A Deep Learning-Based Approach to Forecast Ionospheric Delays for GPS Signals

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***Abstract*— This letter proposes the implementation of ionospheric forecasting model based on the long short-term memory (LSTM) networks. Ionospheric region produces time delay for radio wave propagation of global positioning system (GPS) satellites. The ionospheric delays for GPS signals degrade the position accuracy in the measurements for precise navigation and positioning services. Utilizing the emerging artificial intelligence mathematical tools to forecast ionospheric disturbances using GPS-estimated total electron content (TEC) observations is decisive. In this letter, multi-input LSTM forecasting technique is investigated and tested for evaluating its capability in forecasting the ionospheric delays over Bengaluru station (16.26° N, 80.44° E) using eight years (2009–2016) of GPS measured vertical TEC (VTEC) time-series data. The assessment of the LSTM model performance during geomagnetic quiet and disturbed conditions is carried out in comparison with artificial neural networks model and International Reference Ionosphere (IRI-2016) model based on statistical parameters like root-mean-square error and coefficient of determination (R^2). The experimental analysis delineates that the proposed LSTM model has provided the correlation of 0.99 with the GPS-measured VTEC and with a forecasting error of 1–2 TEC units.**

***Index Terms*— Deep learning, forecast, Global Navigation Satellite System, ionospheric delays, long short-term memory (LSTM) model.**

I. Introduction

GLOBAL positioning system (GPS) is a satellite-based navigation system providing navigation, positioning, and timing ability to surveying, mapping, military, automatic vehicle monitoring, space navigation, and emergency services including societal applications [1]. The major problem in many of the GPS services is inaccuracy due to ionospheric radio wave propagation effects on GPS signals [2], [3]. Ionospheric time delay variations are directly proportional to total electron content (TEC). Vertical TEC (VTEC) is a key parameter for the range error analysis in GPS signals. The ionospheric ionization produced by electromagnetic and particle radiation originating from the sun influence the GPS radio waves. The complicated structures of ionospheric space weather due to various physical and chemical compositions/factors challenge the modern technological infrastructures to model and predict them [4]. The measurements from GPS provide investigating the ionospheric space weather effects along with navigation and positioning services.

International Reference Ionosphere (IRI) and Klobuchar models are mostly used global climatological models in comparison with the GPS-measured VTEC values [5]. However, modeling and forecasting of ionospheric delays for GPS signals using new techniques would be of utmost emergency requirement to improve the GPS services for critical life safety applications [6], [7]. The spatial and temporal ionospheric TEC variations during geomagnetic quiet and disturbed conditions over the low-latitude GPS stations are difficult to model and predict due to dynamic behavior of ionosphere ascribed to equatorial ionization anomaly [8]. In order to ensure successful radio communications, it is required to monitor the variability of temporal and spatial ionospheric characteristics along the path of radio waves.

Holt–Winter method [9] and auto-regressive moving average model [10] are applied for short-term TEC time-series forecast during different geomagnetic conditions. However, these stationary time-series models consider the trend in the given input TEC time series which could not be suitable to forecast the nonstationary patterns/fluctuations present in ionospheric TEC. Thus, artificial neural networks are used further, in order to consider the space weather and geomagnetic factors that influence the variations in the nonstationary patterns of ionospheric TEC. Neural network (NN) models are mostly used for modeling and forecasting of ionospheric TEC variations using the GPS measured TEC time series [11]–[13]. Even though, NNs outperform the statistical methods, the requirement of large input training data set with more number of TEC samples, complexity in adjusting the synaptic weights during the training process, and lack of standard mathematical background that limits the application of NN model for short-term TEC forecast [14], [15]. Apart from those models, various researchers have developed different machine learning approaches to model/forecast ionospheric TEC as they are capable in extracting the information to reveal ionospheric features through exploring the unknown relations between the input and output parameters [16]. However, these models are not well suited for long-term TEC forecasting. In contrast, deep neural network (DNN) model delivers sustained level of accuracy even with a greater number of TEC samples with no prior knowledge of TEC influencing parameters. Forecasting capabilities of deep learning is successfully tested in various fields such as image processing for classification of land cover

Manuscript received October 27, 2018; revised December 22, 2018; accepted January 18, 2019. Date of publication February 11, 2019; date of current version July 18, 2019. The work of D. V. Ratnam was supported by the Department of Science and Technology, New Delhi, India, through the SR/FST/ESI-130/2013(C) FIST Program and Science and Engineering Research Board, Government of India, ECR Scheme ref No. ECR/2015/000410. *(Corresponding author: D. Venkata Ratnam.)*

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Digital Object Identifier 10.1109/LGRS.2019.2895112

and crop types [17], and short-term prediction of sea surface temperature [18]. Cherrier *et al.* [19] and Cherrier and Boulch [20] have proposed the DNN forecast model to estimate the global TEC map with an input of past TEC maps sequentially. Deep learning technique consists of three competing models: 1) feed forward NNs; 2) recurrent NNs; and 3) long short-term memory (LSTM) networks. Feed forward neural networks (FNN) are tending to be straightforward networks, i.e., only in one way from input through hidden layer to output and there is no feedback (loops). It has no memory of previously received information. So, this networks only considers the current input but cannot remember anything about past except their training. FNN will not be able to read functions that depend on input TEC occurring long time ago. Therefore, FNN is used only to train short-term data [25]. Recurrent neural network (RNN) has solved this problem. Tianjiao *et al.* [21] have established the deep learning RNN-based 24 h ahead forecasting model for ionospheric TEC. However, RNN suffers from vanishing gradient and exploding gradient problems due to which the range of input TEC values is limited, and algorithm circulates around the hidden states only. It is difficult to train the standard RNN on the requirement of learning the information from long-term TEC as input, whereas LSTMs are normally extending their memory and an extension of RNN. Thus, LSTM can fully exploits the benefit of training long-period TEC time series in which self-connected hidden units are replaced by memory blocks [22]. In this letter, LSTM model is implemented to process long period of TEC sequential data during the 24th solar cycle.

This letter is organized as follows. First, the methodology of LSTM is discussed. Later, the performance of the proposed LSTM TEC model is evaluated during the testing period of 2016 by considering all the seasons and both geomagnetic quiet and disturbed conditions in 2016. The performance of LSTM model is compared with NN and IRI (IRI-2016) model. The statistical error analysis parameters such as root-mean-square error (RMSE) and coefficient of determination (R^2) are discussed. Finally, this letter is concluded with future scope.

II. Theory

A. Long Short-Term Memory TEC Model

The proposed LSTM architecture contains the following layers: input layers, LSTM layers, hidden layers, and output layers, as depicted in Fig. 1. LSTM networks are extended RNNs which consists of extended memory cells known as gated cells that makes to remember the inputs for long period of time. The information in the memory of LSTM gated cell can be stored or deleted which could be decided by weights/importance assigned by the given algorithm, i.e., it learns the importance of information over time. The connection from present layer output to next layer input indicates the recursive nature of the cell. This allows information from previous intervals to be stored with in the LSTM cell. There are three main gates in LSTM block such as input gate, forget gate, and output gate. Input gate determines whether or not to let in new input. Forget gate decides whether to delete the information that is not useful. If the output of forget gate is 1, the information is kept in the cell state and closer to 0 indicated to forget. Output gate decides to let the input from forget gate to impact the output at the current time step and it determines how much of each unit's activation is preserved. Using the specific RNN architecture, LSTM was designed to model sequential data that includes temporal variations and along with their long-term dependencies [18], [22].

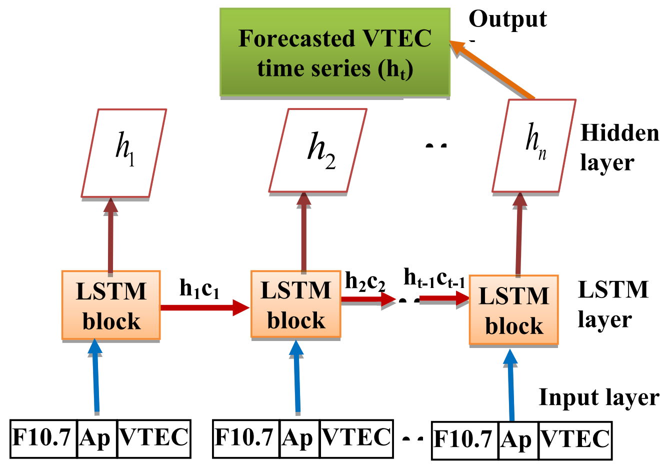

Fig. 1. LSTM network architecture.

The methodology of the proposed system consists of various stages like collecting raw data, data preprocessing, feature extraction, and training NN. LSTM block has two activation functions such as sigmoid and "tanh." Sigmoid function decides required information to be updated and alone it will only add memory but not be able to remove/forget memory. "tanh" regulates the values flowing through the network and allows the cell sate to forget memory [18], [22].

Let i_t, o_t, f_t represent the activations of input–output, and forget gates, respectively, at time step t. Let given input sequence/time series of ionospheric VTEC estimated from GPS measurements is $x_t = (x_1, x_2, x_{3,} \ldots x_n)$, h_t refers to the hidden state vector given by $h_t = (h_1, h_2, h_3, \ldots h_n)$, and c_t is the cell memory which represents $c_t = (c_{1,} c_{2,} c_{3,} \ldots c_n)$. LSTM calculates the output vector for each input x_t by using the iteration for $t = 1$ to n where $n = 24$ h. It is to be noted that h_t persist information from previous step's hidden state h_{t-1} and thus, this algorithm can make use of all previous VTEC values of time series. Initially, before the learning rule is applied, x_1 is given as input to the network with no previous information. At every time step, the learning rule is applied by forwarding the previous trained information to each layer and allowing it to perform sequence prediction. h_t is the output of current LSTM network which is forecasted VTEC data. The output is based on the cell state c_t but it will be filtered version. So, activation function is used like "tanh" to our cell state c_t. The current cell output h_t is as follows [18], [22]:

$$h_t = o_t \tanh(c_t). \tag{1}$$

New memory (c_t) and current output (h_t) are given to next time step and this process repeats. The detailed description of the algorithm is explained in [18] and [22].

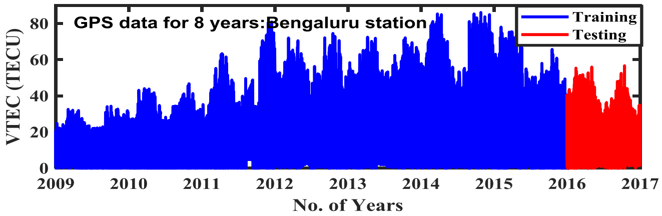

Fig. 2. Experimental data for deep learning forecasting using LSTM TEC model to test descending phase.

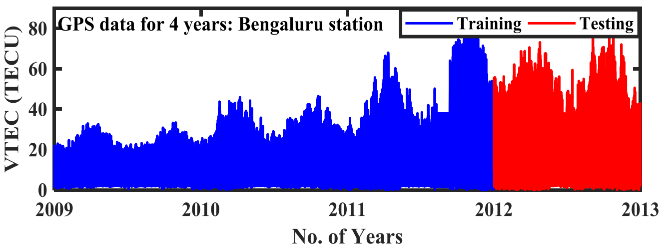

Fig. 3. Experimental data for deep learning forecasting using LSTM TEC model to test ascending phase.

III. Results and Discussion

The experimental VTEC data are obtained from the Bengaluru IGS (International GNSS Service) station (geographic 16.26° N, 80.44° E), Bengaluru, India, for the hourly values of all days for eight years (2009–2016). The GPS VTEC is collected from Scripps Orbit and Permanent Array Center for every 30 s in the form of receiver independent exchange format (RINEX) files [27]. The resulting RINEX files are processed in the GPS TEC analysis software which is developed by Seemala [26]. A single-layer approximation is adopted to convert STEC into VTEC values, where ionospheric pierce point is considered at an altitude of 300 km above the earth's surface [23]. The mean of VTEC values are calculated for each hour from all visible GNSS satellites. Deep learning LSTM model is implemented for forecasting VTEC time series and to evaluate its performance as discussed its methodology in Section-II.

Fig. 2 depicts VTEC data collected during 2009 to 2015 which is used as training period (blue) and 2016 as testing period (red). The impact of ascending phase of 24th solar cycle can be observed from GPS measured VTEC values shown in Fig. 2 during 2009–2015. It is observed that the VTEC values are very low during 2016, as it indicates the impact of the descending phase of 24th solar cycle on ionospheric TEC variations. Therefore, LSTM TEC model has trained with the VTEC values during ascending phase of solar cycle and tested its performance during descending phase of current solar cycle (2016). Afterward, we have analyzed the model using descending phase (2009–2011) as training data and tested during ascending phase (2012); it shows that the model has RMSE of 3.6 TEC units (TECU) due to limited amount of training set which is shown in Fig. 3.

The performance of the proposed LSTM TEC model is tested in three cases: 1) during geomagnetic quiet and disturbed days; 2) during various seasons of 2016; and 3) during the complete year (2016). LSTM model and NN model are

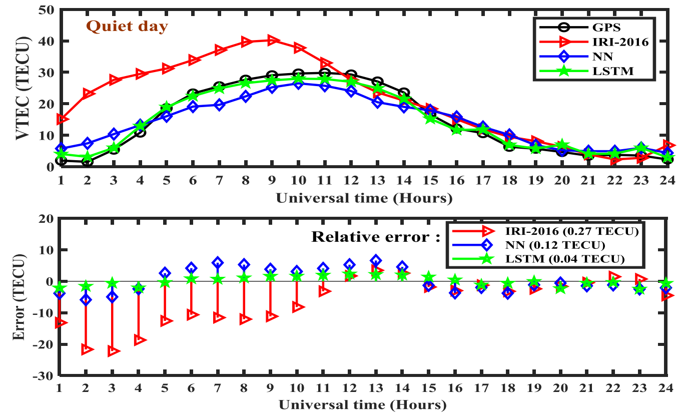

Fig. 4. (Top) Performance of the LSTM TEC model, NN model, and IRI-2016 model and (Bottom) its forecasting errors during geomagnetic quiet day November 19, 2016.

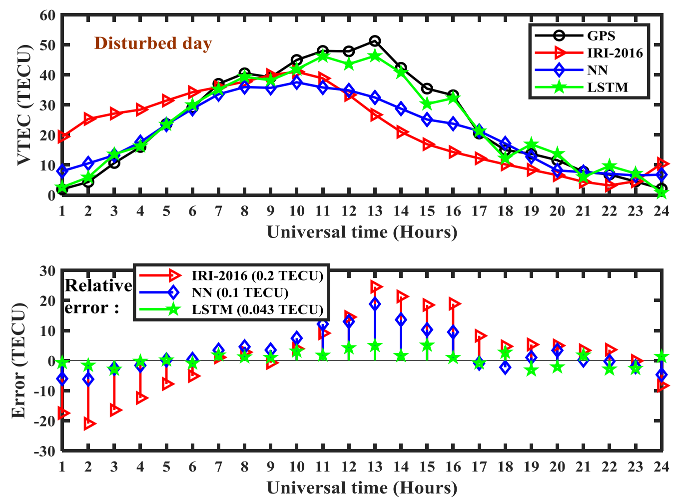

Fig. 5. (Top) Performance of the LSTM TEC model, NN model, and IRI-2016 model and (Bottom) its forecasting errors during geomagnetic disturbed day May 8, 2016.

trained with the inputs of VTEC data, solar flux (F10.7), and geomagnetic activity Ap index parameters. IRI-2016 modeled VTEC values are obtained from www.irimodel.org.

According to the information provided by the National Oceanic and Atmospheric Administration website [28] for 2016, one of the typical quiet day and the disturbed day TEC patterns are listed as November 19 and May 8, respectively. The plots between VTEC modeled and estimated values over GPS station are shown in Fig. 4 (top), and the error analysis of forecasting models with relative errors is shown in Fig. 4 (bottom), during geomagnetic quiet day November 19, 2016. It can be observed that IRI-2016 model overestimates the actual GPS measured VTEC values during all the UT hours of the day except 12–14 UT h, whereas NN model underestimates at peak hours and overestimates at dawn and dusk hours. In contrast, LSTM TEC model has well followed the VTEC patterns for each hour with very less deviations as observed from Fig. 4 (top).

LSTM model has shown few TECU (1–2) of error compared to NN and IRI-2016 model as observed from Fig. 4 (bottom) during geomagnetic quiet day November 19, 2016.

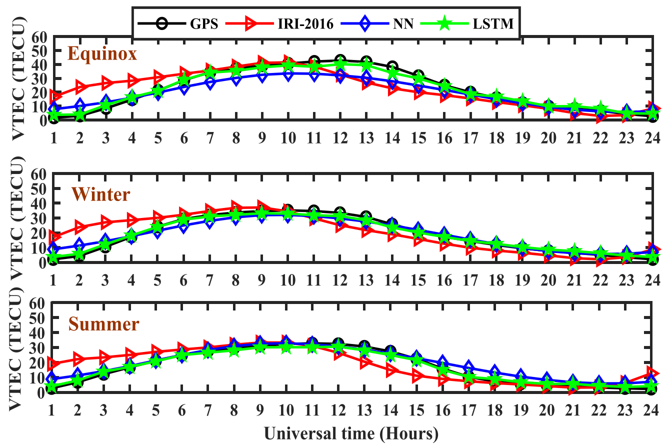

Fig. 6. Seasonal variations, i.e., (Top) equinox, (Middle) winter, and (Bottom) summer of GPS-measured VTEC and forecasted VTEC using LSTM TEC model, NN model, and IRI-2016 model.

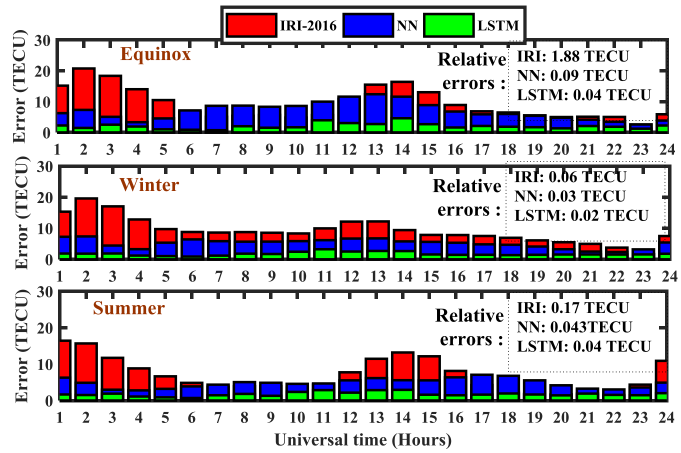

Fig. 7. RMSE bar plots for (Top) equinox, (Middle) winter, and (Bottom) summer to forecast TEC using LSTM, NN, and IRI-2016 models.

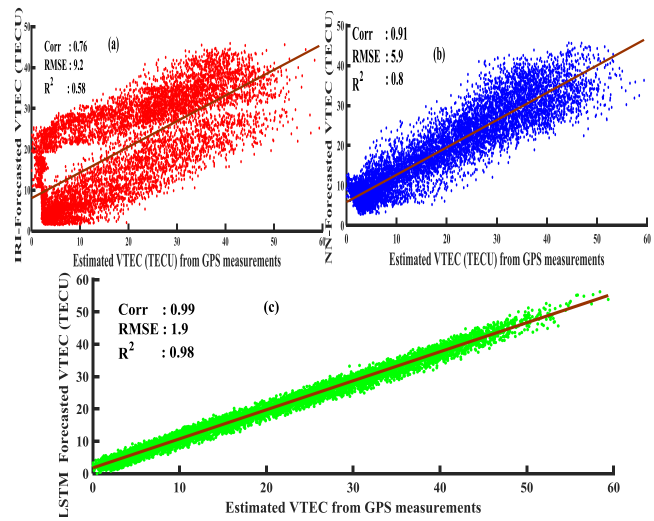

Fig. 8. Scatterplots of GPS measured VTEC versus (a) IRI-2016 model, (b) NN model, and (c) LSTM TEC model during 2016.

TABLE I

ERROR ANALYSIS FOR LSTM ON DIFFERENT SETS OF TRAINING PERIODS FOR TESTING YEAR 2016 AT BENGALURU GPS STATION

LSTM model training data	RMSE (TECU)	MAE (TECU)	MSD (TECU)	MAPE (TECU)	Relative error (TECU)
7 years data	1.9	1.5	3.8	23.7	0.042
6 years data	2.5	2.1	6.7	30.1	0.047
5 years data	3.1	2.8	9.9	31.2	0.05
4 years data	4.2	3.4	18.4	46.2	0.08

It is observed that maximum GPS VTEC value of 30 TECU during quiet day [Fig. 4 (top)] and maximum GPS VTEC data are observed as 50 TECU during disturbed day with steep raise up to peak hour and sudden fall during dusk hours as seen from Fig. 5 (top). Here, in this event, LSTM gives satisfactory response by capturing these changes mostly at peak and post sunset hours on disturbed day (May 8, 2016). The deviations between VTEC forecasted by NN and IRI-2016 models are noticed [Fig. 5 (top)]. The error analysis during disturbed day is presented in Fig. 5 (bottom). It is evident that IRI-2016 model gives poor result compared to NN and LSTM models. IRI model did not respond well to the arrival of storms and exhibit higher deviations from GPS observations [24]. However, LSTM is better forecasting the disturbed VTEC during peak hours including; its performance is relatively affected during geomagnetic disturbed day which is observed in error analysis, as shown in Fig. 5.

Furthermore, to evaluate the forecasting models in capturing the seasonal variations in VTEC values, hourly mean values of VTEC were calculated in three seasons (equinox, winter, and summer). In Fig. 6, the GPS measured VTEC reached maximum in equinox season (March, April, September, and October) (top) compared to winter (January, February, November, and December) (middle) and summer (May, June, July, and August) (bottom). The variations in GPS-measured VTEC are minimal in all seasons between 0:00 and 05:00 UT h, and 19:00 and 24:00 UT h and maximum at noon time between 11:00 and 13:00 UT h. IRI-2016 model is overestimating during dawn hours and underestimating during peak hours to dusk hours (Fig. 6). However, NN model performs better than IRI-2016 model. LSTM is well following the seasonal patterns of GPS-measured VTEC values in the seasons, which is evident from the RMSE bar plots shown in Fig. 7. It is evident from relative forecasting error analysis results [Figs. 4 (bottom), 5 (bottom), and 7] that LSTM model performance is better compared to other models.

Fig. 8 shows the scatterplots that compares the hourly values of GPS-measured VTEC with the forecasted VTEC values using IRI-2016 model (top left), NN model (top right), and LSTM TEC model (bottom) in 2016. It can be observed that the proposed model LSTM outperforms the remaining models. It is evident from Fig. 8 is that forecasted VTEC values of LSTM are suitably correlated with ionospheric TEC values measured from GPS observations with correlation coefficient of 0.99, RMSE of 1.9, and R^2 value of 0.98. It is found that IRI and NN models having less correlation coefficient, R^2 values, and more RMSE compared to LSTM forecasting model, as shown in Fig. 8.

Table I shows the performance of LSTM model for different training sets. From results, it is clearly evident that RMSE error increases as training data set size decreases, because the decreasing number of years in training data for prediction can be highly inconsistent with day to day, seasonal, and semiseasonal variations.

IV. Conclusion

In this letter, it is examined that the performance of LSTM deep learning method outperforms the existing ionospheric forecasting methods. LSTM helps in forecasting the ionospheric time delays for GPS signals accurately. The performance of the LSTM TEC model is compared with NN and IRI-2016 models during 2016 testing period over low-latitude GNSS station, i.e., Bengaluru IGS station. The forecasting capabilities of the LSTM TEC model are tested to capture solar effects on the ionospheric TEC variations during geomagnetic quiet and disturbed conditions besides seasonal effects. It is evident from the experimental forecasting results from eight years of data during 24th solar cycle that LSTM is well suitable deep learning technique with high correlation coefficient of 0.99 and coefficient of determination ($R^2 = 0.98$) with less RMSE (1.9 TECU) values. Thus, LSTM TEC model is a suitable forecast model to capture the VTEC variations corresponding to the solar and geomagnetic activity effects. In future, LSTM performance will be tested at different geographical regions of ionospheric TEC data.

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