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Using ARMA and a linear time series model, an algorithm for multivariate ionospheric TEC forecasting over low-latitude GNSS stations has been developed

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Abstract:

The model combines a linear time series model with Autoregressive and Moving Average (ARMA) methods. It utilizes data from the Bengaluru International GNSS Service (IGS) station during the 24th solar cycle (2009-2016). Various factors, including geomagnetic activity (Ap), solar Extreme Ultraviolet (EUV) irradiance (F10.7), periodic oscillations (annual, semi-annual, terannual, and biennial), and long-term trends, are considered as input parameters along with real-time TEC observations. The model investigates the impact of these factors on TEC and uses ARMA for forecasting each factor. The forecasted factors are then combined to obtain the forecasted TEC values, which show good agreement with observed GPS-TEC. The study reveals that the semi-annual variation has higher magnitudes during the High Solar Activity (HSA) period, while the geomagnetic effect on TEC is relatively low. The proposed model is considered valuable for characterizing low-latitude ionospheric variations under different space weather conditions.

Keywords: Global Navigation Satellite System, Ionospheric TEC, Linear Time Series Model, ARMA and Multivariate TEC Forecast Model

Introduction

Modern satellite-based communication and navigation systems are vulnerable to space weather activities like solar flares, Coronal Mass Ejections (CMEs), solar radio bursts, and ionospheric disturbances. The ionized plasma in the Earth's ionosphere, influenced by solar Extreme Ultraviolet (EUV) radiation, affects the propagation of radio waves used by Global Navigation Satellite Systems (GNSS) [1]. Total Electron Content (TEC) in the ionosphere is a critical

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factor contributing to errors in GNSS Positioning, Navigation, and Timing (PNT) applications. GPS-based TEC measurements provide valuable data for monitoring ionospheric weather and its climatology [2-4]. The advancements in global and regional space and ground-based instruments, along with data-driven ionospheric climatological models, have provided significant insights into ionospheric weather patterns during both quiet and disturbed times.Precise prediction of ionospheric TEC values is crucial for enhancing real-time GPS positioning and navigational accuracy [5]. Ionospheric weather monitoring and understanding can be achieved through both modeling and nowcasting (short-term prediction) as well as forecasting (longer-term prediction). The ionospheric Total Electron Content (TEC) is influenced by various parameters such as the local time of the day, geographic location, season, solar activity, and geomagnetic activity. To model and understand these variations, researchers have developed and evaluated different regional ionospheric TEC nowcasting/empirical models [6]. Earlier studies have included linear time series models to investigate the long-term TEC climatology. Global empirical TEC models were also developed, but they averaged the TEC over the whole day, which might not capture the finer physical features in the ionosphere with time scales of seconds/minutes to hours [7-9]. Therefore, estimating TEC with higher time resolution (e.g., hourly) would be more meaningful. Some models have relied on global ionospheric TEC data, but they may not fully represent the local ionospheric characteristics and seasonal variations, especially over equatorial and low latitude regions. Therefore, there is a need for improved models that can better capture the local ionosphere's unique features and behavior in these regions [10].

The monthly median values of ionospheric parameters are provided by a number of global ionospheric prediction models (IRI, Bent, Nequick, and NTCM-GL) [11]. Due to their sparse regional data base and infrequent updates, global TEC empirical models' accuracy at the regional level is skewed [12]. Over low latitude and equatorial regions, the comparison analysis of the GPS-derived TEC with empirical models such as the IRI model has reported that the predictions of the IRI model are not accurate and relatively large temporal discrepancies, (either overestimation or underestimation) are accounted for [13]. The geographical location affects the inhomogeneous temporal and spatial distribution of electron density in the ionosphere.

Data Structure and Recommend Methodology

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For monitoring, modelling, and forecasting of ionospheric GPS-TEC features throughout an 8-year period (2009–2016) in the 24th solar cycle, Bengaluru, an Indian low-latitude GNSS station (12.97°N, 77.59°E; geomagnetic 4.53°N) is taken into consideration. Every 30 seconds, the GPS observations from the IGS station in Bengaluru are recorded and made available online at http://sopac.ucsd.edu. With the use of GPS satellite azimuthal angles, elevation angles, and receiver coordinates, the VTEC is calculated from slant TEC (STEC) data. Every five minutes, the mean VTEC readings of all GNSS visible satellites are calculated. The hourly VTEC observations, or twenty-four values each day, are used to generate the VTEC values for each day.

2.1. The ionospheric linear TEC model

By breaking it down into several solar-terrestrial and geophysical components according to their relative contributions, the ionospheric linear TEC model can be utilised to determine the ionospheric TEC [14-15],

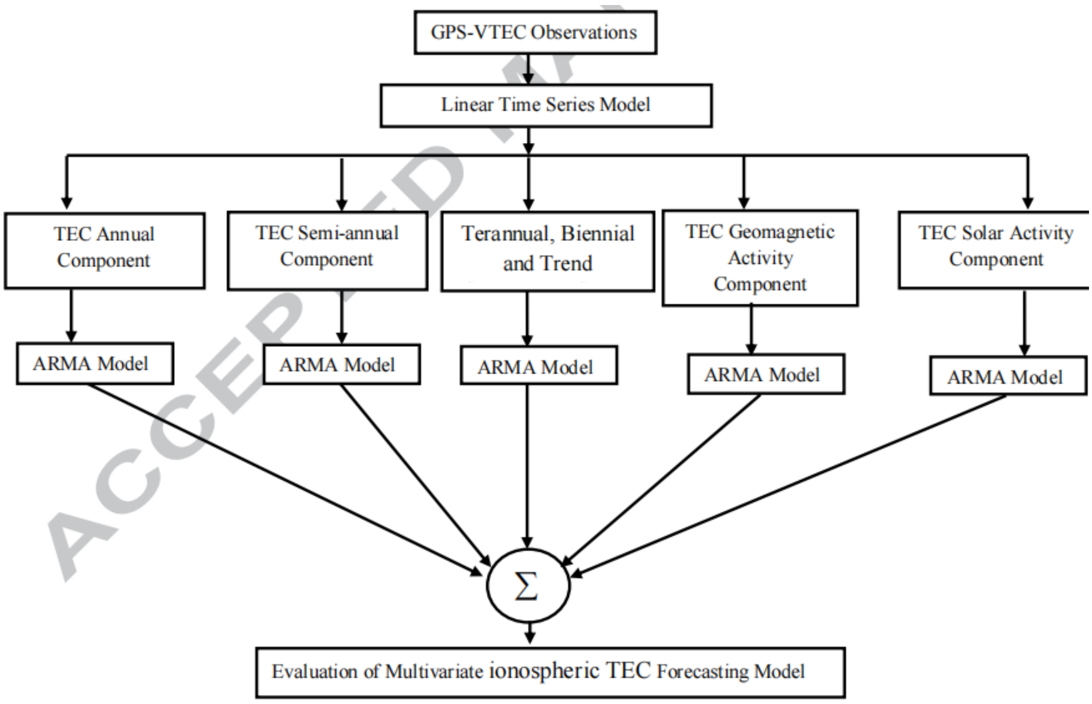

Fig.1. Methodology for the implementation of multivariate ionospheric TEC forecasting model.

3. Results and Discussion

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GPS data from the Bengaluru International GNSS Service (IGS) station in India was collected for the experimental analysis. Hourly GPS Vertical Total Electron Content (VTEC) values were obtained for 8 years (2009-2016) during the ascending and descending phases of the 24th solar cycle. The study analyzed the major components influencing ionospheric space weather and TEC variations, including solar, geomagnetic, and periodic variations. The periodic variations encompassed different cycles, such as annual, semi-annual, terannual, and biennial components. From the analysis shown in Figure 2, it was observed that the solar component was the dominant source of ionospheric TEC variability, with a TEC increase of around 40 TECU from solar cycle minimum (2009) to maximum (2014). The magnitude of periodic variations was more significant during the High Solar Activity (HSA) period (2013-2014) and less during the Low Solar Activity (LSA) period (2009-2010). The planetary geomagnetic disturbance index (Ap) described the influence of geomagnetic activity on ionospheric TEC variations. The magnitude of the geomagnetic component increased during high solar activity years and remained minimum during low solar activity years. Compared to the solar proxy (F10.7) and oscillatory components, ionospheric TEC climatology was less affected by geomagnetic activity (Ap index). However, during storm periods, the maximum geomagnetic influence on TEC was observed.

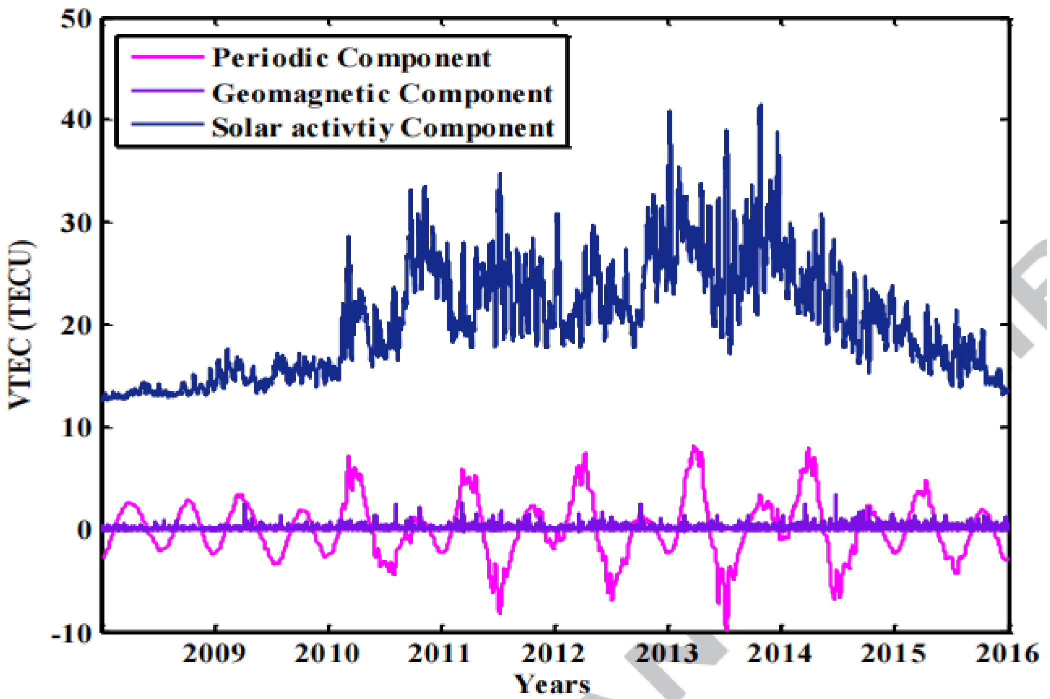

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Figure 2 shows the periodic, solar, and geomagnetic activity components of Bengaluru data for the 24th solar cycle as calculated using a linear TEC model.

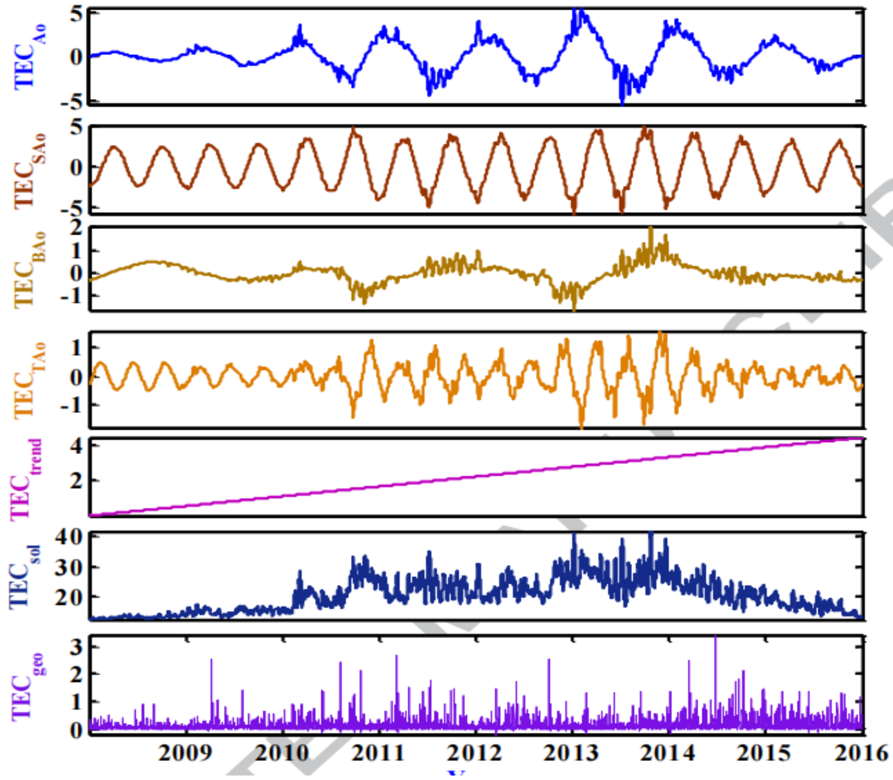

Figure 3 shows the periodic (annual, semi-annual, terannual, and biennial), solar, and geomagnetic components.

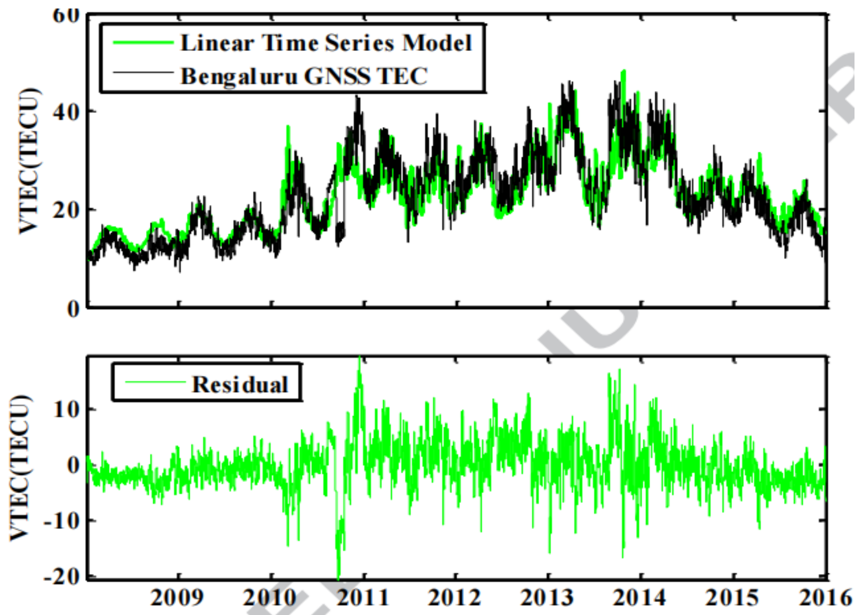

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Figure 4 shows the values of the linear TEC time series model (green) and the GPS-TEC observations (black) over Bengaluru station from 2009 to 2016.

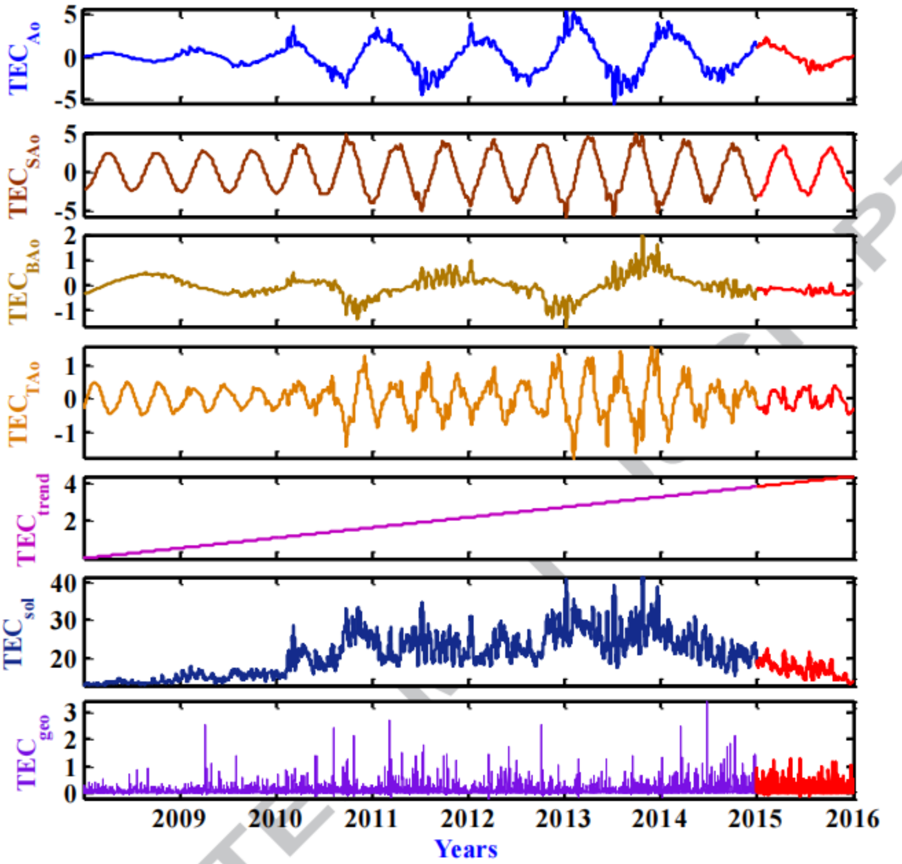

Figure 5 shows the forecast of separate components using the multivariate ARMA model. The solar and geomagnetic components, which are periodic (annual, semi-annual, terannual, and biannual), are generated from the model of a linear time series.

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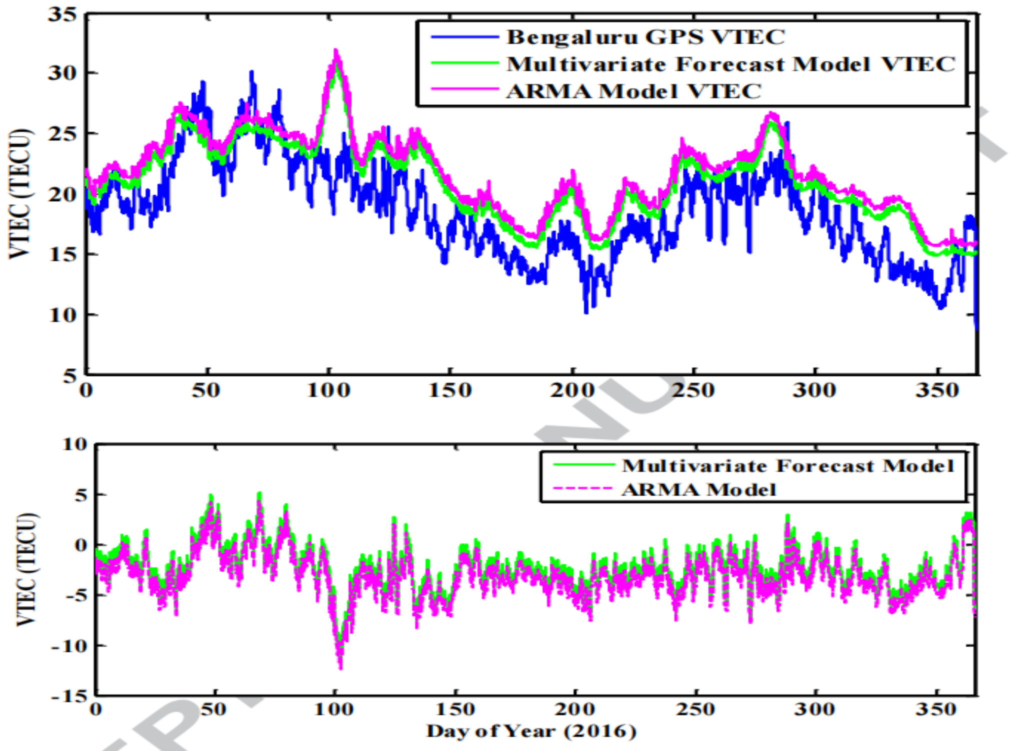

Figure 6 shows a comparison of the multivariate forecast model with the linear time series model in estimating VTEC values over the Bengaluru station.

During the test period in the year 2016, the forecasted VTEC values obtained from various geophysical and solar-terrestrial components were used to reconstruct a multivariate forecast model for VTEC. The top panel of Figure 6 shows that both the direct ARMA model and the proposed multivariate forecast model are following the measured VTEC patterns at the equatorial Bengaluru GNSS station in India. However, the ARMA model tends to deviate more from the measured values compared to the proposed model during the test period.It was observed that the proposed multivariate forecast model performed well during geomagnetic quiet periods but did not capture the VTEC patterns accurately during the geomagnetic storm period on April 7, 2016 (DOY 098, 2016).The bottom panel of Figure 6 shows the estimation error of the ARMA model and the forecast error of the multivariate TEC forecast model. Figure 7 presents the forecasted error distribution of both models, including their absolute error distributions during the testing period in 2016. The multivariate forecast model had a maximum absolute error of 10 TECU with a mean absolute error (MAE) of 2.69 TECU. On the other

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hand, the ARMA model showed a maximum absolute error of 12 TECU and an average forecast error of over 3 TECU.

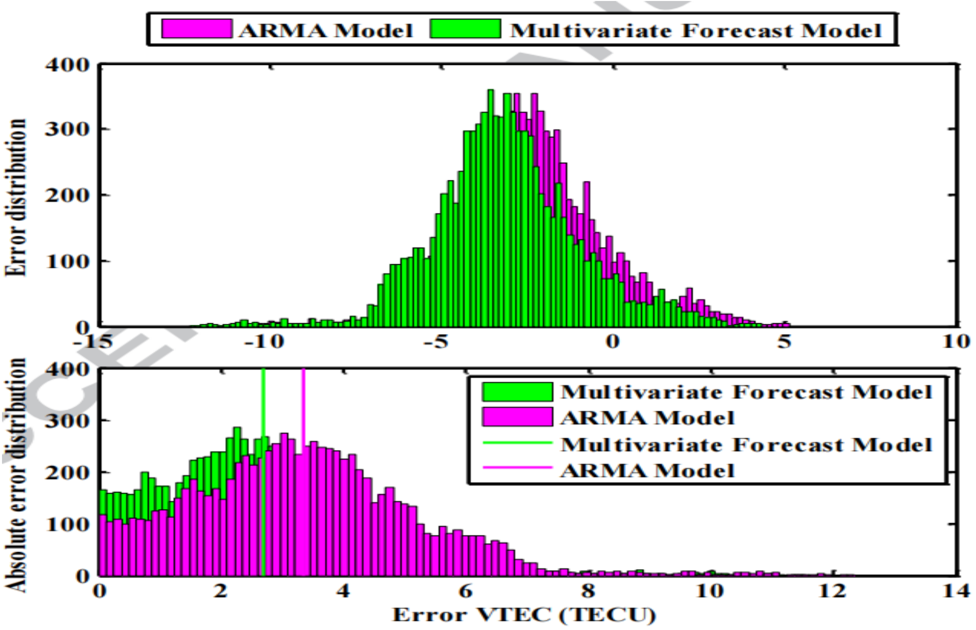

Figure 7 shows an error analysis of the ARMA model, as well as the suggested multivariate TEC forecast model and linear time series model, in estimating VTEC values over the Bengaluru station in 2016.

Table 1 also includes the error measurement metrics, Mean Absolute Error (MAE), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE), for the effective evaluation of forecasting model performance during the test period, 2016 (the descending phase of the 24th solar cycle). The suggested multivariate forecasting model, which is driven by long term periodic components, space weather driven parameters, and geomagnetic activity due to linear TEC (nowcasting) model, performs well. The proposed multivariate forecast model has a MAPE value of 15.91%. Thus, the multivariate forecast model's forecasting accuracy is 84.09% with an MAE of 2.69 TECU during the forecast testing period of 2016. The proposed is 4% more accurate than ARMA TEC for MAPE values.

Conclusion

GPS data from the Bengaluru GNSS station for 8 years were collected for the analysis.The linear TEC model demonstrated a high degree of agreement with the measured GNSS VTEC

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data during geomagnetic quiet days. It effectively interpreted the impact of multiple components on ionospheric TEC for GNSS radio wave propagation. Periodic variations were observed during both periods of high solar activity (HSA) and low solar activity (LSA).The study found that the primary effect of geomagnetic activity on TEC climatology was relatively small compared to the impact of solar activity and oscillatory components. Geomagnetic influence on TEC was more significant during geomagnetic storm periods.

Based on the linear TEC model, a multivariate ionospheric TEC forecasting model was developed. The forecasting accuracy of this model was 84.09% with a mean absolute error (MAE) of 2.69 TECU during the testing period in 2016. The proposed multivariate model performed better than the ARMA TEC forecast model, with a 4% improvement in Mean Absolute Percentage Error (MAPE).

The suggested multivariate forecast model is approximately 4% more accurate than the ARMA TEC forecast model for MAPE values. However, the suggested forecast model needs to be developed in order to better predict the ionospheric time delays for GNSS signals during both geomagnetic disturbed and quiet periods. Monitoring, modelling, and forecasting of ionospheric TEC fluctuations caused by solar, geomagnetic activity, and periodic oscillations are important in the development of near real-time ionospheric space weather forecasting technology systems for sophisticated and resilient GNSS services.

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