractive modulus) will be used. The gradient of the modified refractivity gradient determines the refraction type, while tropospheric ducting phenomena occur when the following conditions are met (Isaakidis *et al.*, 2007):

$$\frac{dM}{dh} < 0, or \frac{dN}{dh} < -157 \quad \text{------- (3.4)}$$

The Neural Network Approach

For the prediction of the tropospheric ducting phenomena, a 3-20-1 feed forward backpropagation network ANN will be implemented, which comprised of the input layer, a linear output layer, and a tangential-sigmoid hidden layer (Table 3.1). Thus, a classifier will be developed, which will associates ground values of pressure, relative humidity and temperature and then predict the presence of a duct for the specific observation time. The number of neurons to be used in the hidden layer will be empirically chosen and will correspond to the value that will maximize the model's performance. The network predictors consist of a 3 x N matrix (as shown in figure 1), where each row will represent the ground pressure, relative humidity and temperature respectively for a total of *N* measurements per dataset, while each column will stand for the days used. The target vector will be in binary form, its elements being 1 in case of duct presence for the specific day and 0 in case of tropospheric duct absence.

Table 1: Artificial Neural Network Characteristics

ANN type:	**Feed Forward Backpropagation**
Training Procedure	Batch Training using Levenberg-Marquardt optimizing algorithm
Number of Layer	1 input – 1 hidden – 1 output
Number of Neuron	3-20-1
Transfer Function	Linear—Sigmoid, Tangent – Linear Sigmoid

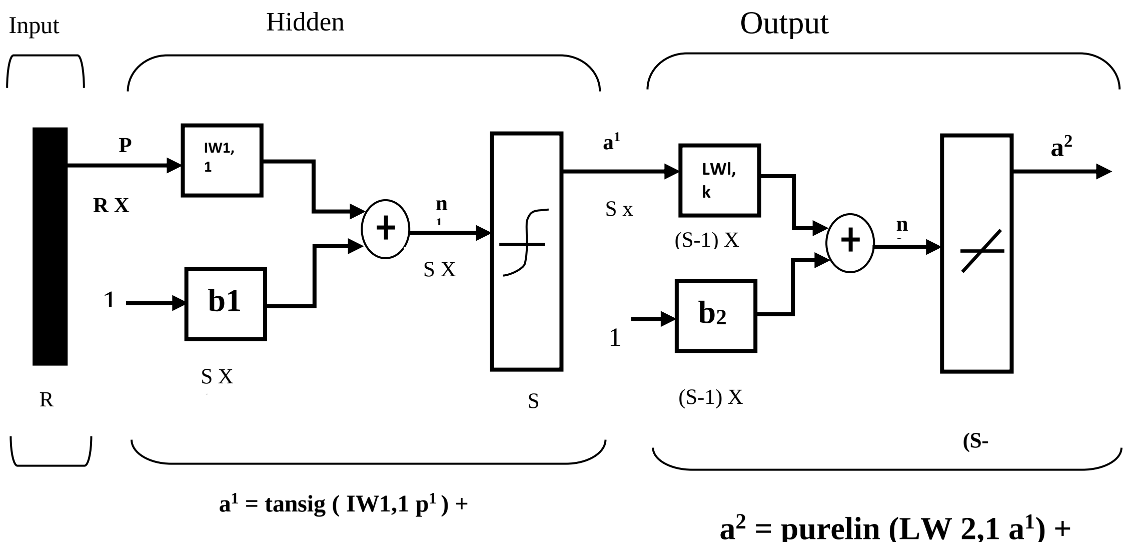


Fig 1. ANN Structure for the feed forward Backpropagation Network

RESULTS AND DISCUSSION

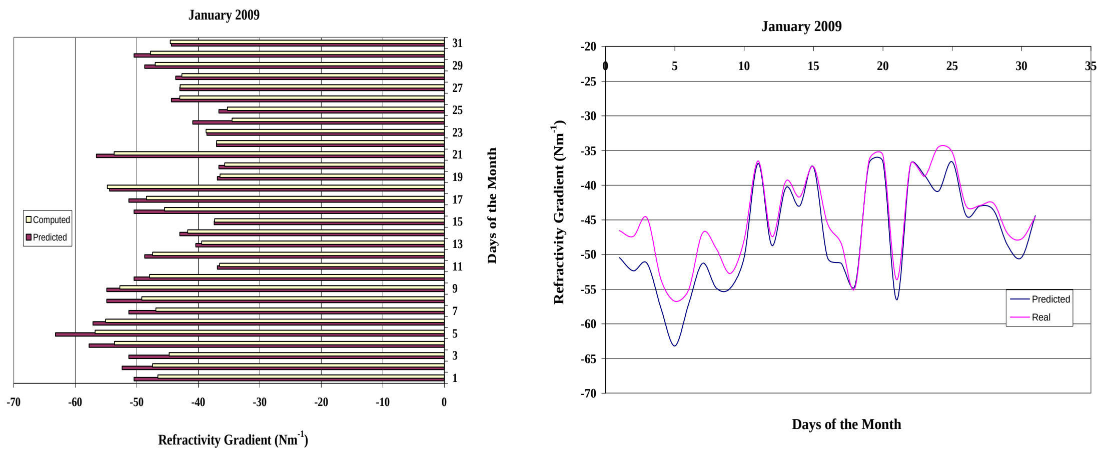
Transforming and Restructuring Meteorological Data

For analyses to be accurate data used must properly account for the influences noted in the research study. Here, gaps (missing) in the meteorological data collected were compensated using ANN to model a network which predicted these missing data.

Sample Desideratum

In a bid to ensure that ANN predicted refractive gradients is in conformity with the desired outcomes, comparison of the computed results is as shown in figures 2 and 4. What was simply done was to select one month data in any year and plot the outcome using bar charts and line graphs to illustrate the comparison. Figure 2(a) is a bar chart view indicating a neck-to-neck value for both the computed and the predicted values of the refractivity gradient for the month of January 2009 for Abuja data sets. Also, figure 2 (b) shows an overlap of the line graph for both computed and predicted values of the same January 2009 for Abuja. This behaviour indicated that the ANN predicted values are the same with the desired output of the computed values using refractivity gradient equation.

This is an indication that the ANN predictions were accurate. And that by extension, the ANN predictions for other months and years for each location are absolutely accurate. Therefore, any inference inferred based on these prediction could be said to be conclusive.



(a) (b)

Fig 2: Profile of Abuja Computed and Predicted Radio Refractivity Gradient Compared

ABUJA SCENARIO

In the case of Abuja, duct occurrence is evenly spread with the exception of year 2012 as depicted in table 1, figure 3 and 4. The year 2011 had the highest number of duct occurrence with 98 followed by year 2013 with 73. Year 2012 had the least with only 32. Figure 2 shows that duct occurrence is predominantly found in the months of March, April, May, June, July, August, September and October. It is completely absent in January, February, November and December, while March, June, July and August had varying degrees of fluctuations. Figure 3 shows duct is absent in the months of January, February, November and December. It is present in small capacity (0-10) for the months of March and October. Strongest (25-30) presence span from May to August. Middle value (15-20) shows low coverage from April to August.

Table 2: Predicted Duct Occurrence

Site/Year	2009	2010	2011	2012	2013	Total
Abuja	51	54	98	32	73	308

Cumulative Distribution and Effects of Radio Duct Occurrence

The tropospheric portrait of Abuja locality indicates that ducting is not absolutely present throughout the year, with more periods of occurrence during raining season. This implies that radio signals operating in this locality over these past years had tendencies of extending radio communication signals beyond their radius of coverage. The predicted percentage occurrence over the past 5 years is put at 13.6%.

Evaluating ANN Network Performance

The ANN model for each dataset is as shown in table 3 below. The various values for the epoch, mean square error (MSE), regression and net performances are given accordingly. The total number of data used in the ANN Network is 1826 in which 60% (1095) of these data is for the training phase

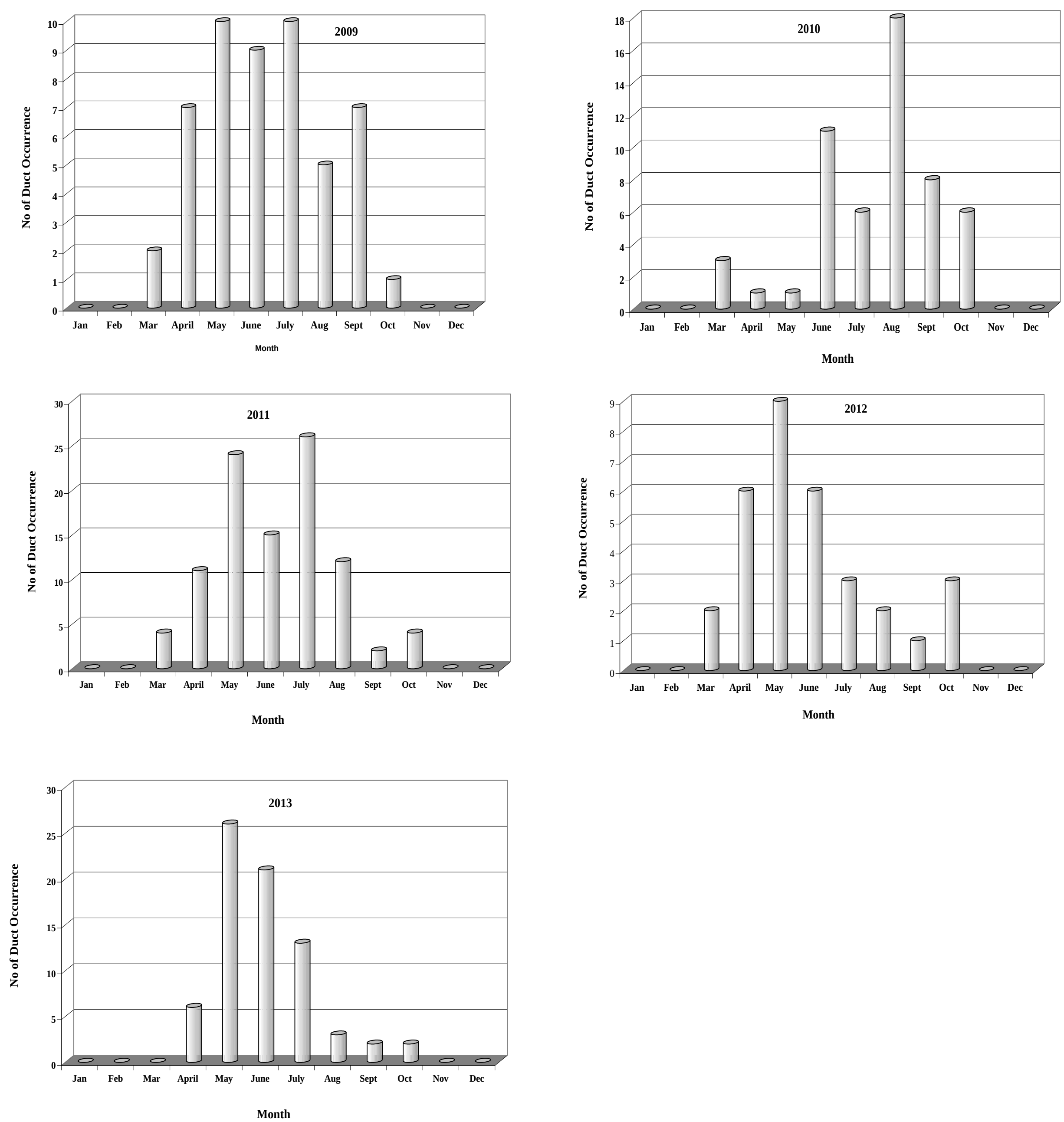


Fig 3: Monthly Radio Duct Profiles for Abuja

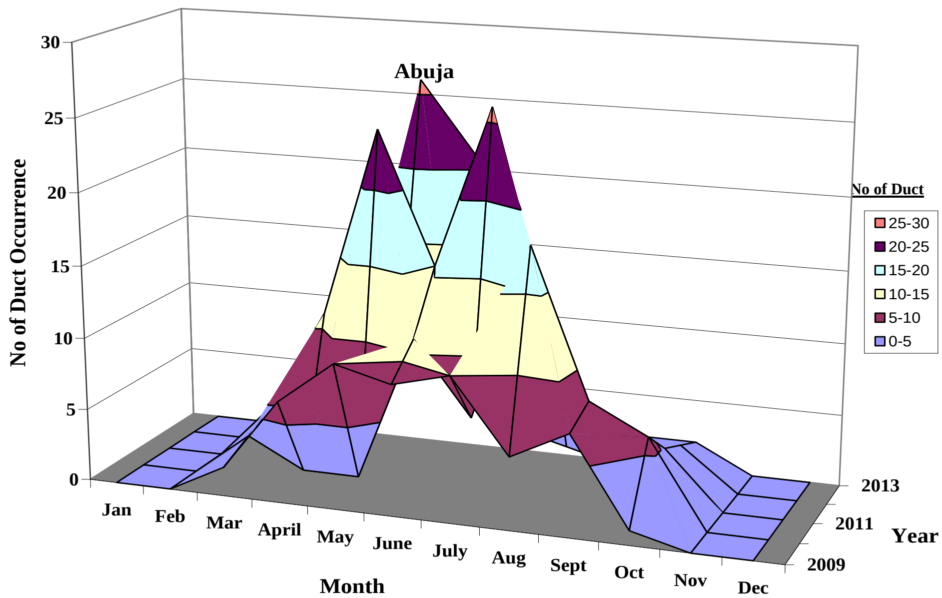


Fig 4: Distribution of Radio Ducts in Abuja

Table 3: Performance Indices for the ANN Prediction

Locations	Epochs	MSE	Regression	Performances
Abuja	30	2.46270e^{-2}	0.91	4.1036e^{-2}

with 20% (365) for validation and 20% (365) for testing; while it is found that the ANN model can make predictions with high degree of accuracy. The learning rate of the network is 0.035. Figures 5 represent the training outputs for Abuja as it converges. Figure 6 represents the Regression outputs and targets, for Abuja. Figures for other locations have similar pattern though not shown.

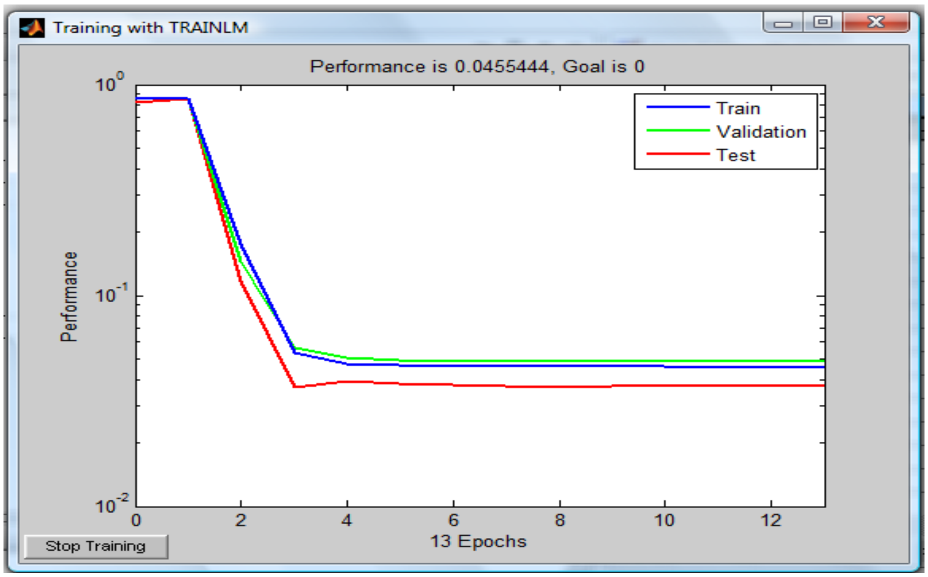


Fig 5: Training Output for Abuja Data

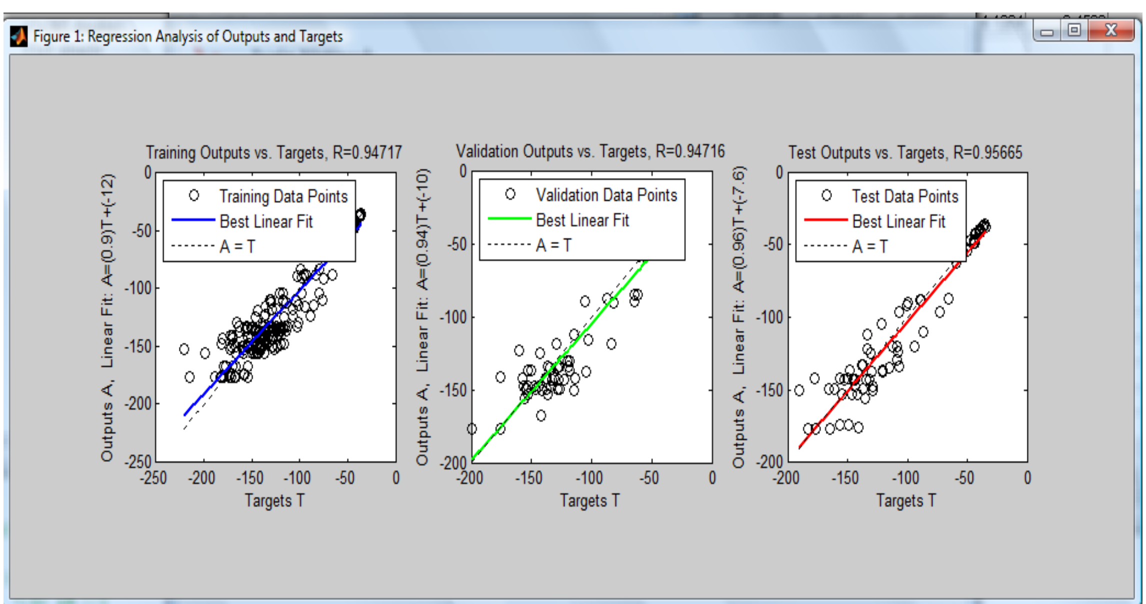


Fig 6: Regression Analysis of Outputs and Targets for Abuja Data

SUMMARY

A set of artificial neural networks was designed to predict duct presence at the selected locations of Abuja, being the Federal Capital Territory which is located within the Middle-Belt region of Nigeria. Our results show that Abuja has strong duct occurrences with tendencies towards seasonal dependence, and duct concentration is shifted toward wet season. Also, Abuja, exhibited low and weak duct presence and have similar trends in that the months of November, December, January and February have no records of duct presence for most part of the five years study.

This study has shown that radio meteorological statistics has help highlight ducting or variation of refractivity gradient as an inevitable phenomenon in radio transmission media and the properties of radio duct themselves. The main results are as follows:

1) The number of duct occurrences is seasonally different, and occurrences in the wet (raining) season accounts for more than half of the total duct presence.
2) The probability of occurrence for radio duct is defined as the percentage of time in which the gradient of refractivity modulus *M* is less than or equal to -157 N/km using the refractivity statistics.
3) The probability of occurrences for radio duct for a long period in Abuja- the Federal Capital Territory is a reality and microwave line-of-sight fading must be grasped more essentially to develop microwave communication systems in the future.
4.) Radio communication signals will be more and severely affected at the Abuja troposphere in the months of March through October than in the months of November through February.
5.) Abuja troposphere displays a classical two-segment pseudo-cyclic pattern with seasonal dependent phenomenon.

CONCLUSION

Meteorological data observed at the Federal Capital Territory - Abuja over five years is analysed. In this study, meteorological data of pressure, temperature and humidity were used to calculate refractivity gradients and, in turn, used to estimate the existence of ducting layers. We have also developed ANN network and have used it to predict duct occurrences from commonly observed meteorological data and have compared the overall effects on radio signals in the Abuja locality. These duct occurrences were examined in relation with the radio meteorological parameters and have shown that the seasonal dependency is a paramount dominant consideration. This implies that radio signals operating in this locality over these years had tendencies of extending radio communication signals beyond their radius of coverage. And radio signals are severely impaired in the months of March through to October in a regular cyclic manner.

RECOMMENDATION

Further work may well concentrate on improvement and extension of the present results, meaning a further modelling of the troposphere that is not limited to the study of this location using meteorological data or measurement campaign. Also, the extent of signal enhancement in the presence of tropospheric ducting should as well be investigated. In addition, further observations and analysis of the shapes of the vertical refractivity profiles with regard to the modes of propagation (such as super refraction and subrefraction in tropospheric propagation) should be made in order to understand the combination of the entire mechanisms that govern the propagation of radiowave in the entire region of the Middle-Belt zone.

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