Real Time TEC Prediction during Storm Periods using AR Based Kalman Filter

B. Arundhati, V. GopiTilak, S. KoteswaraRao

Abstract: Ionosphere total electronic content (TEC) observations available from global navigation Satellite systems are random in nature and these can be described by a stochastic process. During geomagnetic storms, TEC values are further disturbed and the disturbance is also another stochastic process. In this paper, it is tried out to model the process using Kalman filter with autoregressive statistics. Realistic TEC data during quiet days and disturbed days with respect to the geomagnetic storm are modeled in terms of autoregressive coefficients and the original data is reconstructed to find out the accuracy of the process. In this paper, the model is applied for different storm periods (Geomagnetically Quiet to Greatly disturbed) in the span of 23\textsuperscript{rd} and 24\textsuperscript{th} solar cycles i.e., from 1996 to 2018 for a low latitude station Lucknow data and the observations are presented and analyzed graphically. The error values showed that the Kalman filter gives better prediction values.

Index Terms: Kalman Filter, Ionosphere, Total Electron Content.

I. INTRODUCTION

The ionosphere is one of the factors affecting the GPS position accuracy. The ionosphere is the most dispersive layer of earth’s atmosphere due to the presence of highly concentrated electron content whose cause and variations depend on solar radiations [1,2]. This variation is noted using the total electron content (TEC) values derived from satellite signals. The perturbation of TEC dependent on latitude, longitude, altitude, local time, season, solar cycle and magnetic activity along with the characteristics of the ionosphere such as electron density, ion and electron temperature, and ionospheric composition. These perturbations affect all areas of applications offered by satellite systems [3]. Among all these cases, a magnetic storm causes high perturbations compared to the other sources of disturbances [4,5].

From the literature, based on ionosphere characteristics and signal model, first ever ionosphere models were proposed in [1,2] for the global purpose. But some corrections made in both the models on the basis of the region and latitudes proposed in [6,7]. Ionosphere peak layer critical frequency foF2 has its preference in modelling ionosphere in [8,9]. Statistical models like empirical orthogonal function analysis are applied to analyse ionosphere variability due to geomagnetic in [10-12]. Spherical harmonic function and adjusted spherical harmonic functions for a regional and global models based on shell structure of ionosphere in [13,14]. Wavelet analysis and neural networks are also introduced to model ionosphere in [15,16]. As TEC is a linear time series data, models based on auto regression moving average (ARMA), auto regression integrated moving average (ARIMA) incorporated with Wavelet analysis are proposed for ionosphere modelling in [17,18,22].

The dependency and sensitivity of Kalman filter on the state noise covariance and measurement noise covariance are well discussed in [20]. The failure of these models noted as the uncertainty in predictions during storm periods. A study on data point of view suggest that the prediction needs the updating the covariance. The dependency and sensitivity of Kalman filter on the state noise covariance and measurement noise covariance are well discussed in [20]. In present work, an auto regression based Kalman filter is utilized to predict the real-time TEC.

II. MATHEMATICAL MODEL

From a statistical point of view, many signals such as speech, TEC etc., exhibit a large amount of correlation. This correlation can be represented by an auto regressive (AR) process that is the output of an all-pole linear system driven by white noise sequence. The 5 state AR signal model can be represented as

\[ y(k) = a_1 y(k - 1) + a_2 y(k - 2) + \ldots + a_p y(k - p) + w(k) \]  

where \( p \) is the order of the AR model and \( Y(k) \) is present measurement depending on the previous five measurements with respective coefficients from \( a_1 \) to \( a_p \). The state space model is given by

\[ Y_p(k) = X(k)Y_p(k - 1) + W(k) \]  

Where \( W(k) \) is zero mean unit covariance white noise, \( X \) is the state transition matrix with first row as coefficients and the remaining as an unit matrix. Since, the observations are available online, so the initialization as follows, For \( k = p + 1 \) to \( k \).

\[ M(k) = Y_p(k - 1, k - 2 \ldots k - p + 1) \]  

\( M(k) \) is measurement model matrix of length equal to length of coefficients.

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\[ G(k) = \frac{P(k/k-1)^{M^T(k)}}{[M(k)P(k/k-1)^{M^T(k)}+R_k]} \]  \hspace{1cm} (4)

Where \( R, Q \) are the measurement and state noise covariance respectively, which has major contribution in real-time prediction of TEC. The updated error covariance and state are given by

\[ P(k+1/k) = P(k/k-1) - P(k/k-1)^{M(k)^{-1}}M(k)(k)P(k/k-1) \]

\[ Y(k+1/k) = [I - G(k)^{M^T(k)}(k)]Y(k/k-1) + G(k)Y(k) \]  \hspace{1cm} (6)

The modeled or predicted TEC is given by

\[ Y(k+1) = M^T(k)Y(k+1/k) \]  \hspace{1cm} (7)

III. RESULTS AND DISCUSSIONS

A. Figures and Tables

The prediction is performed for TEC variations for two years of data collected covering all types of geomagnetic storms. The Data collected at a low latitude station Lucknow for the 23rd & 24th solar cycle with geomagnetic latitude and longitudes as 26.91 and 80.95 respectively. The data is collected from ftp://cddis.gsfc.nasa.gov/pub/gps/data/daily network and the vertical TEC data extracted using GPS-TEC analysis application by Seemala Gopi [19]. The model is analysed for geomagnetic activity periods such as from quiet to great geomagnetic storm periods. The classification of storms based on [20] which considers the Distribution Storm Time (DST index) in Nano Tesla as a parameter of classification. Based on DST values, the period with DST >-50nT taken as quiet period, for <-50nT moderate storm period, <-100nT strong storm period, <-200nT severe storm period and for <-350nT great storm period. The DST data is taken from http://wdc.kugi.kyu.ac.jp/dstae/index.html. All these classifications are based on manually observed DST variations.

Figure 1 corresponds to the quiet period of 24th solar maximum period. A three days quiet period data is collected from 20-22nd June 2016 with respective day of the year numbers are 172,173,174. Fig 1a shows the diurnal variations of original hourly averaged VTEC in red line and real-time predicted VTEC with the dotted green line. The maximum VTEC reached up to 65TECU during this quiet period. Estimated AR parameters presented in fig 1b. The observation shows the maximum error in predicted VTEC is 0.34TECU.

Figure 2 representing the geomagnetically moderate period with respective DST variations from -50 to -100nT. The three day VTEC variations of moderate period is 8-10 may 2016 with respective day numbers 129-131. Figure 2a shows the true and predicted VTEC in red and dotted green lines respectively. Figure 2b visualizing the estimated AR parameters. The maximum prediction error noted is 0.21TECU.

Fig 1a. True and Predicted VTEC for a quiet period

Fig 2a. True and Predicted VTEC for a moderate period
Figure 3 representing the geomagnetically strong period with respective DST variations from -100 to -200nT. The three day VTEC variation of strong period is 19-21 December 2015 with respective day numbers 353-355. This respective storm period is named as Halloween solar storm. Figure 3a shows the true and predicted VTEC in red and dotted green lines respectively. Figure 3b visualizing the estimated AR parameters. The maximum prediction error noted is 0.1 TECU.

Figure 4 representing the geomagnetically severe period with respective DST variations from -200 to -350nT. The three day VTEC variation of severe period is 17-19 March 2015 with respective day numbers 77-79. Figure 4a shows the true and predicted VTEC in red and dotted green lines respectively. Figure 4b visualizing the estimated AR parameters. The maximum prediction error noted is 0.1 TECU.

Figure 5 representing the geomagnetically great period with respective DST variations less than -350nT. The three day VTEC variation of great period is 19-21 November 2003 with respective day numbers 323-325. Figure 5a shows the true and predicted VTEC in red and dotted green lines respectively. Figure 5b visualizing the estimated AR parameters. The maximum prediction error noted is 0.19 TECU.
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Since no even one great storm is recorded in 24th solar cycle, DST observation leads to consider the 23rd solar cycle as data source.

Figure 6 represents the prediction of one-month temporal data during the 24th solar cycle period from February 3, 2014, to March 2, 2014. Starting 2 days of February data is not available. The respective day numbers are from 34 to 62. Figure 6a shows the true and predicted VTEC in red and dotted green lines respectively. Figure 6b visualizing the estimated AR parameters. The maximum prediction error noted is 0.83 TECU. During this one month period, the observations of DST values shows the occurrence of three consecutive moderate geomagnetic storms on February 19 to 22 and on February 27 with respective DST minima as -102nT and -97nT respectively.

The performance of the model is discussed based on the error between original and modeled VTEC as given below the table.

Table 1. The error between true and modeled VTEC for different geomagnetic activity conditions.

<table>
<thead>
<tr>
<th>Geomagnetic period</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quiet</td>
<td>0.34</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.21</td>
</tr>
<tr>
<td>Strong</td>
<td>0.10</td>
</tr>
<tr>
<td>Severe</td>
<td>0.23</td>
</tr>
<tr>
<td>Great</td>
<td>0.19</td>
</tr>
<tr>
<td>One month</td>
<td>0.83</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

From the present observations, it is noted that the auto regression based Kalman filter model gives the accurate results for ionospheric VTEC with errors less than 1 TEC. The predicted parameters are nearly equates to the calculated auto-regression coefficients. Since this paper covers the one hour prediction of vertical TEC, this method will help to predict in minute wise variations.

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