Computation of Radio Refractivity using Machine Learning Techniques

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Abstract.

In this paper, different programming languages such as R, MATLAB and Python; framework such as Sci-kit learn; and algorithms such as Regression and Artificial Neural Network (ANN) were used to compute radio refractivity in Abuja, Northcentral Nigeria. The upper air data of atmospheric parameters were collected from the Nigerian Meteorological Agency (NiMet), Abuja, Nigeria with a radiosonde. The data collected are pressure, temperature and relative humidity. The algorithm with the best results for radio refractivity computation was selected, though it was observed that all the algorithms utilised for the computation performed well. However, the ANN performed best as predicted and actual values of radio refractivity were closely related and relative errors were lower compared to other programming languages and algorithms. Hence, it was concluded that using ANN along with MATLAB would be the best algorithm and programming language for computing radio refractivity successfully.

Keywords: Atmospheric parameters, machine learning, refractivity

1. Introduction

Radio wave propagation is motivated by the traits of the atmosphere and may be scattered, absorbed, reflected or refracted because of diverse atmospheric behaviours (Adeniji et al., 2021). The troposphere is part of the atmosphere that is closest to human life and starts from the earth's surface to a height of approximately 10 km at the poles and 17 km at the equator (Hall, 1979). Radio links in the troposphere are usually affected by pressure, temperature and relative humidity (Adeniji et al., 2021). These parameters disturb the frequency and power of the radio signal (Afolabi, et al., 2019). Radio waves have significant applications in radio communications, disaster forecasting, aerospace, and environmental monitoring or impact assessments. The application of radio waves is not only restricted to the foregoing as it is also being used in medical fields (Wallnöfer et al., 2020). Also, poor propagation lessens the proper functioning of a communication link, thereby resulting in signal decline at the receiver end. The refractivity changes in the troposphere depend on different factors and consequently on radio waves effects such as refraction and interference from radio stations. Radio refractivity, n is described as the ratio of radio wave propagation velocity in free space to its velocity in an exact medium. It is mathematically written as:

$$n = \frac{vf}{vm} \tag{1}$$

Here, the velocity in a loose space is denoted by vf, while vm describes its velocity with respect to a specified medium. In the troposphere, radio wave propagation is evaluated primarily based on variations in air refractivity. The use of radiosonde by the Nigerian meteorological agency to record meteorological data is expensive and tedious (Afolabi, et al., 2019). This was why radiosonde accents were discontinued for over two decades in most places in Nigeria. Hence, some research efforts in the past such as Igwe and Adimula (2009) and Igwe (2010), at the time, could not get current upper air data for their analyses. Unfortunately, also, predicted or computed values from models used for forecasting radio refractivity are most times far from the measured values, thereby giving higher error margins. Thankfully, in recent times, the introduction of soft computing methods which can handle larger number of atmospheric data (Igwe et al., 2017; Igwe et al., 2021) has been able to reduce this error in the prediction of radio refractivity, thus giving more accurate results.

This paper, therefore, aims at computing radio refractivity by employing different machine learning languages and atmospheric data of temperature, pressure and relative humidity, thereby determining the best algorithm from the computational results.

2. Methodology

Atmospheric parameters within a three-year time frame were used to compute radio refractivity using different machine learning programming languages. Then the best algorithm with the best results for computing radio refractivity was selected. The data collected include pressure, temperature and relative humidity. A radiosonde device was used for the data measurement and collection.

The atmospheric radio refractive index, n, was computed using:

$$n = 1 + N\,X\,10^{-6} \tag{2}$$

N is the radio refractivity, and it is given as:

$$N = 77.6\frac{P_d}{T} + 72\frac{e}{T} + 3.75\ \times 10^{5}\ \frac{e}{T^2} \quad \text{(N-units)} \tag{3}$$

where:

Pd: dry atmospheric pressure (hPa)

e: water vapour pressure (hPa)

T: absolute temperature (K)

2.1 Machine learning and predictive modeling methods

2.1.1 Regression model

As an introduction, notation for regression models are presented. Let Y denote the response (dependent) variable, and let X = X1, X2,...,Xp denote a list or vector of predictor variables (also called covariables or independent descriptors or concomitant variables).

These predictive variables are assumed to be constant for a given individual or subject of the population of interest. Let β = β0, β1, ..., βp denote the list of regression coefficients (parameters). B0 is an optional intercept parameter and β1, ..., βp are weights or regression coefficients corresponding to X1, ..., Xp. A matrix or vector notation is used to describe a weighted sum of the Xs: Xβ = β0 + β1X1 + ...+ βpXp, where there is an implicit X0 = 1. A regression model is hence, stated in terms of a connection between the predictors X and the response Y. Let C (YX) denote a property of the distribution of Y given X (as a function of X). For example, C (YX) could be E (YX). The regression model was used to compute atmospheric parameters and radio refractivity

2.1.2 Scikit-learn framework

The Scikit-learn model is an open-source python machine learning library designed to work alongside NumPy. It features various machine learning algorithms for classification, clustering, and regression. The Scikit-learn model was also used to compute atmospheric parameters and radio refractivity.

2.1.3 Artificial neural network model

Artificial neural network (ANN) with MATLAB as its machine learning algorithm was likewise used to compute atmospheric parameters and radio refractivity. The machine learning process involves: i. Data Preparation ii. Feature Selection iii. Forecast Module. The data preparation involves cleaning and organising the data to make it suitable for building and training the model. The feature selection stage helps selects the appropriate features for the model. The last stage (i.e. Forecast Module) involves using the ANN to compute the radio refractivity from the selected features. The ANN was employed to make the computation via model training. The ANN architecture was used to train the data (temperature, pressure, and humidity) and make refractivity computation.

3. Results and discussion

The data was prepared, analysed and computations were made based on the selected algorithms. The results from these analyses are hereby presented.

3.1 Computation using regression analysis

The computations of atmospheric parameters were carried out first before the computation of radio refractivity was done using regression. The results revealed that pressure decreases as altitude increases (as shown in Figure 1). At a height of 110 m, it was observed that pressure was 1000 hPa. At 800 m, it was observed that atmospheric pressure had reduced to 922 hPa. Relative humidity was directly proportionally to height (as shown in Figure 2). At a height of 100 m, relative humidity was 50%. However, at a height of 805 m, relative humidity rose to 79%.

Figure 1: Relationship between Pressure and Height

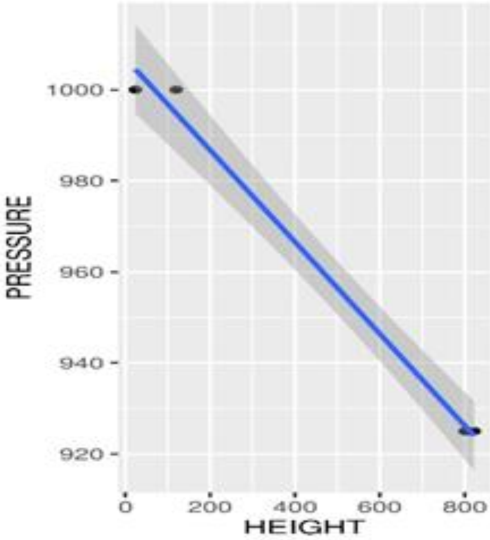
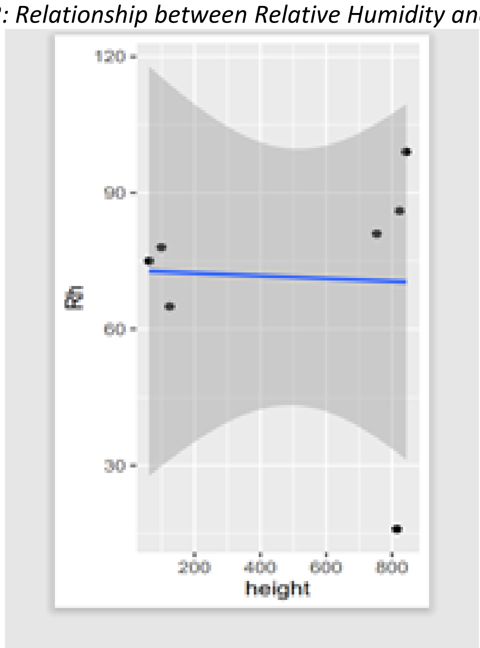


Figure 2: Relationship between Relative Humidity and Height



The predicted and actual values of the atmospheric parameters and relative errors (RE) are presented in Table 1. It was observed that the relative errors were less than 0.5%. This suggests that the regression model used for this study has a high accuracy.

Table 1: Actual and predicted values of atmospheric parameters using Regression

Mnth	Hght	Act Pres	Pred Pres	RE	Act Tem	Pred Tem	RE	Act RH	Pred RH	RE
Jan	1569	850	850	0.001	20.3	25.1	0.002	88	90.1	0.001
Feb	1711	835	849	0.002	20.3	20.7	0.003	31	34.4	0.003
Mar	495	958	957	0.002	31.9	31.9	0.000	54	54.0	0.000
Apr	1460	859	870	0.008	19.1	19.7	0.001	56.7	59.0	0.002
May	827	925	970	0.003	21.9	22.2	0.001	55	55.2	0.001

Jun	789	928	930	0.002	23.5	23.7	0.000	86	87.3	0.001
Jul	1518	855	860	0.004	20.8	20.7	0.001	86	86.0	0.000
Aug	1109	896	896	0.001	24.3	24.7	0.001	81	83.4	0.002
Sep	380	880	900	0.007	21.3	21.5	0.001	50	50.1	0.001
Oct	1897	816	821	0.004	18.7	19.2	0.003	84	87	0.003
Nov	392	970	971	0.003	32.8	33.7	0.001	42	42.2	0.002
Dec	399	972	974	0.002	30.0	30.3	0.000	57	58.1	0.001

3.2 Prediction using scikit-learn framework

Scikit-learn framework (A python machine learning library) was also used for the atmospheric data prediction in this work. The comparison between the predicted and actual values of pressure is shown in Figure 3. The predicted and actual values of pressure agree well with each other till day 100. However, as shown in Figure 4, the predicted and actual relative humidity values are far from each other. The comparison between the predicted and actual values of temperature is given in Figure 5. The error is again less than 0.5%, which guarantees the accuracy of the suggested scikit-learn framework.

Figure 3: Comparison between predicted and actual values of pressure in relation to days

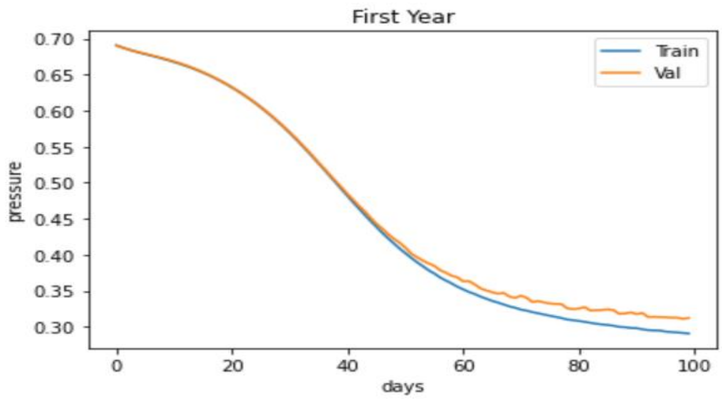


Figure 4: Comparison between predicted and actual values of relative humidity in relation to days

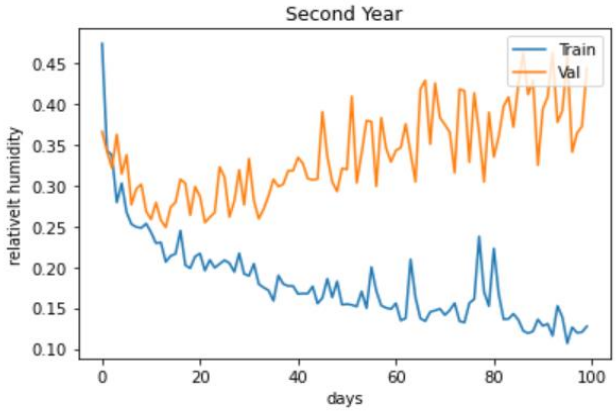
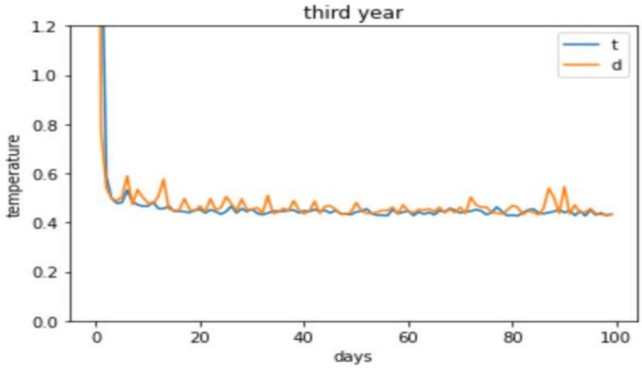


Figure 5: Comparison between predicted and actual values of temperature in relation to days



Also, the predicted and actual values of temperature, pressure, and humidity with the various computed relative errors were compared as shown in Table 2. The study reveals that the error margins between the predicted and actual values were a bit high. For instance, the relative error for atmospheric pressure in June was 0.08 %.

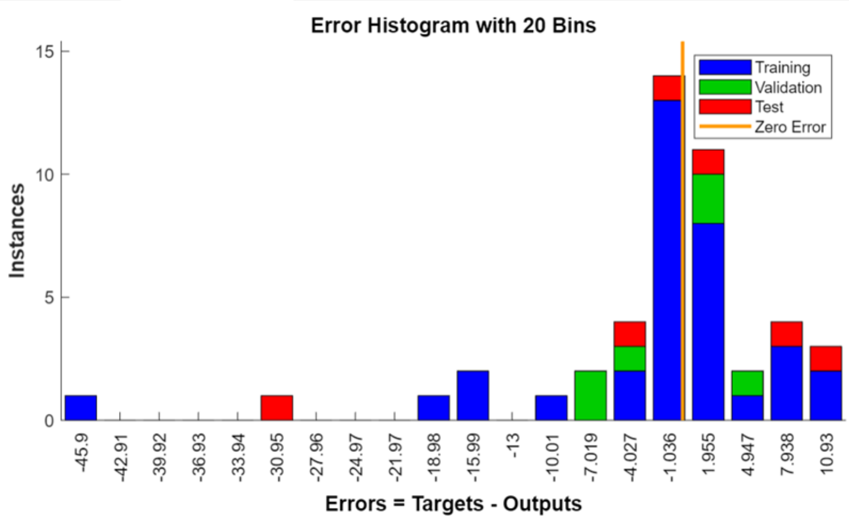
Table 2: Actual and predicted values of atmospheric parameters using Scikit-learn Framework

Mnth	Hght	Act Pres	Pred Pres	RE	Act Tem	Pred Tem	RE	Act RH	Pred RH	RE
Jan	1570	925.0	925.1	0.01	18.0	18.1	0.01	81	81.5	0.04
Feb	1570	925.0	925.6	0.06	18.0	18.3	0.03	94	94.2	0.02
Mar	831	925.0	925.5	0.05	18.5	18.4	0.01	69	69.2	0.02
Apr	1565	925.0	925.3	0.03	19.0	19.3	0.03	54	54.4	0.01
May	1561	925.0	925.5	0.05	18.7	18.5	0.02	82	82.4	0.02
Jun	1550	925.0	925.8	0.08	17.8	17.4	0.04	94	94.5	0.01
Jul	827	925.0	925.1	0.01	19.1	19.4	0.03	86	86.0	0.00
Aug	1546	925.0	925.4	0.04	18.8	18.4	0.04	87	87.2	0.02
Sep	1570	925.0	925.8	0.08	19.7	19.5	0.02	67	67.5	0.05
Oct	1549	925.0	925.5	0.05	20.2	20.3	0.01	76	76.6	0.05
Nov	1570	925.0	925.7	0.07	19.1	19.4	0.03	80	80.5	0.03
Dec	1570	925	925.2	0.02	25	25.2	0.02	84	84.2	0.01

3.3 Prediction using artificial neural network

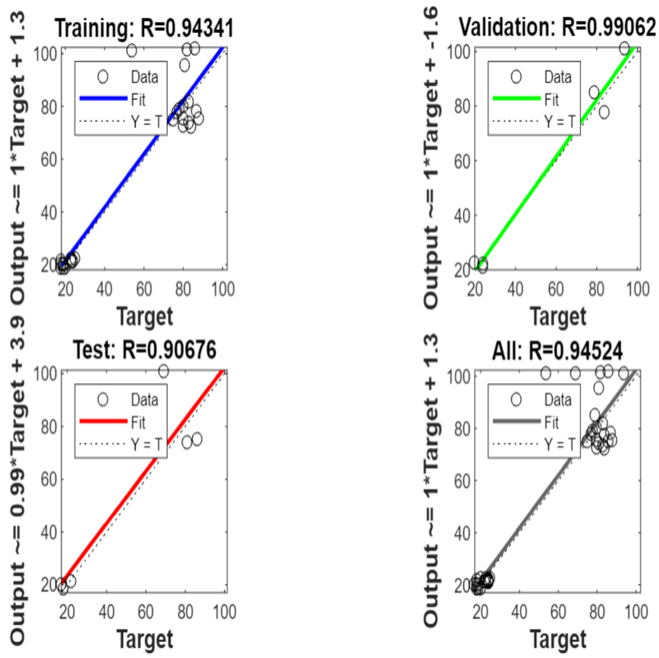
For artificial neural network prediction, information for evaluating the quality of the trained network is available from the error histogram shown in Figure 6. This gives the distribution of the residuals between targets and network outputs. The histogram is also able to indicate outliers. It was observed that most errors lie between - 1.036 and - 1.955. Although the outputs were slightly larger than the targets, the error for the best performance stood at -1.036. This indicates very low error values.

Figure 6: Error histogram of target and artificial neural network



The scatter plot shown in Figure 7 reveal that the predicted values are closer to the actual values. The correlation coefficient between the ANN output and the target values were high. The r-squared values for training, validation and test are 0.94, 0.99 and 0.91 repectively.

Figure 7: Scatter Plots showing Training, Validation and Test results for the ANN model



The actual and predicted values of atmospheric parameters using artificial neural network is shown in Table 3. It was observed that the relative errors were lower than 0.5% for each parameter. The relative errors for pressure, relative humidity and temperature were between 0.001 and 0.003 in most instances.

Table 3: Actual and predicted values of atmospheric parameters using artificial neural network

Mnth	**Hght**	**Act Pres**	**Pred Pres**	**RE**	**Act Tem**	**Pred Tem**	**RE**	**Act RH**	**Pred RH**	**RE**
Jan	1370	872	872.6	0.001	22.0	28.1	0.007	77	77.8	0.002

Feb	818	925	925.3	0.001	21.2	29.3	0.002	15	15.3	0.001
Mar	1544	925	925.5	0.001	22.5	28.7	0.003	52	57.9	0.003
Apr	1546	925	925.3	0.001	21.3	21.5	0.002	62	62.4	0.001
May	1560	925	925.4	0.001	19.1	21.4	0.002	95	95.3	0.001
Jun	1552	925	925.3	0.001	20.4	20.6	0.001	66	78.9	0.007
Jul	1568	925	925.2	0.001	21.4	23.1	0.003	52	52.3	0.001
Aug	1588	924	924.5	0.001	16.2	18.9	0.002	99	99.3	0.001
Sep	1581	925	925.0	0.001	19.0	19.9	0.001	77	77.4	0.001
Oct	1570	925	925.42	0.001	18.2	30.2	0.008	86	89.0	0.002
Nov	1567	925	925.4	0.001	20.0	21.3	0.001	63	63.8	0.001
Dec	832	1000	1000.32	0.001	23.0	23.4	0.001	68	69.7	0.002

The actual and predicted values of refractivity, N_s using the three algorithms (Regression, Scikit learn and ANN) are shown in Tables 4 - 6.

Table 4: Actual and predicted values of Refractivity, N_s using Regression

Mnth	**1st Year**			**2nd Year**			**3rd Year**		
	Act N_s	**Pred** N_s	**RE**	**Act** N_s	**Pred** N_s	**RE**	**Act** N_s	**Pred** N_s	**RE**
Jan	235.57	268.23	0.24	303.97	297.03	0.23	372.37	325.83	0.17
Feb	241.27	270.63	0.22	309.67	299.43	0.21	378.07	328.23	0.23
Mar	246.97	273.03	0.24	315.37	301.83	0.21	383.77	330.63	0.31
Apr	252.67	275.43	0.24	321.07	304.23	0.25	389.47	333.03	0.27
May	258.37	277.83	0.27	326.77	306.63	0.26	395.17	335.43	0.25
Jun	264.07	280.23	0.23	332.47	309.03	0.23	400.87	337.83	0.35
Jul	269.77	282.63	0.24	338.17	311.43	0.13	406.57	340.23	0.34
Aug	275.47	285.03	0.27	343.87	313.83	0.14	412.27	342.63	0.37
Sep	281.17	287.43	0.24	349.57	316.23	0.17	417.97	345.03	0.32
Oct	286.87	289.83	0.26	355.27	318.63	0.12	423.67	347.43	0.31
Nov	292.57	292.23	0.24	360.97	321.03	0.18	429.37	349.83	0.38
Dec	298.27	294.63	0.23	366.67	323.43	0.10	435.07	352.23	0.34

Table 5: Actual and predicted values of Refractivity, N_s using Scikit-learn

Mnth	**1st Year**			**2nd Year**			**3rd Year**		
	Act N_s	**Pred** N_s	**RE**	**Act** N_s	**Pred** N_s	**RE**	**Act** N_s	**Pred** N_s	**RE**
Jan	358.60	341.32	0.12	363.59	353.32	0.21	363.59	358.60	0.23
Feb	360.12	342.32	0.18	363.59	354.32	0.21	363.59	358.60	0.21
Mar	361.13	343.32	0.21	363.59	355.32	0.25	363.59	358.60	0.24
Apr	363.59	344.32	0.22	363.59	358.60	0.23	363.59	358.60	0.22

May	363.59	345.32	0.23	363.59	358.60	0.24	363.59	358.60	0.24
Jun	363.59	346.32	0.20	363.59	358.60	0.23	363.59	358.60	0.24
Jul	363.59	347.32	0.16	363.59	358.60	0.21	363.59	358.60	0.24
Aug	363.59	348.32	0.22	363.59	358.60	0.23	363.59	358.60	0.24
Sep	363.59	349.32	0.23	363.59	358.60	0.23	363.59	358.60	0.24
Oct	363.59	350.32	0.24	363.59	358.60	0.21	363.59	358.60	0.24
Nov	363.59	351.32	0.22	363.59	358.60	0.24	363.59	358.60	0.24
Dec	363.59	352.32	0.22	363.59	358.60	0.23	363.59	358.60	0.24

Table 6: Actual and predicted values of Refractivity, N_s using ANN

Mnth	**1st Year**			**2nd Year**			**3rd Year**		
	Act N_s	**Pred** N_s	**RE**	**Act** N_s	**Pred** N_s	**RE**	**Act** N_s	**Pred** N_s	**RE**
Jan	358.60	357.30	0.21	363.59	352.49	0.22	363.59	356.14	0.20
Feb	360.12	359.01	0.20	363.59	353.56	0.21	363.59	355.87	0.23
Mar	361.13	360.10	0.23	363.59	352.53	0.23	363.59	352.82	0.21
Apr	363.59	362.60	0.21	363.59	356.76	0.20	363.59	350.80	0.22
May	363.59	357.95	0.21	363.59	356.40	0.21	363.59	353.13	0.21
Jun	363.59	359.24	0.20	363.59	355.34	0.22	363.59	353.91	0.22
Jul	363.59	360.94	0.21	363.59	358.00	0.25	363.59	354.85	0.22
Aug	363.59	358.38	0.22	363.59	357.30	0.23	363.59	346.59	0.23
Sep	363.59	359.57	0.21	363.59	357.19	0.21	363.59	353.59	0.20
Oct	363.59	356.39	0.21	363.59	353.49	0.25	363.59	353.59	0.24
Nov	363.59	355.19	0.24	363.59	357.65	0.21	363.59	353.59	0.21
Dec	362.59	354.22	0.22	363.59	357.31	0.21	363.59	353.59	0.22

From Tables 4-6, it is observed that refractivity values are lower for the first year, whereas higher values were observed for the remaining 2 years. It is also noticed that predicted refractivity values were closer to actual values with the relative error values less than 0.5% in all the years. However, radio refractivity computation using artificial neural network gave better results. This agrees with the conclusions of Javeed et al. (2018) and Ayantunji et al. (2019). They concluded that neural networks can be used for successful estimations of atmospheric parameters of humidity, pressure, and refractivity.

4. Conclusion

Radio refractivity has been computed using different algorithms and frameworks in this paper. The best algorithm was selected as the most appropriate. Regression analysis with R programming language, scikit-learn framework with Python programming language and artificial neural network with MATLAB were employed to compute selected atmospheric parameters (pressure, temperature, relative humidity) and radio refractivity. The results revealed that the computed relative errors for the atmospheric parameters and radio refractivity were relatively low. In all, the computed values of all the atmospheric parameters and refractivity were close to their respective actual values, with less than 0.5% relative errors. Also, refractivity values were lower for the first 1 year, whereas higher values were observed for the remaining 2 years. However, computation of radio refractivity using artificial neural network was better in comparison to other algorithms.

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