

## Implementation of the VARMA Model for Ionospheric TEC Forecast over a GNSS Station in India

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### Abstract

The technique combines Variational Mode Decomposition (VMD) with AutoRegressive Moving Average (ARMA) modeling, creating the VMD-ARMA (VARMA) model to predict ionospheric delay values one hour ahead. To evaluate the performance of the proposed VARMA model, the algorithm was tested during geomagnetic storms that occurred in June 2013. GNSS data from April 1, 2013, to June 30, 2013, was collected using a GNSS Ionospheric Scintillation and TEC Monitor (GISTM) receiver located at Koneru Lakshmaiah Education Foundation, Guntur station, India (geographic: 16.37°N, 80.44°E). The results demonstrate that the VARMA model outperforms the ARMA model by 2-3% in terms of forecasting accuracy during storm conditions. This suggests that the VARMA version can be a valuable tool for predicting ionospheric Total Electron Content (TEC) variations in low-latitude regions, even during disturbed ionospheric space weather conditions.

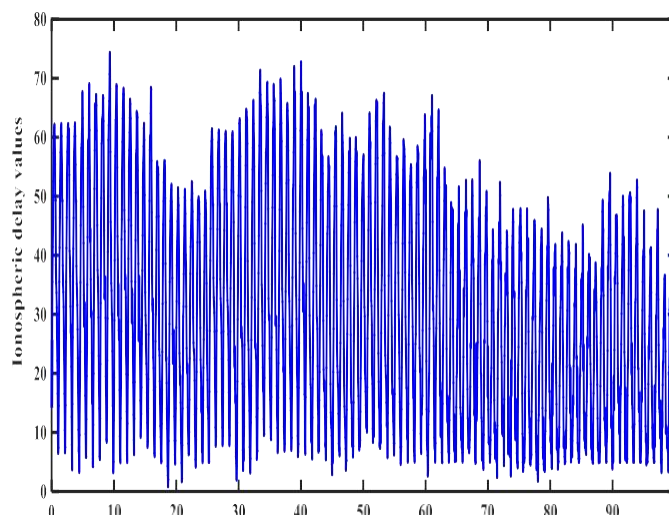
**Keywords—** GNSS, Ionospheric delay, Variational Mode Decomposition (VMD), Auto Regressive Moving Average (ARMA) model, VARMA model.

Decomposition (EMD) has been proposed for ionospheric TEC forecasting. EMD is a non-stationary signal decomposition technique that adapts to the data without requiring a priori selection of wavelets. The EMD-based methods, such as Variational Mode Decomposition (VMD) and VMD-ARMA (VARMA) model, have shown promising results for ionospheric delay forecasting [1]. The ionospheric TEC variation is particularly significant in regions with low-latitude, such as India, due to Equatorial Ionization Anomaly (EIA) conditions. This makes ionospheric TEC forecasting challenging, especially for GPS users. Several experimental models have been employed to enhance the performance and accuracy of satellite-based

navigation systems by correcting ionospheric delays [2-4]. Global models like the International Reference Ionosphere (IRI) model, Klobuchar model, and NeQuick model provide reasonable accuracy on a global scale but may not be sufficient for critical applications that require regional-scale ionospheric corrections [5]. For short-term forecasting of ionospheric TEC, different time series models like Auto Covariance, ARMA, and ARIMA have been explored. However, hybrid models, combining techniques like wavelet-based ARIMA or EMD with ARMA, have shown to be more reliable for ionospheric forecasting under both geomagnetically quiet and disturbed conditions [6-8]. In conclusion, data-driven approaches like EMD-based methods offer promising solutions for ionospheric TEC forecasting, improving the performance and accuracy of satellite-based navigation systems, especially in regions with significant ionospheric variations.

## II. Proposed VARMA Ionospheric TEC Forecast Model

The experimental analysis in this study considers TEC data recorded from 1st April 2013 to 30th June 2013 at a geographic location with coordinates Lat. 16.37°N and Long. 80.44°E in India, using a GISTM receiver [9]. The performance of the Variational Mode Decomposition (VMD) technique in extracting ionospheric response features through VTEC decomposition and the forecasting accuracy of the VARMA model during a geomagnetic storm are evaluated. Figure 2 illustrates the observed ionospheric TEC values over the 91-day investigation period, with a notable geomagnetic storm occurring on 29th June 2013 with a Dst index value of -100 nT. The VTEC values are decomposed into components known as Intrinsic Mode Functions (IMFs) using VMD [10]. Figure 3 shows the decomposed VTEC values of VMD-IMFs during



the training period (1st April 2013 to 27th June 2013) in blue lines and the forecasted VTEC values of VMD-IMFs during the testing period (active geomagnetic days) from 28th June 2013 to 30th June 2013 in red lines [11]. In the second step, the extracted VMD-IMF values during the training period are individually used as input for the Auto Regressive Moving Average (ARMA) technique. The red lines in Figure 3 represent the forecasted VTEC values obtained using the VARMA model during the geomagnetic storm conditions on the pre-storm day (28th June 2013), storm day (29th June 2013), and post-storm day (30th June 2013). Finally, the forecasted VTEC values from the VARMA model are compared with the measured GPS-VTEC data and the predicted values of VTEC using the ARMA model, as depicted in Figure 4. This analysis aims to assess the performance and accuracy of the VARMA model in forecasting ionospheric TEC during geomagnetic storm conditions.

Figure.2. The observed VTEC ionospheric delays of the input GNSS signal.

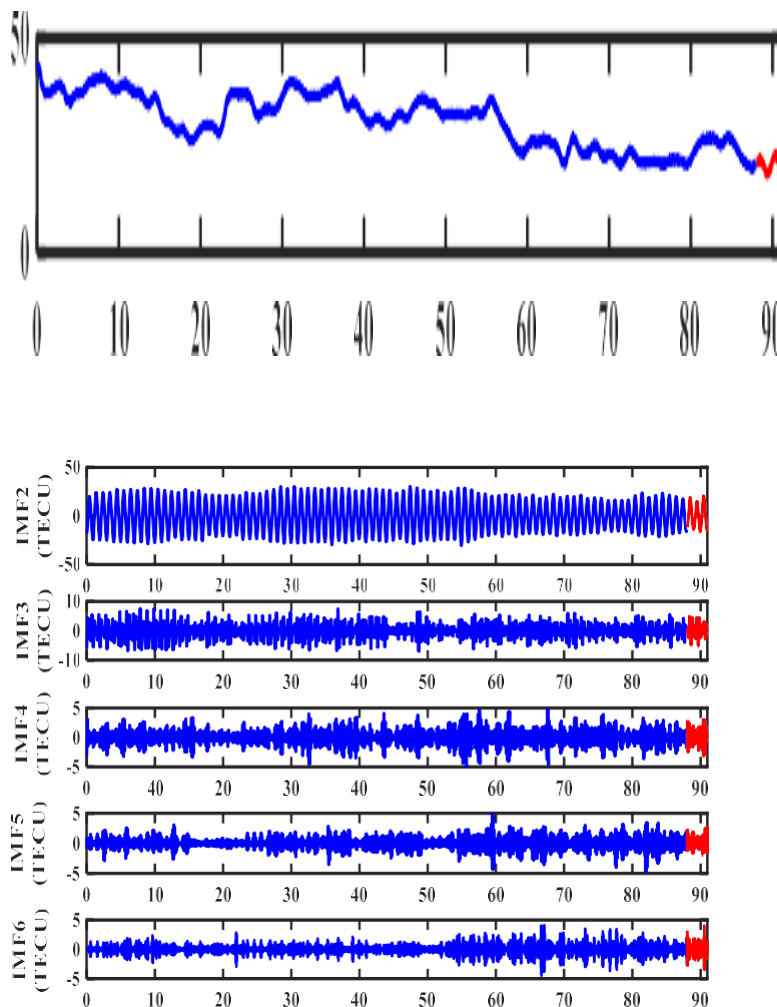
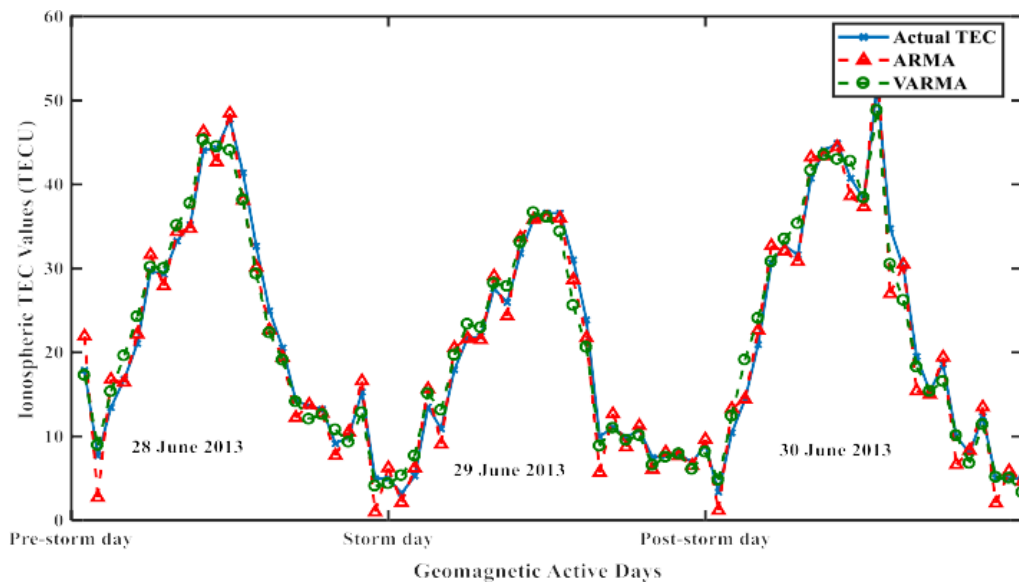


Figure.3. The VTEC decomposed into IMFs using the VMD technique. (Blue color refer to VMD IMFs during the training period and Red color refers to VARMA forecasted VTEC values during the testing period in TECU)

Figure.4. Comparison of ARMA and VARMA model forecast ionospheric delays during Pre-



storm, storm and Post-stormgeomagnetic days.

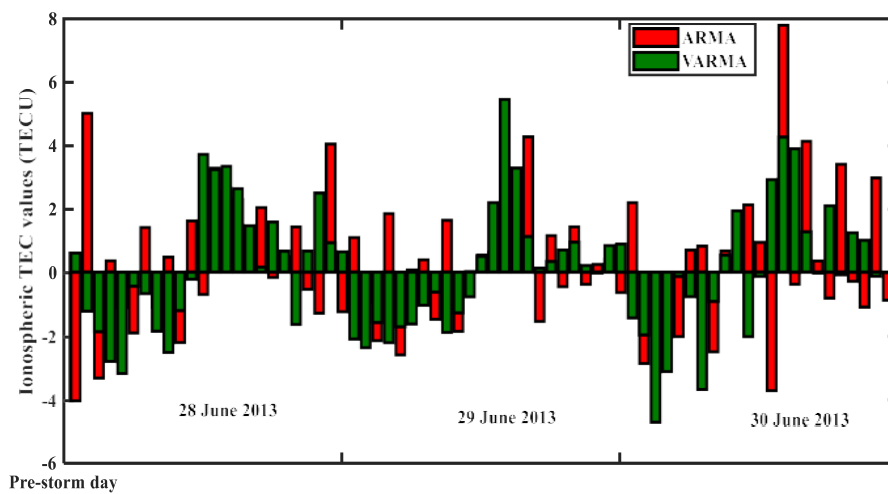


Figure 5 shows fore casted error plots for pre-storm, storm, and post-storm geomagnetic days.

As seen in Figure 4, the VARMA model performs significantly better than the ARMA model in comparison to the reported VTEC values. Figure 5 depicts the anticipated ARMA and VARMA model errors for the pre-storm, storm, and post-storm testing periods. The suggested VARMA model has smaller forecasting errors than the ARMA model, as shown in Figure 5. The ARMA model has forecast errors ranging from -4 TECU to 8 TECU, whereas the VARMA model has forecast errors of 4 TECU.

Table 1 presents the error measurements for both the ARMA and VARMA models. The comparison includes metrics such as Mean Absolute Percent Error (MAPE), Mean Absolute Error (MAE), and Mean Square Error (MSE). From the table, it can be observed that the VARMA model outperforms the ARMA model, as it shows lower error values for these metrics. During intense space weather conditions, the ionospheric Total Electron Content (TEC) response exhibits complex and intricate patterns in the measured GPS-TEC values. In such situations, the GPS-TEC data becomes highly non-stationary, meaning that its statistical properties vary over time. To account for these non-stationarities and improve forecasting accuracy, a combination of the non-stationary data/signal decomposition technique known as Variational Mode Decomposition (VMD) and the linear time series model ARMA is used, resulting in the VARMA model. By employing the VMD-ARMA (VARMA) model, the forecasting of non-linear GPS-TEC values becomes more effective, considering the non-stationary nature of the ionospheric TEC response during intense space weather conditions. This approach allows for a more accurate and reliable forecast of ionospheric TEC even in challenging space meteorological conditions.

## CONCLUSION

In this article, the VARMA model is tested for both geomagnetic storm conditions over Indian territory. The VARMA model was effective in projecting temporal ionospheric time delays in the short term. During geomagnetic storm circumstances, the VARMA hybrid TEC forecast model has an accuracy of 90%. The VARMA model can be extended for long-term forecasting of ionospheric delay values for big data sets. It can be extended to include GNSS mid- and high-latitude forecasting stations.

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