ISSN PRINT 2319 1775 Online 2320 7876

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A machine learning approach can calculate ionospheric time delays using data from the Global Navigation Satellite System

D. Venkata Ratnam

Department of ECE, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Andhra Pradesh 522 502, India

K saikumar, Department of ECE, Koneru Lakshmaiah Education Foundation, India-522302, saikumarkayam4@ieee.org

ABSTRACT

In this study, Gaussian Process Regression (GPR) is employed for forecasting low-latitude ionospheric conditions. The GPS receiver data from the International GNSS Services (IGS) station in Bengaluru, India, is used for 8 years (2009–2016) during the 24th solar cycle. The performance of the GPR model is evaluated using statistical parameters such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and correlation coefficient. The results of the proposed GPR model are compared with those of the Auto Regressive Moving Average (ARMA) model and Artificial Neural Networks (ANN) model during the solar maximum period and descending phase of the 24th solar cycle. The experimental results demonstrate that the GPR model significantly outperforms the ARMA and ANN models in forecasting ionospheric time delays for GNSS signals. The outcomes of this work hold promise for developing a web-based Ionospheric TEC forecasting system to provide alerts to GNSS users.

INTRODUCTION:

In order to improve scientific and technological applications, the Global Navigation Satellite System (GNSS) offers satellite-based all-weather societal and safety services to humanity. The Earth's ionosphere, which is constantly affected by solar radiation and the geomagnetic field, causes the radio communication signals of GNSS satellites to be affected (delayed/scintillated) [1]. In order to safeguard the radio communication links during the unfavourable space weather event, monitoring the effects of the ionospheric on the Global Positioning System (GPS) satellite systems has received considerable attention. Total Electron Content (TEC) data obtained from GPS measurements can be used to quantitatively describe ionospheric variability. Investigating the ionospheric physics requires mathematical methods that use

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scientific instrument-based remote sensing observations, theoretical models, or empirical models that require theorems on interactions between diverse geo-psychical phenomena according to [2]. To enable reliance on cutting-edge technology applications, modelling and forecasting of the ionospheric hazards to GPS systems remain difficult [3]. The effectiveness of these linear time series models has been tested over low, mid, and high latitude GNSS stations, and findings have been compared with widely used Ionospheric Reference (IRI) Models [4-6]. Although linear time series regression models perform better than the IRI model on a regional scale [7-9], their performance is constrained in estimating the local ionospheric TEC temporal variations, especially over low-latitude GNSS. This is revealed by comparison results of ANN, ARMA, and HW models with the IRI model.

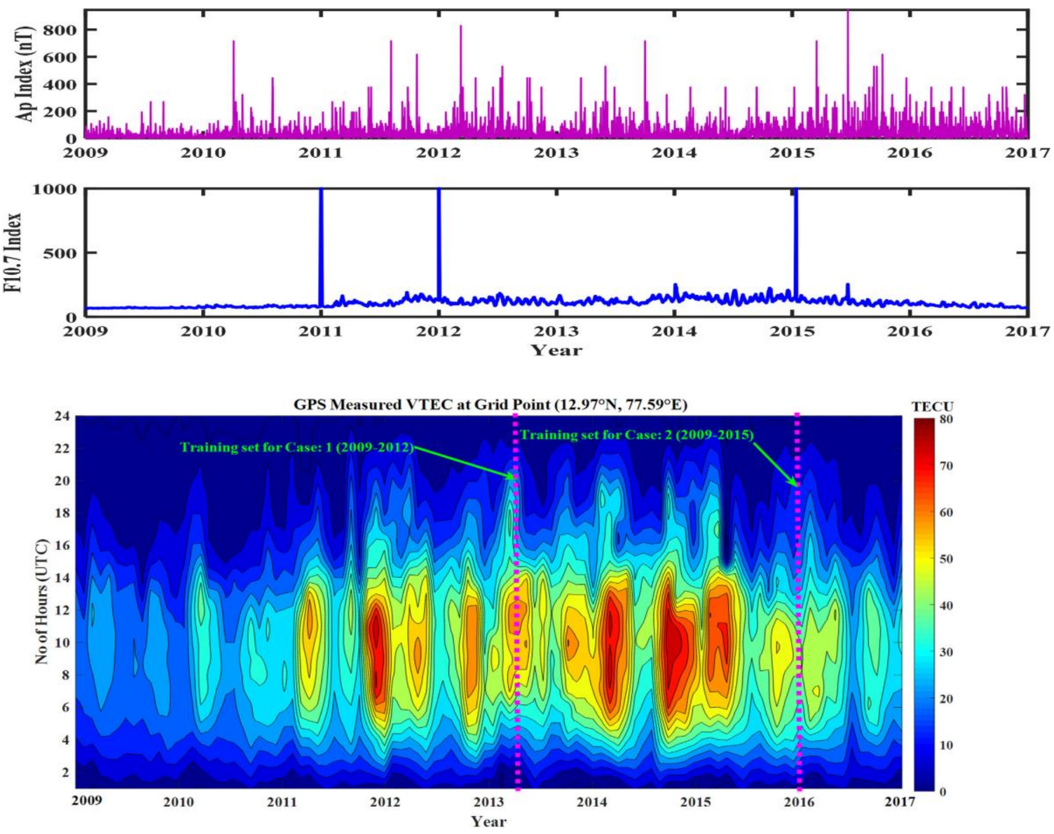

Fig. 1 shows the ionospheric TEC values determined by GPS observations between 2009 and 2016 along with the geomagnetic activity parameter (Ap Index), solar activity parameter (F10.7 Index), and associated values.

Information and techniques for GPR-based TEC projections

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In this work, the experimental GPS-TEC data is collected from the International GNSS Services (IGS) station located in Bengaluru, India (Geographical latitude: 12.97° N, Geographical longitude: 77.59° E). The GPS data over the IGS station is available at a high frequency of every 30 seconds and can be accessed from the Scripps Orbit and Permanent Array Centre (SOPAC) website (http://sopac.ucsd.edu).To obtain the required GPS VTEC data over the IGS station, the [10] GPS TEC analysis software [11] is used to process the data from the years 2009 to 2016.Gaussian process regression (GPR) is a non-parametric Bayesian theorem-based probabilistic model. It is a supervised machine learning algorithm that can handle high-dimensional, complex, and non-linear data. GPR is commonly used for data-driven modeling to solve classification and regression problems in supervised machine learning [12]. The performance of GPR relies on the choice of mean and covariance functions of the Gaussian process (GP). GPR establishes an unknown functional relationship from the given GPS TEC, solar, and geomagnetic indices, which serve as the training dataset. By placing a prior on the space of functions and updating it with training samples, GPR generates a posterior functional model. The combination of the prior distribution and training data yields the posterior signal model [13-15]. The learning process of the GPR model also depends on specific parameters known as hyperparameters, which are related to the covariance function (kernel function) used in the algorithm. Overall, GPR is a kernel-based machine learning algorithm that is effective in handling spatial data and providing probabilistic predictions.

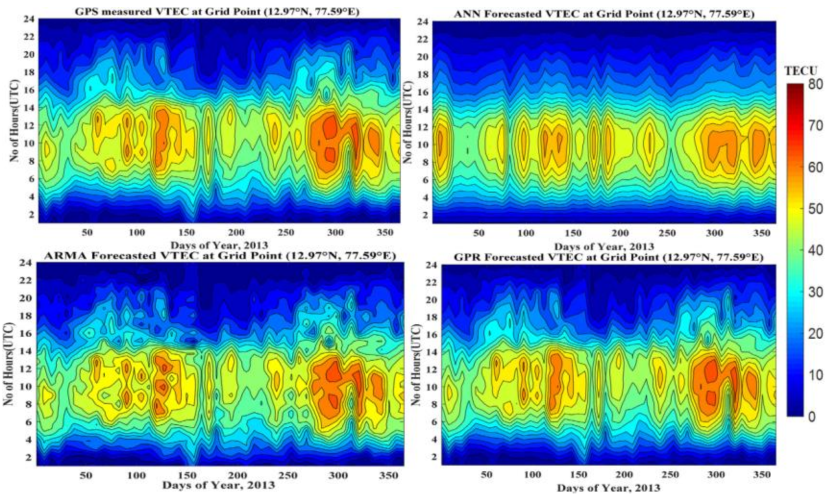

Figure 2 compares the GPS-measured VTEC values for 2013 with the comparable VTEC values calculated using ANN, ARMA, and GPR models.

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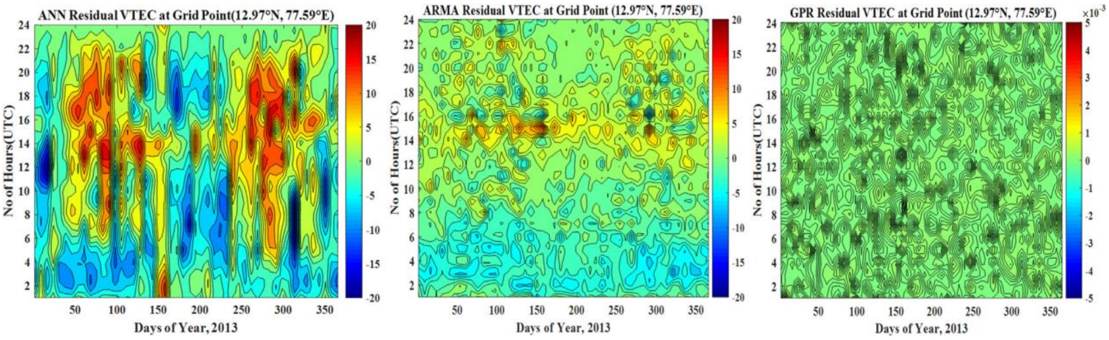

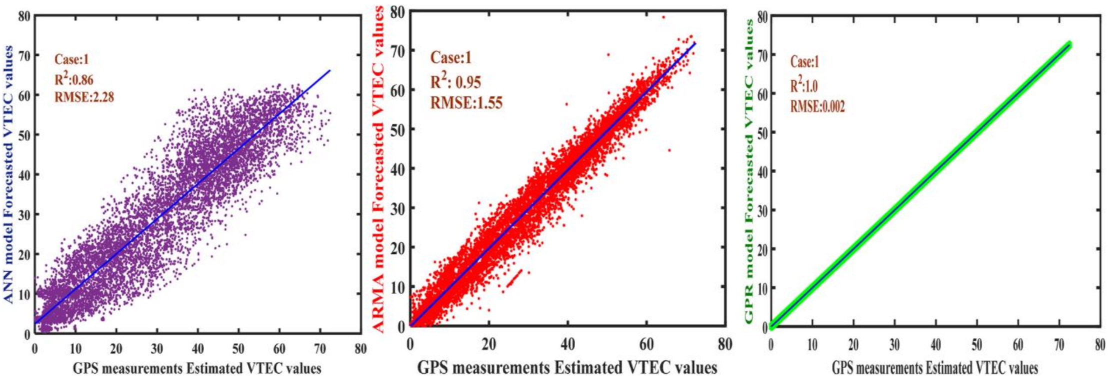

Figure 4 shows the scatter plots of the VTEC values predicted by the model in relation to the VTEC values calculated from GPS measurements for case-1, the 2013 year.

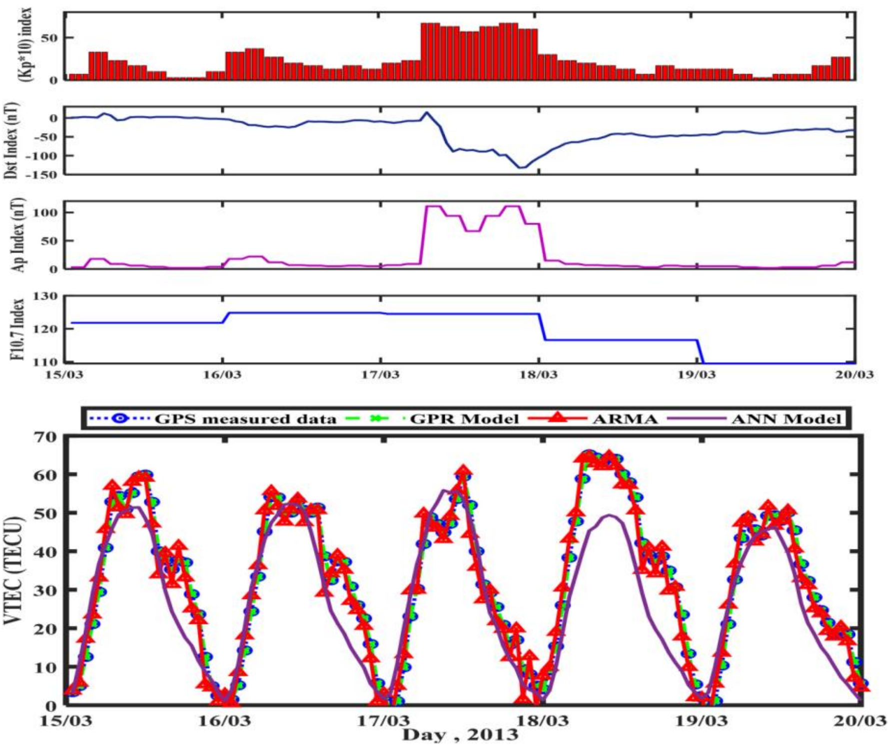

Fig. 10 shows the geomagnetic and solar activity characteristics and associated ionospheric storm time responses that forecast models used to guide their predictions during the geomagnetic storm on October 13, 201

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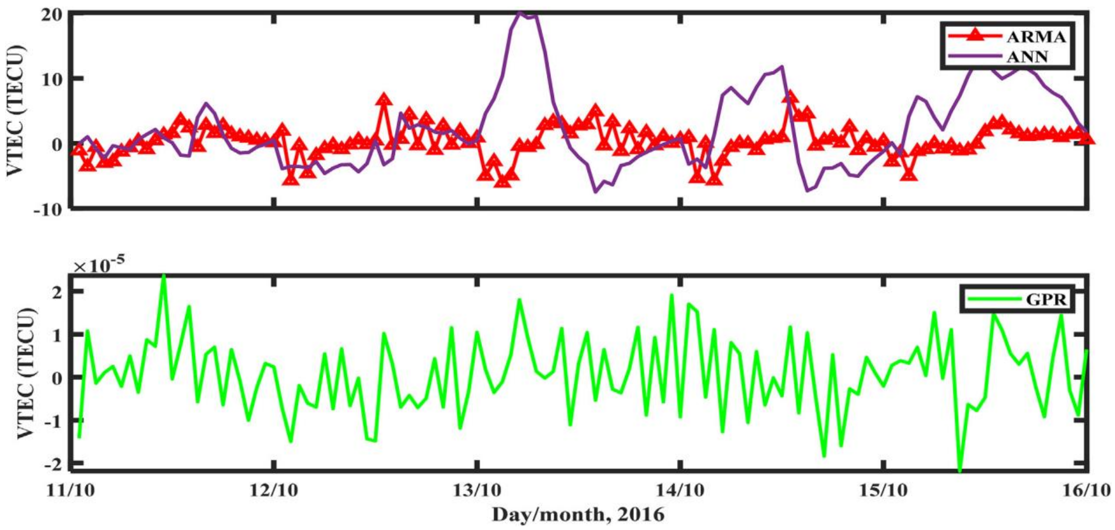
Results and discussion



The experimental analysis and evaluation of the forecasting models are conducted using GPS-VTEC time series data collected from the Bengaluru IGS station in India. Fig. 1 shows the variations in geomagnetic activity (AP Index) and solar activity (F10.7 Index) over the years 2009 to 2016. The corresponding ionospheric TEC responses are observed from GPS measurements during the same period. The VTEC patterns exhibit diurnal, seasonal, and annual variations influenced by solar and geomagnetic activity.The performance of the Gaussian Process Regression (GPR) model, Auto Regressive Moving Average (ARMA) model, and Artificial Neural Networks (ANN) model are analyzed during different test cases, including solar maximum and descending phases of the 24th solar cycle. These test cases involve geomagnetic quiet and disturbed days. The accuracy of VTEC forecasts from these models is evaluated for the specified test cases.For the comparison, GPR requires fewer parameters due to the specified structure of the kernel function, which results in a shorter training period for input data compared to ANN.Two test cases are considered: case-1 involves training the models on data from 2009 to 2012 and testing on the year 2013 (solar maximum year), while case-2 involves training the models on data from 2009 to 2015 and testing on the year 2016 (solar descending phase). In case-1, a geomagnetic storm occurred on March 17, 2013, while in case-2, a geomagnetic storm occurred on October 13, 2016. The performance of the models is analyzed in relation to the intensity of the geomagnetic storms (indicated by the Dst index).

In Fig. 2, the comparison of GPS measured VTEC values with the VTEC forecasts from ARMA, ANN, and GPR models for the year 2013 is shown. The GPS VTEC values during March and September equinoxes are approximately 60-70 TECU, while during June and December solstices, they are around 40-50 TECU. The GPR model outperforms the ANN and ARMA models in representing the temporal patterns of VTEC values during all seasons of 2013.

Fig. 3 displays the residuals of the forecasted VTEC values from GPS measurements for the GPR, ARMA, and ANN models. The residual of the ANN model is around ±20 TECU, while the ARMA model has residuals ranging from -10 to 15 TECU. In contrast, the GPR model shows very low residuals with negligible differences (around 0.00005 TECU) from the GPS measured VTEC values for 2013.

Fig. 4 shows scatter plots of the forecasted VTEC values versus GPS-VTEC values, along with the correlation coefficient and root mean square error (RMSE) values. The correlation coefficient for the GPR model is 1, while it is 0.95 for the ARMA model and 0.86 for the ANN model. The RMSE values are 2.28, 1.55, and 0.002 for the ANN, ARMA, and GPR models, respectively. Additionally, the statistical error measurements (MAE, MSE, and MAPE) from Table 3 indicate that the proposed GPR model is more accurate with lower MAE, MSE, and MAPE values compared to the ANN and ARMA models.

In Fig. 10, the ionospheric TEC response recorded by GPS measurements and the performance of the forecast models are shown during the pre and post geomagnetic storm days from 11 October 2016 to 15 October 2016. The geomagnetic and solar activity parameters recorded on 13 October 2016 include Kp*10 Index value of 65, Dst Index of -104 nT, Ap Index of 100 nT, and F10.7 Index of 98 sfu. During the sudden storm commencement (SSC) on 13 October 2016, a noticeable increment in VTEC values is observed in the GPS measurements compared to pre and post storm days, and both GPR and ARMA models have followed this sudden raise in GPS-VTEC values, while the ANN model did not capture the storm-time variations as effectively.

Fig. 11 displays the residuals of the forecast models during the pre and post storm days of 13 October 2016. It is evident that the proposed GPR model has accurately forecasted the storm-time variations of the ionospheric responses compared to the traditional models, ANN, and ARMA models.

Conclusion

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The performance of the GPR model is evaluated in two test cases: 1) during the maximum of the solar cycle in 2013, and 2) during the descending phase of the solar cycle in 2016. The GPR model's performance is compared with the univariate linear model (ARMA) and non-linear ANN models during both geomagnetic quiet and disturbed days in the two test cases.The GPR model's potential lies in its kernel-based approach and Bayesian rules, allowing it to accurately forecast ionospheric TEC variations with almost 100% accuracy. The GPR model demonstrates good forecasting performance and stability with a relatively small training data set, thanks to its adoption of flexible kernel functions. It outperforms the ARMA and ANN models, providing better results with less Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and a correlation coefficient (R2) of 1.In the future, the GPR model and other machine learning algorithms will be implemented over different geographical regions across India to create a web-based ionospheric forecasting system. This will further enhance ionospheric weather prediction capabilities and provide valuable insights for various applications.

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