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PREDICTION OF TOTAL ELECTRON CONTENT OF THE IONOSPHERE USING NEURAL NETWORK

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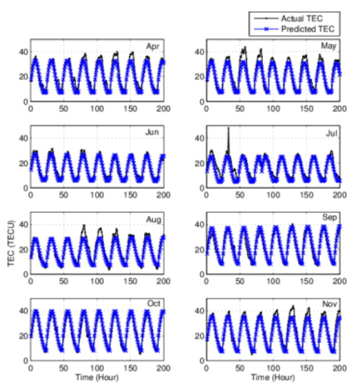
Graphical abstract



Abstract

This paper presents the prediction of hourly Vertical Total Electron Content (VTEC) using a neural network by utilizing the data from a GPS Ionospheric Scintillation and TEC Monitor (GISTM) receiver for six years (from 2005 to 2010) during low to medium solar activity (Sunspot number (SSN) between 0.0 and 42.6). Several network configurations were investigated to observe the effect of the number of neurons, and hidden layers. Overall testing process for several network set-up yielded Root Mean Square Error (RMSE) value of 3 to 7 TECU, absolute error of 2 to 6 TECU and relative error of 8% to 28%. Testing using April 2010 to November 2010 data (SSN from 8.0 to 25.2) produced RMSE value of 2.95 to 3.88 TECU,absolute error of 2.39 to 3.09 TECU and relative error of 8.11% to 16.18%, which are within the acceptable range.

Keywords: Ionospheric propagation; total electron content; artificial neural network

1.0 INTRODUCTION

The Total Electron Content (TEC) is one of the main characteristicsof ionospheric propagation. The electron contents of the ionosphere are affected by several parameters, such as the altitude, location, time of day, season, solar activity, and solar disturbances. These factors, in turn, affect the signal propagations that travel using or through the ionosphere. TEC is defined as the number of free electrons in a unit cross sectional area (m^2) along the ray path; its unit is TEC Unit (TECU) where 1 TECU = 1×10^{16} electrons/m^2. Given that TEC continually varies, forecasting its values in advance is beneficial. The forecasted values can be valuable to radio operators, and navigation and space control systems, especially during disturbed ionospheric conditions.

This study focuses on the capability of a neural network in predicting TEC values. Data from a GPS Ionospheric Scintillation and TEC Monitor (GISTM) receiver installed at Parit Raja, Johor, Malaysia (1°52' N, 103°06’ E) during low to medium solar activity for a period of six years (from 2005 to 2010) were used.

TEC forecasting can be performed using several methods, including neural network models. A neural network is able to learn and later, generalize. Generalization refers to the ability of a neural network to create acceptable outputs for a set of inputs not used during training (learning) [1]. The neural network approach has been applied in TEC modelling using GPS data (including GISTM receivers) at different locations and periods with promising outcomes [2–8].

1.1 Total Electron Content

TEC can be derived from a dual-frequency GISTM receiver.The delay of the transmitted signal from a GPS satellite on L1 (1575.42 MHz) and L2 (1227.60 MHz) is used to measure the electron content along the propagation path as these delays are proportionate to each other. TEC can be determined as follows using a GISTM receiver [9]:

$$TEC = 9.483(PR_{L2} - PR_{L1} - \Delta_{C/A-P,PRN}) + TEC_{RX} + TEC_{CAL} \quad (1)$$

where PR_{L2} and PR_{L1} are the pseudoranges (in meters) for L1 and L2, respectively; $\Delta_{C/A-P,PRN}$ is the input bias between satellite C/A- and P-code chip transitions (meters); TEC_{RX} is the TECcaused by the internalreceiver L1/L2 delay (TECU); and TEC_{CAL} is the user defined TEC offset (TECU).

The GISTM receiver-computed slant TEC (STEC) can be transformed into a vertical TEC (VTEC) by assuming a thin-shell model and a horizontally uniform ionosphere as follows [10]:

$$VTEC = STEC\cos(\chi) \quad (2)$$

where $\cos(\chi)$ is the mapping function given by [10]:

$$\cos(\chi) = \sqrt{1 - \left(\frac{R_E}{R_E + h_{pp}}\cos(E)\right)^2} \quad (3)$$

where χ is the satellite zenith angle at the sub-ionospheric pierce point, R_E is the radius of the earth, E is the satellite elevation angle, and h_{pp} is the height of the sub-ionospheric point.

1.2 Neural Network

In the neural network, interconnected artificial neurons can learn the relationship between input and output when given a sufficient set of data [11]. A neural network consists of input, hidden, and output layers with several numbers of neurons in each layer. Having more than one hidden layer is possible; however, this condition does not contribute significantly to the accuracy of the result [1] although it can help the training process [11]. The training process in the back propagation algorithm of a neural networkinvolves two phases, namely, forward and backward. The input in the forward phase propagates through the layer, whereas the error signal in the backward phase propagates backs through every layer.This training process can be stopped based on several criteria, including the mean squared error (MSE). The back propagation algorithm is assumed to converge when the MSE per iteration is satisfactorily small [1].

In addition, the network is tested for its generalization performance after the iteration of each learning stage is completed. The learning procedure terminates if the generalization performance is satisfactory. The network should be sufficiently trained to properly learn the past and generalize the future [1]. After the network has been trained to learn the relationship between the input and output, it can produce the output in the testing stage when presented with only the input.

The neural network has been used to model radio parameters with non-linear characteristics, such as prediction of solar cycle 23, ionospheric peak electron density at the equatorial anomaly regions, and TEC [2 and the references therein]. TEC forecasting using the neural network method has been previously performed, including the use of data from different locations such as South Africa [2–4], Brazil [5], India [6, 12], Cyprus [7], Malaysia [8], Japan [13], China [14], and the U.K [15].

In Malaysia, previous study on the feasibility of the neural network to predict the TEC has been conducted using limited GISTM data from 2005 only [8], where monthly SSN varied from 8.5 to 41.2. The configuration utilizing December 2005 as the testing data yielded poorer result compared to the configuration using November 2005 as the testing data. This is due to the higher monthly SSN for December 2005 that contributed to the difficulties for the neural network to produce more accurate prediction. Higher SSN corresponds to more active ionosphere, which in turn has greater effect on the radio propagation utilizing the ionospheric layer.

2.0 DATA AND METHODOLOGY

In this work, we used more data covering the period of 2005 to 2010 to include wider range of monthly SSN and more training data. Data were utilized from a GISTM receiver installed at the Wireless and Radio Science (WARAS) Centre, Universiti Tun Hussein Onn Malaysia (UTHM) (1°52' N, 103°06' E). TEC data from 2005 to 2009 were used for the training, whereas 2010 data were used for testing. The input for theneural network was considered from the parameters known to affect the TEC, which include solar activity and both seasonal and diurnal variations. Solar activity was indicated by the monthly sunspot number (SSN).

The monthly SSN from 2005 to 2009 (training data sets) was between 0.0 and 42.6 with an average of 11.71, whereas the monthly SSN for 2010 (testing data sets) was between 8.0 and 25.2 with an average of 17.03. These values are considered as low to medium solar activity. A total of 38,078 data were used in training, and another 4,478 data in testing. All data were checked for outliers, which have been eliminated.

The seasonal and diurnal variations are represented by four components [2]:

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

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

$$HRS = \sin\left(\frac{2\pi \times HR}{24}\right) \quad (6)$$

$$HRC = \cos\left(\frac{2\pi \times HR}{24}\right) \quad (7)$$

where *DNS*, *DNC*, *HRS* and *HRC* are the sine and cosine components of day number (*DN*) and hour of the day (*HR*), respectively.

The output of the neural network was the hourly Vertical TEC (VTEC) acquired from the GISTM receiver.A feed forward neural network with the back propagation algorithm was selected for this study. We applied one and two hidden layers to observe the network performance based on the hidden layer.Several different numbers of neurons were also applied on each hidden layer to observe the effect of neurons selection to the neural network capability to predict a valid output. The Levenberg–Marquardt algorithm ("trainlm") was selected as the training function because of its fast processing, although it requires more memory compared with other algorithms.

New unseen data, which were different than those in the training process, were applied to the neural network in the testing process. All of the parameters of the trained network were saved and later applied to the testing phase. The root mean square error (RMSE) was selected as an indicator for successful testing. In addition, the absolute error, $|\alpha|$, can be calculated as follows [5]:

$$|\alpha| = |VTEC_e - VTEC| \quad (8)$$

where *VTEC* is the value computed from the GISTM receiver and $VTEC_e$ represents the value predicted by the neural network.

The relative error, ε, can also be established as follows [5]:

$$\varepsilon = \frac{|\alpha|}{VTEC} \times 100 \quad (9)$$

In addition, the coefficient of correlation, *R*, can also signify the relationship between the actual output and output produced by the neural network.

3.0 RESULTS AND DISCUSSION

The outcomes from the training process were saved, and then applied to the testing process. Table 1 shows the result of the testing process for the data from 2010 using several network configurations by adding neurons and hidden layers. Neural network capability was tested on each month from April 2010 to November 2010. The monthly SSN varied from 8.0 to 25.2 for these months. These results indicate that adding more neurons did not provide better RMSE, as well as both the absolute and the relative errors. The highest number of neurons of 30 only managed to produce the worst RMSE and errors, both in one-and two-hidden-layer configurations, after several trials.

Having more than one hidden layer also did not necessarily help the accuracy of the neural network. The RMSE and errors were mostly higher in a two-hidden-layer configuration. Certain options of number of neurons also took longer time to train and only resulted in higher RMSE in the testing process.

Considering all network configurations, the RMSE range was 3 to 7 TECU, the absolute error was 2 to 6 TECU, the relative error was 8% to 28%, and the coefficient of correlation, *R* was 0.87 to 0.98. The results were in agreement with other works. An RMSE of ~4 TECU was observed in South African stations, which was higher depending on the time of the day [3]. Earlier work utilizing smaller set of data for 2005 only from the same station (WARAS Centre) yielded RMSE values of 3 to 5 TECU, absolute error of 2 to 4 TECU, and relative error of 9% to 16% [8].

Table 2 shows the absolute and relative errors, and the coefficient of correlation for each month (April 2010 to November 2010) using 5 neurons in the hidden layer. Given that the monthly SSN for all the months in 2010 did not differ significantly (SSN from 8.0 to 25.2),the neural network is able to provide a suitable match between the actual and the predicted TEC. Testing process produced RMSE value of 2.95 to 3.88 TECU, absolute error of 2.39 to 3.09 TECU, relative error of 8.11% to 16.18% and the coefficient of correlation was 0.93 to 0.97, which are within the acceptable range. This scenario is also shown in Figure 1, where a comparison between these values is presented for the first 200 hours in each tested month.

A neural network can produce outputs similar to the actual ones in most cases. Neural networks have difficulties in providing suitable approximation during periods of high solar activity [5].

Table 1 Testing results using different network configurations

No. of neuron in hidden layer(s)	Testing Results			
	RMSE (TECU)	Absolute error (TECU)	Relative error (%)	Coefficient of correlation, R
5	2.95–3.88	2.40–3.09	8.1–16.2	0.93–0.97
10	3.00–4.86	2.42–4.16	8.4–17.5	0.92–0.97
15	3.16–4.79	2.58–4.06	10.0–20.2	0.92–0.98
20	2.79–4.53	2.26–3.79	10.2–15.6	0.93–0.97
30	2.61–5.21	2.02–4.24	8.4–18.9	0.87–0.98
[5, 1]	3.19–4.12	2.53–3.35	9.6–16.0	0.93–0.97
[10, 1]	2.84–4.70	2.33–3.76	7.3–20.4	0.89–0.98
[15, 1]	2.99–4.87	2.41–4.07	11.4–17.9	0.93–0.98
[20, 1]	2.58–5.23	2.08–4.34	6.6–19.6	0.93–0.98
[30, 1]	3.01–6.24	2.25–5.50	9.0–27.8	0.93–0.98
[15, 5]	3.11–4.87	2.53–4.04	11.7–16.4	0.93–0.98
[30, 5]	2.86–6.64	2.35–5.95	8.01–24.6	0.91–0.97

Table 2 Testing results for April 2010 to November 2010 using 5 neurons in the hidden layer

Month	Monthly SSN	Testing Results			
		RMSE (TECU)	Absolute error (TECU)	Relative error (%)	Coefficient of correlation, R
Apr	8.0	3.88	3.05	13.07	0.95
May	8.7	3.54	2.57	13.92	0.94
Jun	13.6	3.19	2.61	14.06	0.94
Jul	16.1	3.85	3.09	16.18	0.93
Aug	19.6	3.59	2.80	12.70	0.94
Sep	25.2	3.07	2.41	8.42	0.96
Oct	23.5	2.95	2.39	8.11	0.97
Nov	21.5	3.69	2.93	12.41	0.96

4.0 CONCLUSION

This study focused on the capability of a neural network in TEC value prediction during low to medium solar activity using data from 2005 to 2010 for a single station.The results indicated that the neural network can be a suitable tool for predicting TEC values. Acceptable RMSE, absolute and relative errors, and coefficient of correlation were obtained in certain network configurations. It is also found that adding more neurons and hidden layer has little effect on the ability of the neural network to provide good prediction. Overall testing yielded RMSE range was 3 to 7 TECU, the absolute error was 2 to 6 TECU, the relative error was 8% to 28%, and the coefficient of correlation, *R* was 0.87 to 0.98. Testing process using data from April 2010 to November 2010 (SSN from 8.0 to 25.2) produced RMSE value of 2.95 to 3.88 TECU, absolute error of 2.39 to 3.09

TECU, relative error of 8.11% to 16.18% and the coefficient of correlation was 0.93 to 0.97. These are within the acceptable range and in agreement with the findings in other works.

This work shows the ability of neural network in predicting the electron content which will be useful to the radio operators or navigators in order to know the condition of the ionosphere in advance. Future work will involve more training and testing data covering a wider range of solar activities.

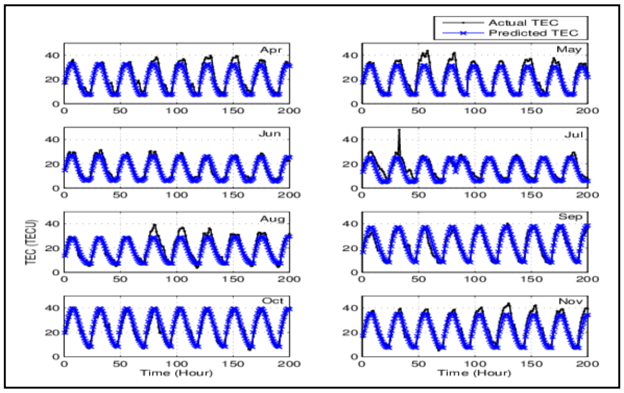


Figure 1 Comparison between the actual and predicted VTEC values using five neurons in the hidden layer. Only the first 200 hours of the TEC values are shown in each month

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