Short Term Prediction of Ionospheric Total Electron Content (TEC) based on Solar and Geomagnetic Data

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Abstract—Deep learning algorithm are useful for investigation of ionospheric weather using past ionospheric data under various space weather conditions. The Total electron content (TEC) is an important parameter of the ionosphere and prediction of TEC are very challenging task, mainly in anomaly crest station. This research develops and analyzes a technique based on long short-term memory (LSTM) neural network (NN) for the short-term ionospheric TEC prediction. In this work, multi-input LSTM forecasting technique is utilized and tested for evaluating its capability in prediction of ionspheric TEC over Lhasa, China station (Longitude: 91.10397200 , Latitude : 29.65734166) using vertical Total Electron Content (TEC_V) with Solar and Geomagnetic time series data. The results were then compared with the observed TEC collected by the IGS network. The result shows that the model could recognize the variation trend of typical TEC profile and have a good performance of the short term ionospheric TEC prediction.

Keywords— Total Electron Content (TEC), LSTM, Neural Network

1. Introduction:

Prediction of space weather and the solar-terrestrial relationship is necessary for scientific and economic purposes and it has been under investigation for a long time. Prediction of ionospheric variability is one of the important parameters for the study of space weather. The ionospheric total electron content (TEC) is important in the study of ionospheric varaibilty (Goodman, 1992). Actual Prediction of TEC is very much challenging for Earth- and space based systems like positioning of satellite and remote sensing applications (Belehaki et al, 2009; Samardjiev, 1993). In general TEC is an important parameter for ionospheric description and has lots of practical applications like Satelite navigation, civil aircraft landing, missile guidance application, time delay, range error correction for GPS satellite signal receivers (Bhyuan and Borah, 2007). Inospheric parameters like electron density, Total Electron Content (TEC) describe the condition of ionosphere, which show regular diurnal and seasonal variations as a function of altitude and geomagnetic conditions. One of the major indications of magnetosphere –ionosphere coupling is the significant variations of electron density during a storm.(Buonsanto 1999; Danilov 2001). It is observed that, from the study of Total Electron Content (TEC) we can characterized the of ionospheric variations during geomagnetic storms (Jakowski 1996, Lu, Richmond & Roble 1998). Deep learning algorithms are considered to be a second-generation NNs (Hinton & Salakhutdinov, 2006) and may be applied to better model prediction and variations in ionospheric TEC (Orus Perez, 2019).

Hochreiter and Schmidhuber(1997) developed a model which is very popular in the field of deep-learning known as a long short-term memory NN (LSTM NN). For analysis of Time series data the model have been developed. This LSTM NN model is used to perform short-term regional ionospheric TEC prediction. In the variations of ionospheric TEC, solar and geomagnetic parameters play significant roles. Realistic solar irradiance and geomagnetic activity index are also needed for accurate prediction of TEC. Therefore Multiple input data, including historical time series of TEC, disturbance storm time (Dst) index, geomagnetic Kp, Ap , Solar flux F10.7 and hour of the day, are used in the developed of LSTM NN model.

2. Analysis and techniques

2.1 Data Collection and Pre-Processing

The TEC data of dual frequency GPS receiver's data from Lhasa China station is obtained from IGS network stations. TEC derived from GPS receivers are used for predicting the future TEC values.

Gopi Seemla ,GPS-TEC processing software was used to processing of GPS data. The software allows to extract the vertical TEC from GPS measurements. The software also reads raw data, processed the cycle slips and reads satellite biases from International GNSS service. It also calculates receiver bias, and calculates the inter channel biases for different satellites in the receiver and then calculates the slant TEC (TEC_S) along the path of the GPS signal using the following equation :

$$TECs = \frac{1}{40.3}\left(\frac{f_1^2 f_2^2}{f_1^2 - f_2^2}\right)(P_1 - P_2)$$

In the above equation, on L1and L2 signals, P1 and P2 are pseudo ranges observable and f1 is the high GPS frequency and f2 is low GPS frequency. Then using the mapping function M(e), TEC_S measured at an interval of 10 s were converted to TEC_V ,which takes the curvature of the Earth into account (Shim 2009) as follows:

$$TEcv = M(e) \times TECs - (b_s + b_r + b_{rx})$$

Where b_s is satellite bias, b_r is a receiver bias and b_{rx} is a receiver inter channel bias, and

$$M(e) = \left[1 - \left(\frac{\cos(e)}{1 + h/R_E}\right)^2\right]^{\frac{1}{2}}$$

Where e is an elevation angle of a satellite, h is ionospheric shell height and R_E is the Earth's mean radius. To ensure the data used have no undesirable errors which might result from the effect of multipath, a minimum elevation angle of 30° was used.

2.2 Algorithm Selection

Hochreiter (1991) and Bengio et al. (1994) underlined a weakness of RNN which is the vanishing gradient problem occurring during the training phase of RNN. LSTM are designed to avoid this problem depending upon the characteristics and relations between the input data different features are extracted using deep learning algorithm. The parametric algorithm like LSTM NN is used to prediction of TEC, because NN increase the number of neurons to reduce the error would give maximum accuracy. The data set is categorized into Training set ,Testing and validated using classification categories of probabilistic root Mean Square Error (RMSE) to check the performance of the model.

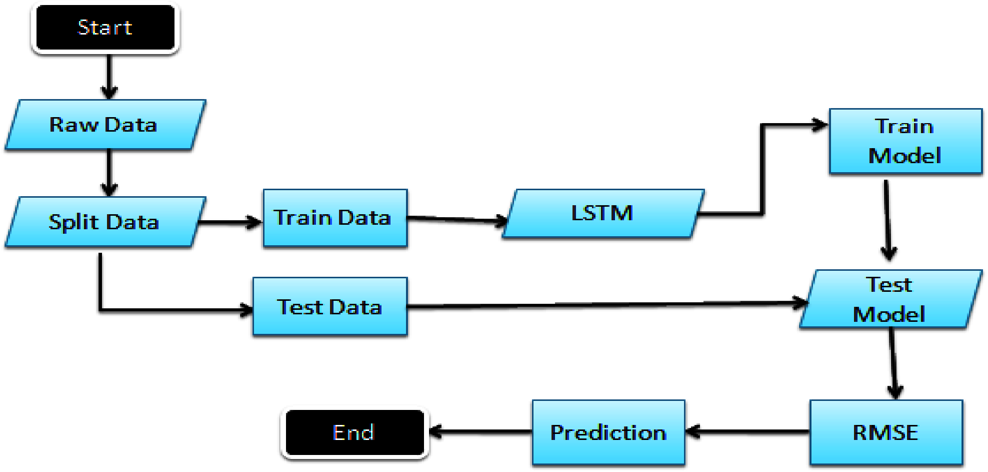

Figure 1. LSTM NN algorithm workflow

2.3 LSTM NN model:

Models based on LSTM neural networks and Deep learning is seeing a rise in popularity in space physics. In particular, prediction and the forecasting of TEC and geomagnetic indices with LSTM neural network models is becoming a popular field of study. In this work, LSTM modeling the data are first split into a training, test and validation set. Using scaling parameters each training, test and validation set is scaled and normalized. A sliding window is used for removal of invalid measurements. Before assigning entries to one of the data sets, the data are split into daily samples and hourly samples which are highly correlated and causes the model to artificially perform better on the test set. Then the data set is fit into the LSTM model, train and tests the model and calculated RMSE to check the performance of the model and predict the vertical TEC as an output.

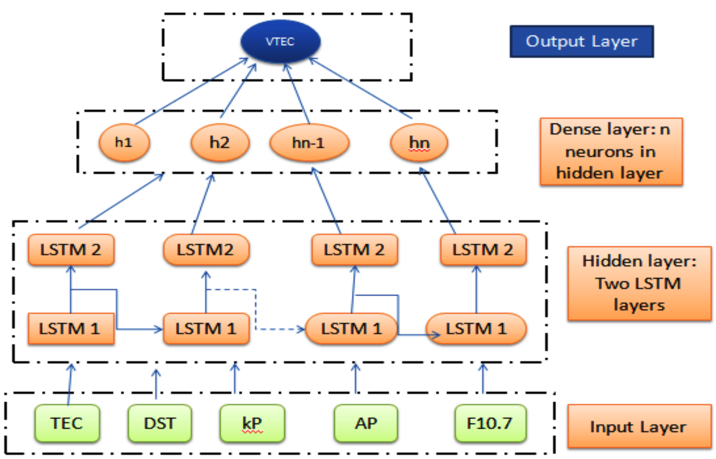

Figure 2. Architecture of LSTM nueral network for TEC prediction

The neural network model's architecture consists of an LSTM combined with a dense neural network; LSTMs are a type of recurrent neural network in which the previous iteration's output is used as an additional input.. In the model, the LSTM has a few hyper parameters that have impact on its performance. First is the number of neurons in the LSTM hidden layer and .second is the number of layers in the LSTM. Two LSTM's layers are applied on top of each other. The first LSTM gives the intermediate hidden states as input for the second LSTM, and so on. In the input layer, the input time span is set to 24 hr and in the hidden layer, two LSTM layers are used to extract their features from the input data and then are connected to the complete hidden layer. In the output layer, the output parameters are the vertical Total Electron Content.

3. Results and discussion:

In this work vertical TEC trend of quiet day is presented in the figure 1and 2 . Disturb day is presented in figure3. It is observed from the figures that, time series of TEC data showing diurnal behavior. This time series of TEC, Solar and Geomagnetic data are applied to the LSTM model for prediction of ionospheric TEC values. The predicted values are compared with actual TEC values to determine the accuracy of the prediction.

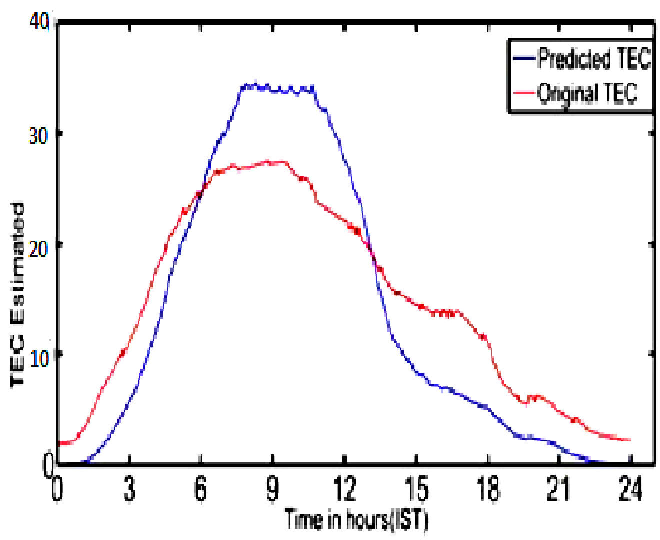

Figure 1. An hourly comparison of GPS TEC and predicted TEC for 16th January 2017 on Quiet day

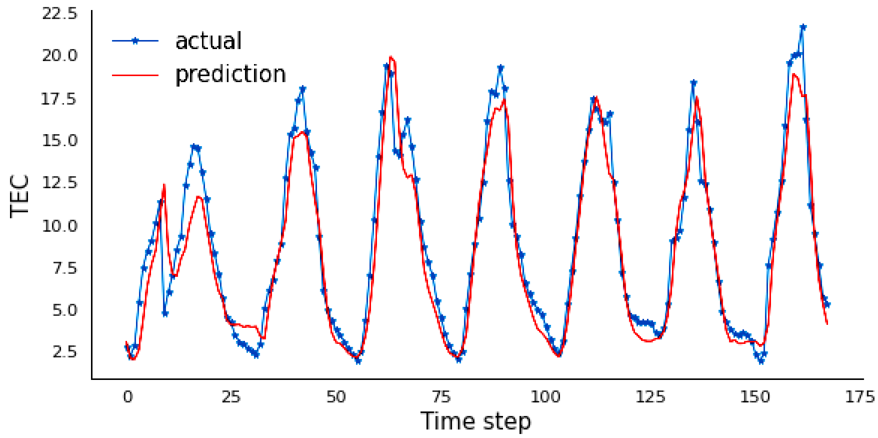

Figure 2. An hourly comparison of GPS TEC and predicted TEC from 1-7 January 2017 On Quiet day

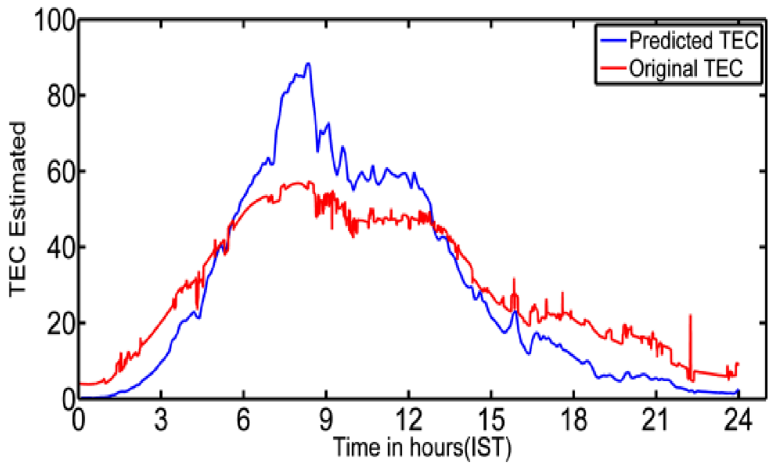

Figure 3. An hourly comparison of GPS TEC and predicted TEC for 28th May 2017 on Disturb day

The performance of LSTM model is investigated on a quiet day 16th January 2017 and continuous hourly comparison of 7 days of January 2017 on quit days and disturbed day 28th May 2017. It is observed that TEC values resulting from a disturbed day have a higher prediction error than TEC values resulting from a quiet day. It is found that the RMSE obtained from both the training and validation sets reaches minimum when the input Combination of TEC, D_{st} ,K_p,A_p, $F_{10.7}$ is used in the input layer.

This suggests that the combination of the solar and geomagnetic activity information is able to improve the TEC prediction. The developed LSTM NN model has shown satisfactory short-term TEC prediction performance based on experimental results obtained. The result shows that the model recognize the variation trend of typical TEC profile and have a good performance of the short term ionospheric TEC prediction.

4. Conclusion:

In this paper ionospheric total electron content data obtained from GNSS receiver over Lhasa, China station has been used for predicting short term variation trend of typical TEC profile. For this purpose, LSTM model with a dense neural network has been utilized. It is found that the RMSE obtained from both the training and validation sets reaches minimum when the input Combination of TEC, D_{st} ,K_p,A_p, $F_{10.7}$ is used in the input layer. These preliminary results indicated that, LSTM model is able to perform well in both disturbed and quiet day conditions.

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