PERFORMANCE ESTIMATION OF NEURAL NETWORK TEC PREDICTION MODELS OVER TORO STATION.

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ABSTRACT
This paper presents the prediction of hourly Total Electron Content (TEC) obtained from a Global navigation satellite system (GNNS) receiver at Toro station (10.12°N, 9.12°E), Bauchi, Nigeria and developed an ionospheric model using a neural network (NN) by utilizing the TEC data. The studied period is based on the available data during the period from 2014 to 2016. Four neural network configurations with different inputs which include the day number, hour number, sunspot number (SSN) and solar radio flux (F10.7) were used. Each configuration was trained with Total Electron Content (TEC) data between the years 2014 to 2016. The best neural network used for prediction had the least mean squared error (MSE) of 8.68 TECU and root mean squared error (RMSE) value of 2.95 TECU. The comparison was made between TEC from the observatory station and predicted TEC from the best neural network (NN) model. The developed NN model was used to predict some selected days that fall between the four astronomical seasons. The results show that the model performed well on the 17th of March 2014 with an MSE of 12.35 TECU and an RMSE value of 3.11 TECU.

Keywords: Neural network, Ionosphere, Total Electron Content, GNSS, Ionosonde.

INTRODUCTION
The ionosphere is a portion of the Earth's upper atmosphere where ions and electrons are present in sufficient quantities to influence radio wave propagation. The ionospheric region is electrically conducting and can support large electric currents which can affect traversing electromagnetic signals causing signal delay due to its dispersion and non-linearity characteristics. The investigation of the ionosphere becomes paramount for the trans-ionospheric propagation of radio waves. The ionospheric profile parameters that are used to describe the behaviour of the region are subject to several variations depending on the space weather conditions. Hence, the reliable operations of radio communication, navigation systems and spacecraft control systems principally depend on the availability of information on the state of the ionospheric parameters such as total electron content (Sur et al., 2012). The total electron content (TEC) is defined as the number of electrons in a column of the cross-sectional area of $1\,m^2$ along a signal path through the ionosphere (Kumar et al., 2021)

$$TEC = \int N_e(s)ds \qquad (1)$$

The characteristics of the variability of ionospheric TEC quantity and its modelling are important to radio communication operators, as they depend on the ionospheric electron density gradient along the Line of Sight (LOS) from a satellite in space to a receiver on the ground. As a consequence, the development of ionospheric modelling capability to predict and forecast the state of the ionosphere has continued to be an important ionospheric research topic. Several studies have reported various modelling approaches for the prediction of TEC across different ionospheric regions (Seemala and Valladares, 2011; Sethi et al., 2009; Siemsen et al., 2010; Sivavaraprasad et al., 2020; Van Aelst et al., 2008; Zeng et al., 1997; Zolesi and Cander, 2013; Zou et al., 2011).

The use of machine learning for time-series modelling is becoming an essential modelling technique for data predictions and forecasting. The neural network (NN) which is a type of machine learning is a simplified model of the functionality of the human brain works. It is implemented by simulating a large interconnected neuron (processing units). The processing units are typically in layers in the network. These layers are the input layers, hidden layers and output layers. Several works have used NN for the prediction of the state of the ionosphere (Habarulema et al., 2009; Muslim et al., 2018; Oyeyemi et al., 2005; Poole and McKinnell, 2000; Sivavaraprasad et al., 2020). In this research, the diurnal and seasonal variation of TEC during the geomagnetic quiet period is investigated and a neural network model is developed and compared with the observational TEC values.

METHODS

The TEC data used in this study is obtained from a measurement taken by Toro (10.12°N, 9.12°E), the station's GNSS receiver. The station is among the International GNSS Service (IGS) stations serving as a continuously operating reference station (station code: CGGN) located in Bauchi state, Nigeria. The TEC data is archived on Scripps Orbit and Permanent Array Center (SOPAC) which can be downloaded on their website via http://sopac-csrc.ucsd.edu/. The GPS data were recorded in Receiver Independent Exchange (*RINEX*) file format which was converted from STEC to VTEC using GPS-TEC analysis software developed by Gopi Krishna Seemala. This software has been used by many researchers for processing TEC data (Akala et al., 2013; Okoh et al., 2021; Seemala and Valladares, 2011; Sivavaraprasad et al., 2020).

Following the description of Ogwala et al. (2021), the GPS-TEC analysis software loads the raw TEC data in the RINEX file format, then processes the cycle slips in phase data, fetch satellite biases from the IGS code files (or calculates it if unavailable), calculates receiver bias and inter-channel biases for different satellites in the constellation, and finally provide visualization of TEC variation as plots in the software and then writes the processed files as a text document. In this analysis, the VTEC for the years 2014 to 2015 were processed. This period falls within the solar maximum (2014 to 2015) and the descending phase of the solar cycle 24. Largely due to equipment failure, the three years of data used are currently the available dataset for this station and there are periods with years without data.

The inputs for the neural network (NN) were based on independent parameters that can modulate the ionosphere. Typically, the variation in the ionosphere can be influenced by day-to-day variability, season, solar activity, magnetic activity and space weather. The solar activity indices used for the development of the NN model are the daily sunspot number (SSN) and the solar flux index, F10.7 (s.f.u = 10^{-22}W m^{-2} Hz^{-1}). The seasonal and diurnal variations are represented by the day number (DN) and hour (HR). The VTEC data is a time-series data and as a consequence, none time-series input data into the NN model must is encoded into cyclical data for continuity by transforming the data into two dimensions using sine and cosine components (Habarulema et al., 2009; Poole and McKinnell, 2000). Since the ionosphere is generally known to exhibit daily and diurnal variations, thus the sine and cosine components of the day number (DN) and hour (HR) are computed and fed as inputs into the NN model. By adopting the methods of Oyeyemi et al (2005) and

Habarulema (2009), the transformation of the DN into sine (DNS) and cosine (DNC) components is given as (Habarulema et al., 2009; Poole and McKinnell, 2000):

$$\mathrm{DNS} = \sin\left(\frac{2\pi\times \mathrm{DN}}{365.25}\right) \quad (2)$$

$$\mathrm{DNC} = \cos\left(\frac{2\pi\times \mathrm{DN}}{365.25}\right) \quad (3)$$

where DNS and DNC represent the sine and cosine components of the day number of the year.

Similarly, the capability of the model to respond to the diurnal changes in the ionospheric VTEC is done by transforming the hour values into sine (HRS) and cosine (HRC) components and are given as (Habarulema et al., 2009; Poole and McKinnell, 2000):

$$\mathrm{HRS} = \sin\left(\frac{2\pi\times \mathrm{DN}}{365.25}\right) \quad (4)$$

$$\mathrm{HRC} = \cos\left(\frac{2\pi\times \mathrm{DN}}{365.25}\right) \quad (5)$$

where HRS and HRC represent the sine and cosine components of hourly values of the day. In equation (2-5), the normalization of the DN to 365.25 takes into account the fact that part of the data used was for leap years. The flow process of the implementation of the NN model on MATLAB is illustrated in figure 1. The NN model architecture used is two-layer feed-forward networks with the *nth* number of hidden layers. The model is designed with different configurations by using different combinations of input parameters as shown in figure 2. The NN models are designated as NN1 which has DNS, DNC, HRS and HRC as the inputs. The NN2 model configuration has five inputs which include DNS, DNC, HRS, HRC and SSN. The NN3 has DNS, DNC, HRS, HRC and F10.7 as the model inputs while NN4 inputs are the DNS, DNC, HRS, HRC, SSN and F10.7.

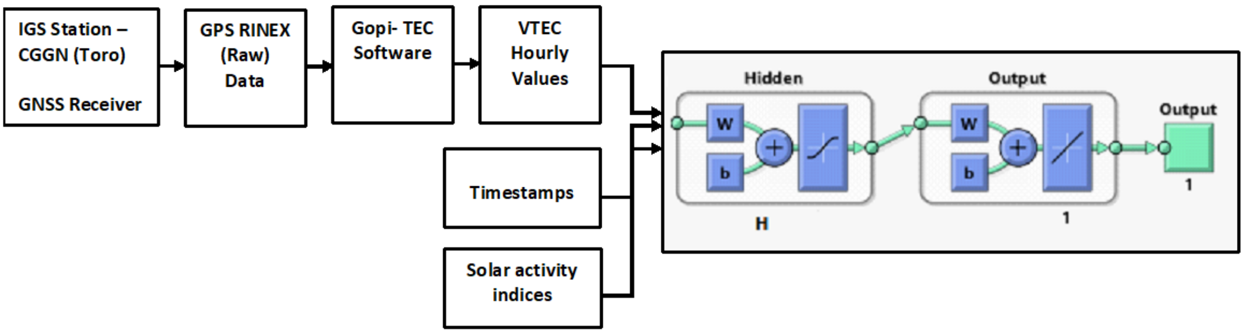

Figure 1: The flow process of the NN model on MATLAB

The Levenberg-Marquardt algorithm was chosen as the training technique (see the work of Kişi and Uncuoğlu (2005) on the comparison of three backpropagation NN algorithms: Levenberg-Marquardt, conjugate gradient and resilient back-propagation). This Levenberg-Marquardt typically requires more memory, but less time hence admired for its speed and efficiency in learning with weights and bias values were updated according to the optimization method. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. Thus, the training and testing patterns were monitored based on mean square errors (MSE), and training was allowed to proceed as long as the errors on the testing patterns decreased. When the errors started increasing, training was terminated as it is believed that the network is no longer generalizing due to the memorization of the training pattern. The output nodes provided the predicted VTEC values. The optimum architecture for the NN was determined by iterating over a range of hidden (H) layers within $\{H|\ 5 \leq H \geq 50\}$ in the interval of 5. MATLAB software-based Neural Network Toolbox was used to implement these NN Models.

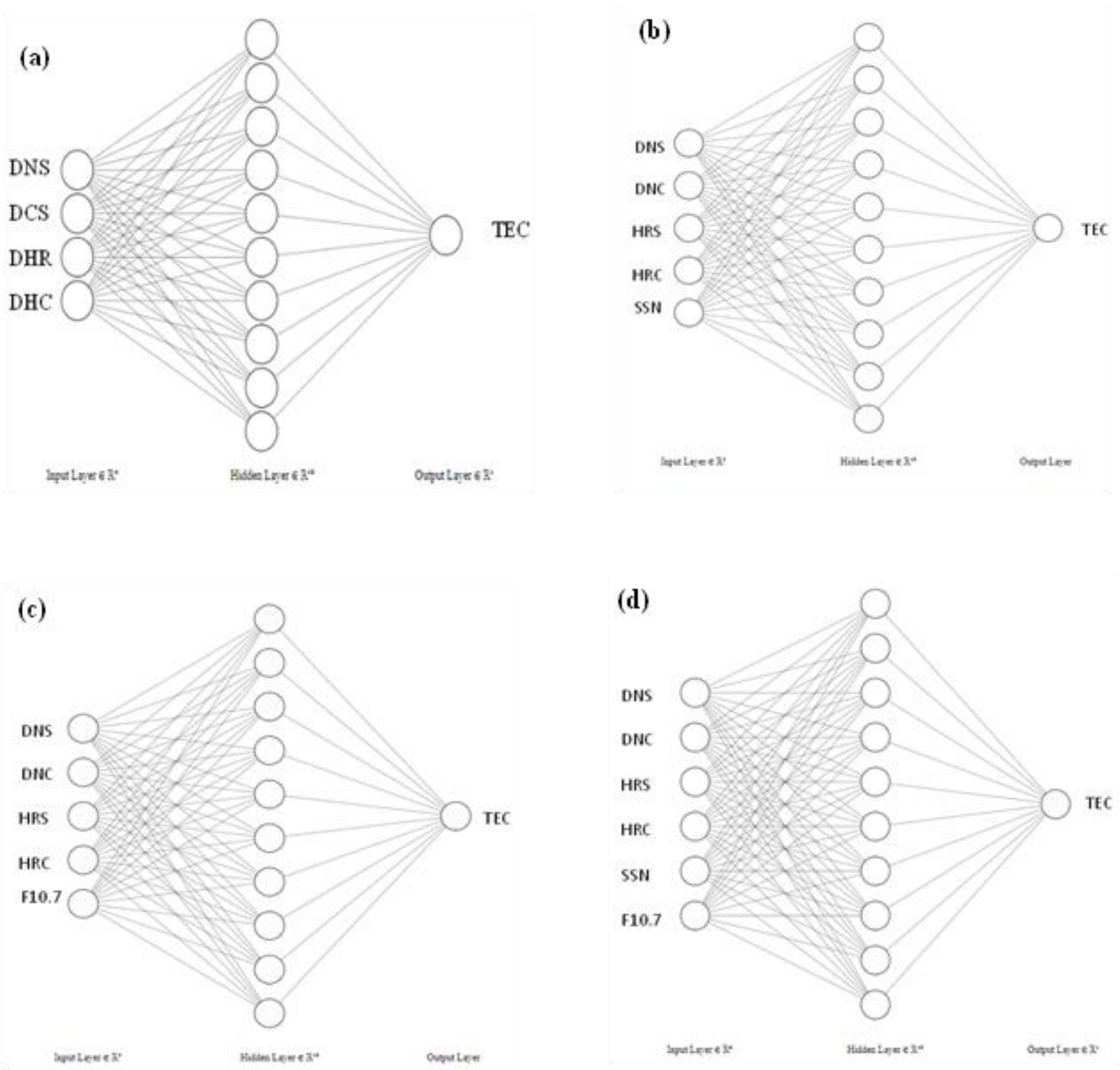

Figure 2: Schematic diagram of proposed neural network models. (a) NN1 model, (b) NN2 model, (c) NN3 model, (d) NN4 model.

RESULTS AND DISCUSSION

The diurnal variation of TEC over the studied period is given in figure 3. Generally, the value of TEC is highest in the year 2014 than in the rest of the other years. The observed increase in TEC during the year 2014 can be attributed to the solar activity conditions and this is shown in figure 4. The SSN and F10.7 are 113 and 146 s.f.u respectively. For the year 2015, the values of SSN are 70 and F10.7 118 s.f.u respectively. For the year 2016, the SSN value is 40 and 89 s.f.u respectively. The highest observed value for the year 2014 is 88 TECU while the years 2015 to 2016 have a peak value of ~57 TECU, where 1 TECU is equivalent to $1 \times 10^{16}\,m^{-2}$.

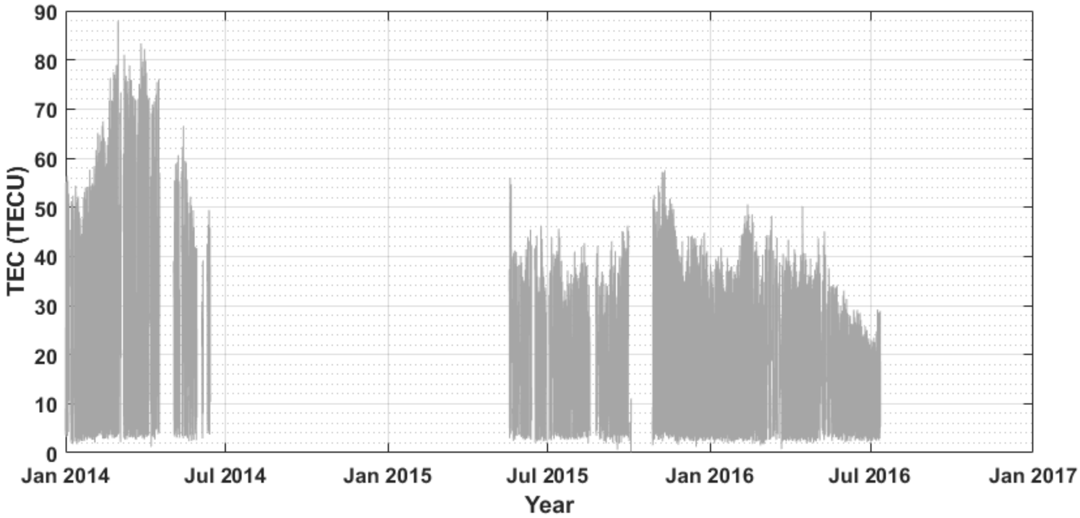

Figure 3: The variation of TEC between 2014 to 2016

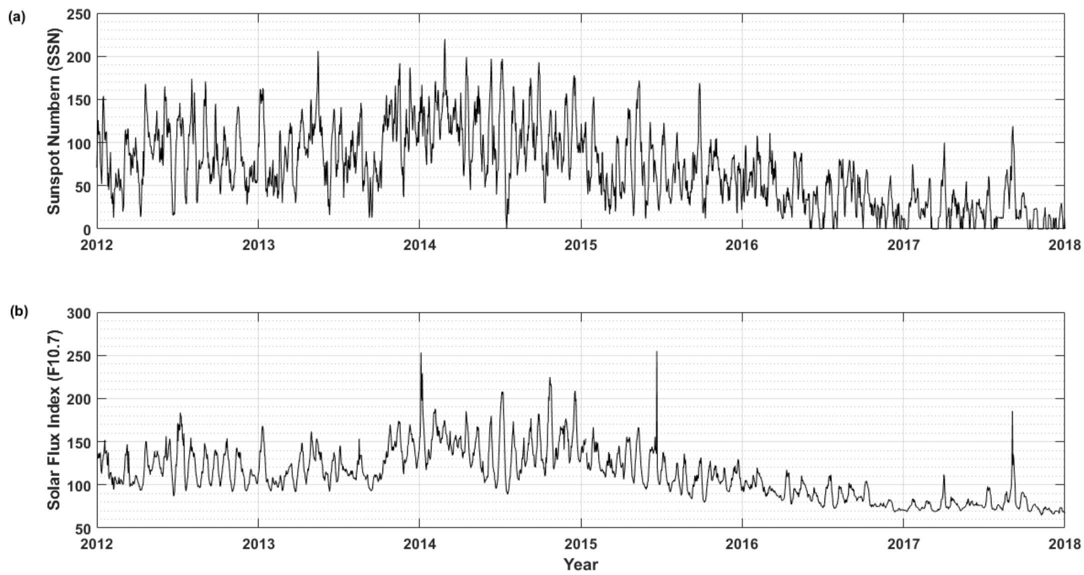

Figure 4: The solar activity indices between 2012 to 2017 (a) daily averages of SSN (b) daily average of F10.7.

The result obtained is similar to the findings of Sur et al. (2012). Where they have compared the TEC values during low and moderate solar activity in solar cycle 24 around the northern crest of Equatorial Ionization Anomaly in the Indian longitude sector. From figure 4, it can be seen that both SSN and F10.7 are in the solar maximum phase during the year 2014. This background condition increases the solar intensity which intermittently increases the photo-ionization in the ionosphere thereby responsible for the observed increase in TEC values in 2014.

By reshaping the TEC values in figure 3 into their respective months, the results of the diurnal monthly variation of TEC values between 2014 to 2016 are presented in figure 5.

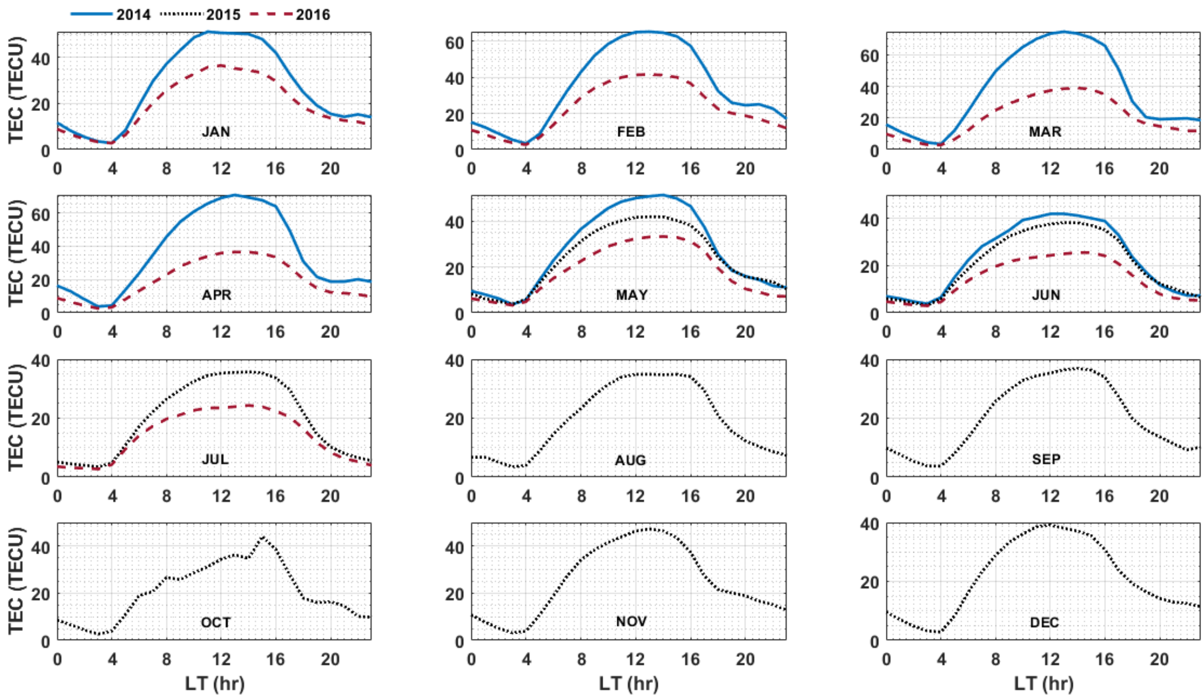

Figure 5: The diurnal monthly variation of TEC between 2015 to 2016

Largely due paucity of data, the TEC data for the year 2014 is between January to June, the year 2015 has data between May to December and that is only available between January to July for the year 2016. It is can be seen from figure 5 that there is a general behaviour of TEC across the months. The values of TEC are observed to increase gradually from a pre-sunrise minimum at 0400 LT (~3 to 4 TECU) to a daytime maximum between 1200 and 1400 LT before reducing to a post-noon minimum. The daytime TEC peak from January to June is higher than the months in the years 2015 to 2016. It is also observed that the TEC value during March is higher than the rest of the other months. This is indicating the occurrence of seasonal variation in TEC. The value of TEC during March of 2014 is 75 TECU and 39 TEC for the year 2016 during 1300 LT.

By developing the NN model using the four configurations illustrated in figure 2, the performance of the obtained network was calculated using the mean squared error (MSE) and root mean squared error (RMSE). The MSE is a network performance function. It measures the network’s performance according to the mean of squared errors. The results obtained for the network configurations NN1, NN2, NN3 and NN4 are summarized in tables 1 and 2.

Table 1: MSE for the NN models in TECU

Hidden Layer	NN1	NN2	NN3	NN4
5	20.04	19.43	21.94	18.05
10	18.15	17.11	17.78	15.12
15	17.11	14.41	15.63	13.88
20	17.62	14.01	13.59	13.07
25	16.70	13.75	14.47	12.53
30	13.56	12.25	14.02	14.56
35	16.63	13.10	12.73	11.87
40	**12.97**	12.11	12.32	11.03
45	16.34	**10.79**	**11.33**	**8.68**
50	13.01	11.43	11.50	9.53

Table 2: RMSE for the NN models in TECU

Hidden Layer	NN1	NN2	NN3	NN4
5	4.48	4.41	4.68	4.25
10	4.26	4.14	4.22	3.89
15	4.14	3.80	3.95	3.73
20	4.20	3.74	3.69	3.61
25	4.09	3.71	3.80	3.54
30	3.68	3.50	3.74	3.82
35	4.08	3.62	3.57	3.44
40	**3.60**	3.48	3.51	3.32
45	4.04	**3.28**	**3.37**	**2.95**
50	3.61	3.38	3.39	3.09

It can be seen from the performance result of the NN models given in tables 1 and 2 that the model improves as the number of hidden layers increases. However, the lowest MSE (8.68 TECU) and RMSE (2.95 TECU) are obtained for 45 hidden layers. As a consequence, the model simulation used for the prediction of the TEC values given in figure 6 is based on the obtained optimal hidden layer of 45 with NN4 (figure 2d) model configurations. In figure 6, it can be observed that the simulation of TEC by the NN model (NN4) fairly reproduces the morphology of the observational TEC from the GNSS receiver. The model simulation on the 17th March 2014 can be seen to be close to the observational measurements with an MSE of 12.35 TECU and RMSE value of 3.11 TECU. The daytime peak of GNSS TEC around 1200 LT is 48 TECU while the NN TEC prediction is 52 TEC. The obtained result is similar to that of the simulation of TEC on the 18th of September, 2015. The observed daytime peak of both the GNSS TEC (44 TECU) and the NN TEC (45 TECU) was almost equal but with an hour lag in the observed daytime peak which occurred around 1400 LT for GNSS TEC and 1500 LT for NN TEC. Outside the daytime period, the NN TEC overestimate TEC values during the nighttime and pre-sunrise period and this makes the MSE (7.96 TECU) and RMSE (2.58 TECU) values higher than that of March.

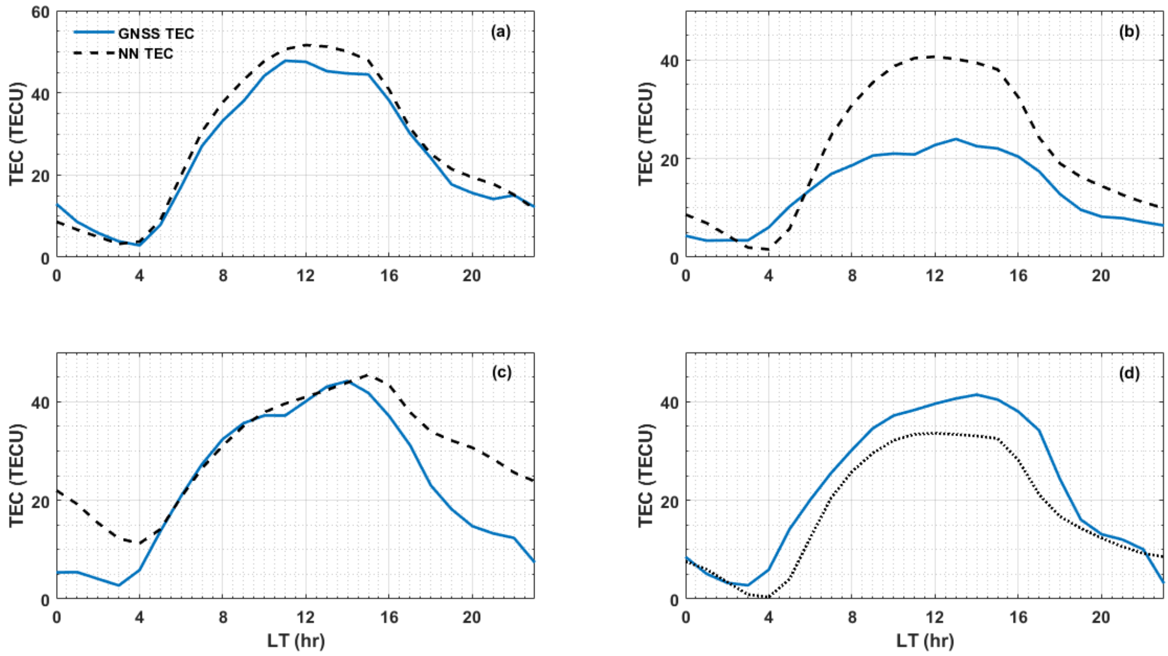

Figure 6: Comparison of observation GNSS TEC value with NN TEC value for some selected days (a)17th March 2014 (b) 6th June 2016 (c) 18th September 2015 and (d) 6th December 2015

For the solstice months, June and December, the NN TEC model overestimates the observational TEC values with greater discrepancies on the 6th of June 2016 with MSE of 15.52 TECU and RMSE of 3.37 TECU.

CONCLUSION

This work shows presented the result of the characterization of TEC over three years from 2014 to 2016. The results indicate the influence of solar activity as a major driver in the modulation of ionospheric electron density as observed on TEC data. It was observed that TEC is highest in the year 2014 as this period falls in the solar maximum of solar cycle 24. Similarly, TEC was highest in the equinoctial month (e.g., March) than in the solstice month. The study also developed neural network (NN) based modelling using four different configurations. It was observed that the fourth configuration (NN4) which has the day number, hour number, sunspot and solar flux index as input was found to perform better than the other three configurations. The model performance was in terms of the estimated MSE and RMSE values. The NN4 model was used to simulate the TEC and compared with the actual measurements from the GNSS receiver installed at Toro. It was observed that the NN TEC model prediction performs fairly with that of the observational TEC and has a closer prediction during the equinoctial days with a considerable error margin. This indicates that the model can be improved by considering the influence of space weather events.

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