Atmospheric Temperature Prediction across Nigeria using Artificial Neural Network

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ABSTRACT

Atmospheric temperature is one of the dominating atmospheric parameters that impact on the propagation of radio waves through the troposphere. Adequate knowledge of the atmospheric temperature of an environment is therefore essential for radio wave propagation planning. In this study, thirty-four (34)-year (1981-2014) atmospheric temperature data of 10 selected weather stations across the climatic zones of Nigeria, obtained from the Nigerian Meteorological Agency (NIMET) through the data bank of the West African Science Service Centre on Climate Change and Adaptive Land Use (WASCAL) of the Federal University of Technology Minna, Nigeria was used in Artificial Neural Network (ANN) for the prediction of mean monthly atmospheric temperature. The ANN architecture comprised of 2 inputs (the climatic zones and the corresponding month for the mean monthly atmospheric temperature), 1 hidden layer and 1 output (atmospheric temperature). Levenberg-Marquardt algorithm was used with 9 different pairs of activation functions formed from 3 activation functions (logsig, purelin and tansig). The number of neurons in the hidden layer was varied from 33-39 with an increasing steps of 2 (33, 35, 37 and 39). The network architecture of 2-37-1 (2 inputs, 37 neurons in the hidden layer and 1 output), with tansig/tansig pair of activation functions had the least mean square error value of 2.2280, and was used for the prediction process. The computed correlation values for measured and predicted atmospheric temperature ranged from 0.9733 to 0.8787, depicting strong positive correlation and good accuracy of the developed model. Comparisons of the measured and the ANN predicted atmospheric temperature across selected stations in the climatic zones of Nigeria, showed that the developed model can effectively predict mean monthly atmospheric temperature, using month and climatic zone as input parameters.

KEYWORDS

Temperature, prediction, refractive index, artificial neural network

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1 INTRODUCTION

Temperature is a major meteorological variable with regards to the climate variability of an environment. It has direct and indirect impact on the dynamics and physical properties of the troposphere. The thermal structure of the troposphere is dependent on the rate of change of temperature with altitude. The troposphere is the lowest layer of the Earth's atmosphere, and it greatly impacts on radio waves as they propagate through it. The troposphere is transparent to most of the solar energy that gets to the Earth. The Earth gets heated by the sun, and consequently heats up the troposphere through the process of radiation, conduction and convection. When the air adjacent to the ground gets heated by thermal contact, it moves upwards to bring in cooler air to be in contact with the ground. Thus, convective air movements are set up, transporting heat upwards. The temperature of the troposphere varies with time, changing from season to season, and from day to night, as well as irregularly due to exceeding weather systems.

Propagation of radio waves through the troposphere depends on the refractive index of the medium. Change in refractive index introduces uncertainties in the time of arrival of transmitted radio signals due to excess path length or delay. The refractive index of a medium depends on atmospheric pressure, temperature and humidity [1].

Studies have shown that atmospheric temperature does have impact on the propagation of radio waves through the troposphere. The results of the study by [2] showed surface atmospheric temperature having positive correlation values ranging from 0.57 to 0.88 with RxLevel of GSM signals. [3] observed increase in signal level with increase in atmospheric temperature. Since temperature has dominating impact on the propagation of radio waves through the troposphere, adequate knowledge of atmospheric temperature trend will enhance planning for wireless communication industries. This study is focused on the prediction of atmospheric temperature and provision of accurate atmospheric temperature data for various applications such as weather monitoring, and propagation model development. The use of Artificial Neural Network (ANN) in solving specific task, such as prediction, optimisation and control, has proven to be flexible and with the ability to learn the connections between the inputs and outputs of a process, without needing definite information on the relationship between these variables [4]. It can therefore be useful in the development of prediction models.

1.1 Theoretical Background

Refractive index is a dimensionless numerical value that indicates how a wave travels through a particular medium in relation to how it travels through a vacuum. The troposphere may also be considered a pure dielectric and its refractive index, n, may be given as [5]:

$$\mathrm{n} = \frac{\mathrm{c}}{\mathrm{v}} = \frac{\sqrt{\mu_r \varepsilon_r \mu_o \varepsilon_o}}{\sqrt{\mu_o \varepsilon_o}} = \sqrt{\mu_r \varepsilon_r} \tag{1}$$

For air, $\mu_r \approx 1$. Hence,

$$\mathrm{n} = \sqrt{\varepsilon_r} \tag{2}$$

where ε_r = relative permittivity and μ_r = relative permeability. The radio refractive index, for clear air, at the Earth's surface is about 1.0003 and it falls to a value of unity at great heights. The variation of the refractive index in the horizontal direction is negligible compared with the vertical profile, and change in refractive index with height has much consequence for radio wave propagation at frequencies greater than about 30 MHz. The refractive properties of the troposphere is expressed by the radio refractivity, N, given by

$$\mathrm{N} = (\mathrm{n} - 1) \times 10^6 \tag{3}$$

where n = refractive index. N depends on meteorological factors of air pressure, P (hPa), air temperature, t (^{o}C) and water vapour pressure, e (hPa), which are related to N as [6]:

$$\mathrm{N} = \mathrm{N}_{dry} + \mathrm{N}_{wet} = 77.6\left(\frac{\mathrm{P}}{\mathrm{T}}\right) + 3.732 \times 10^5 \left(\frac{\mathrm{e}}{\mathrm{T}^2}\right) \tag{4}$$

where T(K) = t + 273, and

$$\mathrm{e} = \frac{\mathrm{He_s}}{100} \tag{5}$$

where e is water vapour pressure, H is relative humidity, and $\mathrm{e_s}$ the saturated water vapour pressure given as [7]:

$$\mathrm{e_s} = 6.11\exp\left(\frac{17.502\mathrm{t}}{\mathrm{T}}\right) \tag{6}$$

1.1.1 Temperature and radio refractive index. The terms 77.6 (P/T) and 3 x $10^5(\mathrm{e}/\mathrm{T}^2)$ in equation 4 are referred to as the dry term (N_{dry}) and the wet term (N_{wet}) [8]. At very low temperatures N_{wet} becomes very small, thus N is almost independent of relative humidity. With increasing temperature, N_{dry} slowly decreases but N_{wet} steeply increases because for a given relative humidity, the water vapour pressure increases rapidly with increasing temperature. At high temperatures N_{wet} can become larger than N_{dry}. At high temperature and high relative humidity, N is very sensitive to small changes in temperature and relative humidity [9]. Temperature is a contributing factor to the variability of radio refractive index.

1.1.2 Effect of radio refractive index on radio wave propagation. Averagely, N decreases by about 40 N units/km in the lowest kilometre of the troposphere [5]. Decrease of N with height causes refraction or ray bending of radio waves and to a degree that depends on the vertical refractivity gradient [10]. Refractive bending causes extension of the radio horizon beyond the optical horizon [9]. The vertical gradient of radio refractivity in the lowest part of the atmosphere is an important parameter for the estimation of propagation effects such as ducting, surface reflection and multipath on terrestrial line-of-sight links [11]. The radio refractivity gradient *dN/dh* (N-units km^{-1}) is expressed as [12]:

$$\frac{dN}{dh} = \frac{N_1 - N_2}{h_1 - h_2} \tag{7}$$

where N_1 and N_2 are radio refractivity values at heights h_1 and h_2 respectively. Refractivity gradient statistics for the lowest 100 m from the Earth surface are used to estimate the probability of occurrence of ducting and multipath conditions. The change in radio refractivity in the first 1 km height above the Earth's surface, ΔN, can be computed using the equation [13]:

$$\Delta\mathrm{N} = \mathrm{N_s} - -\mathrm{N_1} \tag{8}$$

where $\mathrm{N_1}$ is the radio refractivity at a height of 1 km above the Earth's surface and $\mathrm{N_s}$ is the surface refractivity. $\mathrm{N_s}$ can be derived from surface meteorological parameters of pressure, temperature and water vapour pressure. $\mathrm{N_s}$ is known to have high correlation with radio field strength values [9, 14] and seasonal variations in $\mathrm{N_s}$, have been found to agree in general with the observations of the variation of radio field strength at VHF and UHF in Nigeria [15, 16].

The surface refractivity gradient, which depends on $\mathrm{N_s}$, determines the refractivity condition of the troposphere which may be characterised by a normal, sub refractive, super refractive or ducting layer, each of which has important influence on propagation of radio waves in the troposphere.

i. Normal or standard atmospheric condition occurs dN/dh = -40 N-units/km.
ii. Super-refractive condition occurs when the refractivity gradient is less than -40 N-units/km but greater than -157 N-units/km. In this condition, radio waves bend more toward the Earth than the normal condition and the radius of curvature of the ray path is smaller than the Earth's radius [5]. The rays leaving the transmitting antenna at small angles of elevation will undergo gradual and successive bending in the troposphere and return to the Earth at some distance from the transmitting antenna [8].
iii. Sub-refractive condition occurs when the refractivity gradient is greater than -40 N-units/km. This condition lowers the elevation angle of radio waves and reduces the radio horizon, causing a path initially free from obstructions to become obstructed, with resultant loss of energy reaching the receiver [17]. The radio waves may bend upward and away from the Earth's surface.

Trapping or ducting condition occurs when the refractivity gradient is less than -157 N-units/km, depending on the radio wavelength and duct thickness [18]. A consequence of ducting is the extension of the radio horizon which sometimes leads to interference between neighbouring transmission links [19].

1.2 Overview of Artificial Neural Network (ANN)

Artificial Neural Network (ANN) has been proven to be efficient in development of prediction models. ANN is constituted by an assembly of simple processing elements that are interconnected to perform a parallel distributed processing in order to solve specific

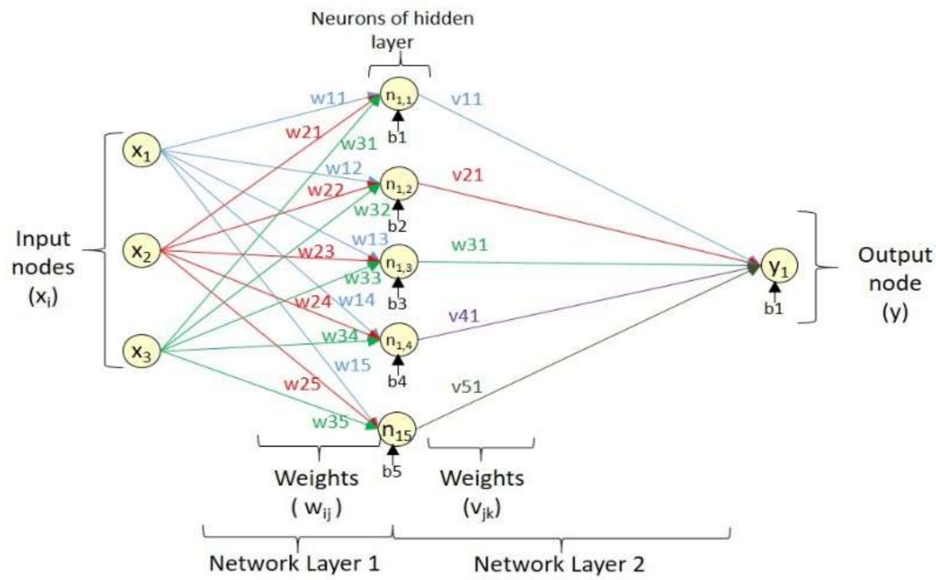

Figure 1: A 2 Layered MLP [2]

task, such as pattern classification, function approximation, clustering (or categorisation), prediction (forecasting or estimation), optimisation and control [4]. It is a simulation of the learning ability and processing methods of the physical biological neurons of the human brain. The fundamental principle of ANN is based on finding coefficients between the inputs and outputs of a problem, making connections between input and output layers and performing operations on a learning system [20]. The fundamental element of ANN is the neuron. Each neuron is made up of two parts (the net function and the activation function) that handle the three distinct operations of the neuron.

The multiplication of the network inputs by the associated input weights and the summation of the weight and input product to the bias value associated with the neuron, are handled by the net function.

$$u = \sum_{i=1}^{n} x_i w_i + b \tag{9}$$

where b is the bias value, w_i , is the weight of the respective inputs x_i, and u is the argument of the activation function. The output of the net function, u, is passed through a transformation called the activation function, φ. The neuron's output, y, is the result of the action of the activation function.

$$\varphi = f(u) \tag{10}$$

$$y = \varphi\left(\sum_{i=1}^{n} x_i w_i + b\right) \tag{11}$$

$$y = \varphi\left(w^T x + b\right) \tag{12}$$

where, w^T is a transpose of the weight vector. The weight and bias are adjustable parameters of the neuron that causes the network to exhibit some desired or interesting behaviours.

A multilayer layer perception (MLP) ANN consists of a set of input nodes, one or more hidden layers and a set of output nodes in the output layer. A schematic of an MLP network with variable neurons in the hidden layer is shown in Figure 1.

where x_i (where $1 \leq i \geq 3$) are the set of inputs; w_{ij} and w_{jk} are adjustable weight values: w_{ij} connects the i^{th} input to the j^{th} neuron in the hidden layer, w_{jk} connects the j^{th} output in the hidden layer to the k^{th} node in the output layer; y_k (where k = l) is the output. Each neuron and output node has associated adjustable bias values: b_j (where $1 \leq j \geq 5$) is associated with the j^{th} neuron in network layer 1, b_k (where k =1) is associated with the node in the network layer 2. Within each network layer are: the weights, w, the multiplication and summing operations, the bias, b, and the activation function, φ [2].

The operations within an N layered MLP network can be mathematically represented by;

$$\underbrace{y_l = \varphi_N\left(\sum_{l=1}^{p} W_{kl} \ldots \varphi_2\underbrace{\left(\sum_{j=1}^{m} W_{jk}\, \underbrace{\varphi_1\left(\sum_{i=1}^{n} W_{ij}\chi_i + b_j\right)}_{layer\ 1} + b_k\right)}_{layer\ 2} + \ldots + b_l \;\vdots\right)}_{layer\ N} \tag{13}$$

where l is the number for the l^{th} neuron in layer N, p is the maximum number of neurons in layer N and N is the total number of network layers.

The rest of this paper is organized as follows: Section 2 presents related studies while section 3 presents methodology. Results are presented in section 4 while conclusion is in section 5.

2 RELATED STUDIES

Levenberg-Marquart back propagation was used by [21] to develop a model for the prediction of atmospheric temperature for Anyigba, Kogi State, Nigeria. Atmospheric temperature data of a four-year period was used in the study. Comparison of the predicted values with the measured values revealed that the prediction model had the potential for temperature prediction for Anyigba. [22] applied ANN in the prediction of hourly indoor air temperature and relative humidity in modern building in a humid region. The air temperature and relative humidity results simulated by the developed ANN model were strongly correlated with the measured data, with coefficient of correlation values of 0.9850 for air temperature and 0.9853 for relative humidity. These results testified that ANN can be used for hourly air temperature and relative humidity prediction.

Simulation and prediction of specific future time trend of land surface temperature in Ikom city of Nigeria was carried out by [23]. The study was based on time series ANN. Past land surface temperature values were studied to understand the pattern of change within the dataset and were further used in ANN to predict future time values. Results of the study reaffirmed the efficiency of ANN in learning, understanding and making accurate predictions.

In the study carried out by [24], ANN was used to predict dew point temperature from 1 to 12 h ahead using prior weather data as inputs. Three years from 20 locations in Georgia, United States, were used in a three-layer back propagation ANN to develop general models for dew point temperature prediction anywhere within Georgia. Dew point temperature was adequately predicted using previously unseen weather data. [25] examined the applicability of ANN approach in developing effective and reliable nonlinear predictive models for weather analysis. Different transfer functions, hidden layers and neurons were used in the model development stage. The developed model was used to forecast maximum, temperature for 365 days of the year.

The above studies has shown ANN to be reliable for prediction model development. The studies were mainly for a location and data of one to four years maximum were used in the studies. For climate related studies, data of more number of years yield more reliable findings as compared to 1 to 10 years data. This study is focused on the prediction of atmospheric temperature across the climatic zone of Nigeria, using a thirty four-year period data in ANN. There are some other existing machine learning techniques, but ANN has proven to be flexible and with the capability to learn the underlying relationships between the inputs and outputs of a process, without needing the explicit knowledge of how these variables are related, and it is adequate for prediction.

3 METHODOLOGY

The study was carried out in Nigeria, located in the west coast of Africa. Nigeria occupies an area of 923,768 km and her climatic zone is divided into five namely Sahel, tropical rainforest, Guinea savannah, Sudan savannah and Coastal zones [26]. Two weather stations were selected from each of the climatic zones for the study. Figure 2 shows the selected weather stations and Table 1 shows the coordinates and elevation of the selected weather stations.

Thirty-three (34)-year (1981-2014) atmospheric temperature data of the selected weather stations, was obtained from the Nigerian Meteorological Agency (NIMET) through the data bank of the West African Science Service Centre on Climate Change and Adaptive Land Use (WASCAL) of the Federal University of Technology Minna, Nigeria and used in the study. The data was divided into 2. A 24-year period (70.59 %) was used for the training of the network and 10-year period (24.41 %) was used for the testing of the developed model.

The ANN architecture comprised of 2 inputs (the climatic zones and the corresponding month for the mean monthly atmospheric temperature), 1 hidden layer and 1 output (atmospheric temperature). Levenberg-Marquardt algorithm was used with 9 different pairs of formed from 3 activation functions (logsig, purelin and tansig). In order to avoid over-fitting, the network parameters such as number of neurons in the hidden layer, types of activation functions; number of epoch etc, were varied and the optimal configuration was selected. Furthermore, the epoch was allowed not to be too high in order to avoid memorization. The number of neurones in the hidden layer was varied from 33-39 with an increasing steps of 2 (33, 35, 37 and 39). The 4 neurone numbers were used with each of the 9 different pairs of activation function. Data fed in for logsig or tansig activation functions were pre-processed into 0 to 1 or -1 to +1 using the normalization equations below.

$$X_{norm\_0-1} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{14}$$

$$X_{norm\_-1-1} = 2\,x\,\frac{X - X_{min}}{X_{max} - X_{min}} - 1 \tag{15}$$

The network outputs from the simulation process were then post processed to the original range. The performance of the developed model was evaluated using Mean Squared Error (MSE).

$$MSE = (1/N)\left(\sum_{i=1}^{N} (e_i)^2\right) \tag{16}$$

$$MSE = (1/N)\left(\sum_{i=1}^{N} (t_i - y_i)^2\right) \tag{17}$$

where N is the number of sets in the output data.

4 RESULTS

The network architecture of 2-37-1 (2 inputs, 37 neurons in the hidden layer and 1 output), with tansig/tansig pair of activation functions had the least MSE value of 2.2280, and was used for the prediction process. Plots of the model predicted and measured mean monthly atmospheric temperature values obtained during the testing of the model for each of the selected weather stations are shown in figure 2

The predicted atmospheric temperature values were observed to be in good agreement with the measured atmospheric values. Pearson correlation coefficient values for the predicted and measured mean monthly atmospheric temperature were computed for the selected weather stations using Pearson Product Moment Correlation

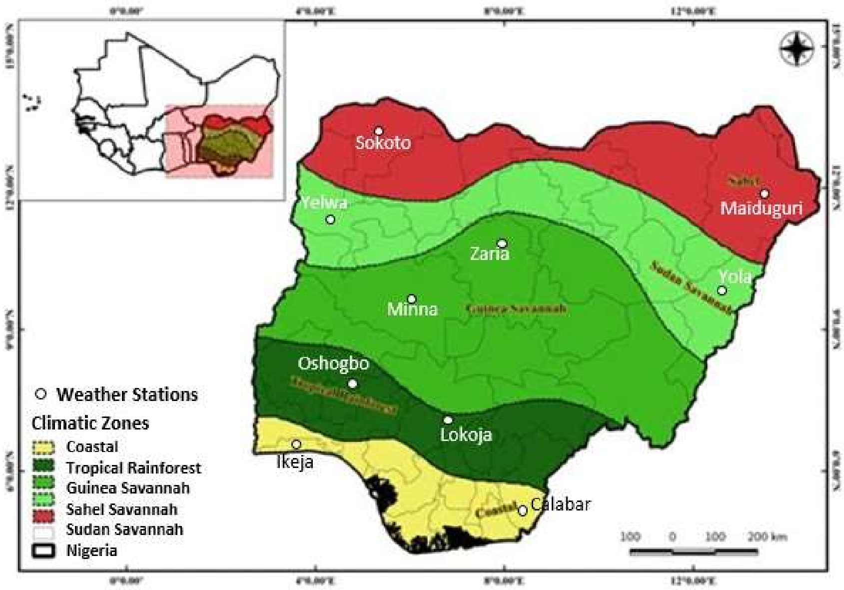

Figure 2: The selected Weather Stations within the Climatic Zones of Nigeria [21]

Table 1: The Coordinates and Elevation of selected Weather Stations

Climatic Zone	Station	Latitude (^{o}N)	Longitude (^{o}E)	Elevation (m)
Coastal	Calabar	4.97	8.35	63
	Ikeja	6.59	3.34	36
Tropical Rainforest	Lokoja	7.81	6.74	44
	Oshogbo	7.78	4.54	304
Guinea savannah	Minna	9.60	6.55	260
	Zaria	11.09	7.72	640
Sudan savannah	Sokoto	13.02	5.25	302
	Maiduguri	11.83	13.15	354
Sahel savannah	Yelwa	10.88	4.75	243
	Yola	9.23	12.47	174

Coefficient (PPMC) formula,

$$r = \frac{n\left(\sum^{x} y\right) - \left(\sum^{x}\right)\left(\sum^{y}\right)}{\sqrt{\left[n\sum^{x^2} - \left(\sum^{x}\right)^2\right]\left[n\sum^{y^2} - \left(\sum^{y}\right)^2\right]}} \tag{18}$$

where;
r = Pearson correlation coefficient
x = values in first set of data
y = values in second set of data
n = total number of values.

The computed correlation values ranged from 0.9733 to 0.8787, as shown in Table 2, depicting strong positive correlation and good performance of the developed model.

5 CONCLUSION

In this study ANN parametric model was used for the prediction of mean monthly atmospheric temperature across the climatic zones

Table 2: Pearson correlation coefficient values for predicted and measured mean monthly atmospheric temperature

Climatic Zone	**Weather Station**	**Correlation Coefficient**
Coastal	Calabar	0.9682
	Ikeja	0.9771
Tropical Rainforest	Lokoja	0.9474
	Oshogbo	0.9664
Guinea Savannah	Minna	0.9733
	Zaria	0.9341
Sudan Savannah	Yelwa	0.9553
	Yola	0.8787
Sahel Savannah	Sokoto	0.9411
	Maiduguri	0.9283

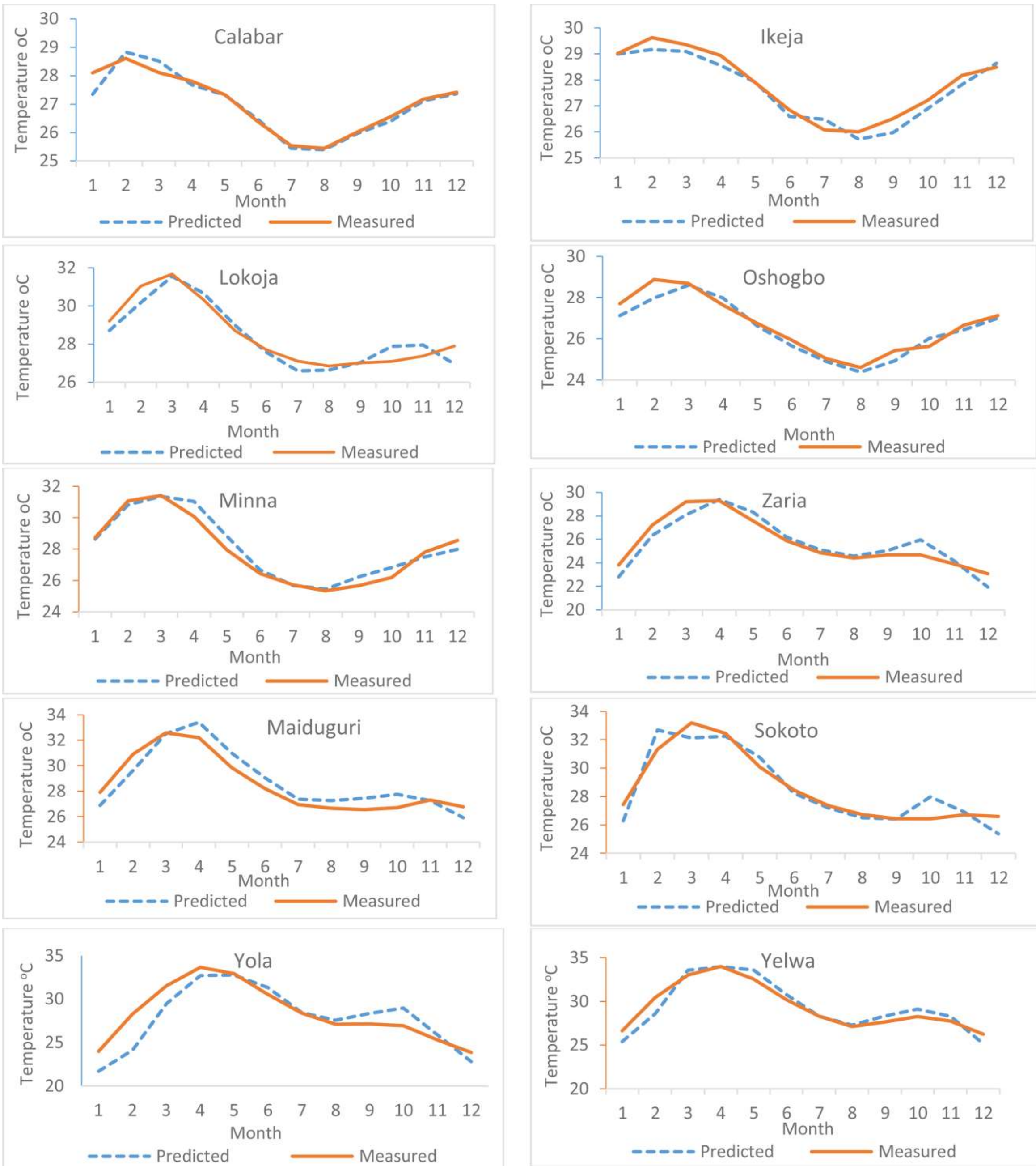

Figure 3: Plots of the model predicted and measured mean monthly atmospheric temperature values

of Nigeria. The ANN architecture comprised of 2 inputs (the climatic zones and the corresponding month for the mean monthly atmospheric temperature), 1 hidden layer and 1 output (atmospheric temperature). Levenberg-Marquard algorithm and 33 neurons in the hidden layer were used with tansig activation function in both the hidden layer and output layer of the ANN. Comparisons of the measured and the ANN predicted atmospheric temperature across selected stations in the climatic zones of Nigeria, showed that the developed model can effectively predict mean monthly atmospheric temperature, using month and climatic zone as input parameters. With correlation coefficient values ranging from 0.9733 to 0.8787, the ANN based model showed good accuracy. Adequate knowledge of the atmospheric temperature of an environment is essential for radio wave propagation planning.

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