Prediction of Total Electron Content using Nonlinear Autoregressive Models with Exogenous Input Recurrent Neural Network

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Abstract

The satellite navigation system needs the prediction of the ionospheric information. It is crucial to select a competent ionospheric model and predict the value of Total Electron Content (TEC) data. Determining the TEC from dual-frequency GPS observations has become important since it is used by many researchers for different research areas. In this paper, an attempt is made for predicting TEC parameter by using Nonlinear Autoregressive models with eXogenous input recurrent neural network. The work is based on TEC data collected from the GPS receiver at Guwahati (26º 10' N, 91º 45' E).

Index terms—

1 Introduction

otal Electron Content (TEC) of ionosphere measured by GPS satellite is an important parameter since it is used by many researcher around the globe in different application areas. TEC is a measure of the total number of electron per square meter along the line of sight from the satellite to receiver on ground where 1 TECU (TEC Unit) = 1x10 16 electron/m 2 . TEC provides an overall description of the ionosphere and used in many applications like satellite navigation, time delay, relative positioning etc. The variations and characteristics of TEC at low, high and middle latitudes have been studied by a number of research workers (Shim J. A., 2009, Bagiya et. al., 2009). The time series analysis has been used for prediction in the field of atmospheric study, market analysis, earthquake prediction and so on (Kalita S, 2012, Devi M et. al., 2001, Kothari et. al., 1997). In this paper, based on time series analysis, we have developed and analyzed a new ionospheric TEC prediction technique using Nonlinear Autoregressive models with eXogenous input recurrent neural network (NARX) to perform shortterm regional ionospheric TEC prediction. Thus, the predicted TEC were compared with the TEC measured by GPS located at Gauhati University to assess the performance and feasibility of the forecasting model built. For the experiment the GSV4004 receiver have been utilized for collection of TEC in Gauhati University Laboratory. The receiver can track up to 11 GPS signals at the L1 frequency (1575.42 MHz) and the L2 frequency (1227.6 MHz). It measures phase and amplitude (at 50-Hz rate) for each satellite and computes TEC from combined L1 and L2 carrier phase measurements which also collects ionospheric Scintillation data.

2 II.

3 Description of Modeling and Prediction Mechanism

The ionosphere is greatly affected by the solar activities, the sunspot index and the solar radio flux index can be regarded as the main independent variables which impact the variation of the TEC, and therefore for the experiment the 10 minute average data of the TEC parameter is considered as the input to the model. The slant TEC data are converted to the vertical TEC (TEC v) using mapping function. Given a time series X = {TEC v (t), t = 1, ..., n}, where TEC v (t) is a value at discrete time t and n is the number of data points in the time series, we wish to predict the value TEC v (t + 1) at time t + 1.

In the first step, the vertical TEC is transformed to an equivalent volatility index using the following formula:V(t)=log ((?????? ?? (?? + 1)/?????? ?? (??))

Volatility is used to determine the abrupt local changes in the TEC time series. Since the neural networks do not provide accurate predictions for the data that are not within the range of training data sets, therefore, instead of the estimated TEC data, the volatility TEC time series is considered as training data instead of original VTEC data.

In the second step, the nonlinear autoregressive network with exogenous inputs (NARX) prediction model is constructed using the volatility series. The NARX is a recurrent network (dynamic), with feedback connections containing several layers of the network. The model is based on the linear ARX model, which is basically used in time-series modeling. The defining equation for the NARX model is:y(t)=f(y(t),y(t?1),?,y(t?d y),u(t),u(t?1),?,u(t?d u))

where u(t) and y(t) denotes the input and output of the model at time t, the lags of the input and output of the system are represented by du and dy respectively and f is a nonlinear function.

NARX networks are better for time series prediction than conventional recurrent neural networks because (a) Learning is more effective in NARX networks than in other neural network and (b) These networks converge much faster and generalize better than other networks.

The state space representation of recurrent NARX neural networks can be expressed as (O. M. Mohamed Vall and R. Mhiri, 2008)Z k (k+1)= ? ????(??)?, ?? ?? (??)), ?? = 1, ?? ?? (??), ?? = 2,3, ? ?? ?

The NARX model for approximation of a function f can be implemented in many ways, but the simpler seems to be by using a feed forward neural network with the embedded memory and a delayed connection from the output of the second layer to input.

For learning, a dynamic back-propagation algorithm is required to compute the gradients, which is more computationally intensive than static backpropagation and takes more time.

In this research work, Marquardt optimization (Martin T et. al., 1994) was modified for network training function to include the regularization technique. It reduces the squared errors and the weights and, then determines the correct combination so as to construct a network which generalizes well which is called Bayesian regularization. In function approximation problems, for networks that contain a few hundred weights, the Marquardt algorithm provides the fastest convergence, since this advantage is noticeable if very accurate prediction is required.

In the third step, the output volatility predicted by the NRAX model is converted for comparison with the original data using.TEC v (t + 1) = exp(V(t)) .TEC v (t) III.

4 Experimental Results

The ionospheric TEC data for the year 2011 to 2012 was considered for analysis and for each day the 10 minute average TEC data have been utilized for modeling and prediction. The network is trained according to the seasonal variation of the ionospheric TEC values. For each month the first ten quietest days are considered for modeling and the next day is considered for checking the validity of the prediction. The prediction of TEC data on 14 Sep 2011 and 20 March 2012 are presented in figure **??** In this paper, an artificial neural network models with two levels i.e. input layer, output layer are considered for the general prediction equations. For computing the next value of the time series TEC v (t+1) using model, the past observation TECu(t), TECu(t-1), ?, TECu(t-d u) and the past outputs TECy(t), TECy(t-1), ?, TECy(t-d y) as inputs, may be written in the form: In Table 1, the statistical deviations between the predicted TEC by model and the observed TEC at Guwahati for 24 Hours, 48 Hours and 72 Hours respectively, are listed. The accuracy of prediction for the 24 Hours is remarkably very good than that of prediction for 48 Hours and 72 Hours.The results indicate that the model produces very well prediction of TEC over time and have good performance. From the experiment it is also observed that the performance of prediction of short term TEC values is better than long term prediction.

5 IV.

6 Conclusion

In this research, a new technique for the ionospheric TEC prediction based on time series analysis theory and technology has been developed and analyzed. From the experiments it is observed that the NRAX model can be used for TEC prediction. The Predicted TEC by the developed model is then compared with the TEC measured by GPS Gauhati University station to assess the performance of the model. Preliminary results show that NRAX model could well describe the variation trend of the ionospheric TEC and has a good short-term performance of the ionospheric TEC prediction. The prediction model can be made more efficient if certain other parameters like kp, Rz, fof2 data on the inputs and targets are performed. Further study will necessary. [1]

1

Forecast time	?<=1TECU	1TECU<= ?<=2TECU
24 Hours	84%	22%
48 Hours	53%	29%
72 Hours	37%	33%

Figure 1: Table 1 :

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