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Ionospheric delays in GPS signals: A Deep Learning-Based Prediction Method

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ABSTRACT

The ionospheric delays degrade the position accuracy of GPS measurements, leading to challenges in precise navigation and positioning services. Leveraging emerging artificial intelligence mathematical tools to forecast ionospheric disturbances using GPS-estimated Total Electron Content (TEC) observations is of utmost importance. In this study, a multi-input LSTM forecasting technique is investigated and tested to evaluate its capability in predicting ionospheric delays over Bengaluru station (16.26° N, 80.44° E). The research utilizes eight years (2009–2016) of GPS measured vertical TEC (VTEC) time-series data for training and validation. The successful implementation of the LSTM-based model demonstrates the potential of deep learning techniques in addressing ionospheric challenges, paving the way for further advancements in space weather prediction and its impact on satellite communication systems.

INTRODUCTION

The Global Positioning System (GPS) is a satellite-based navigation system that offers precise navigation, positioning, and accurate timing capabilities. It serves a wide range of applications, including surveying, mapping, military operations, automatic vehicle monitoring, space navigation, emergency services, and various societal applications.For short-term Total Electron Content (TEC) time-series forecasting under various geomagnetic conditions, researchers have applied two different methods: the Holt-Winter method [1] and the auto-regressive moving average (ARMA) model [2]. These techniques are used to predict TEC values and provide valuable insights into ionospheric behavior during different geomagnetic scenarios.In addition to the Holt-Winter method and the auto-regressive moving average (ARMA) model, researchers have explored and developed various machine learning approaches to model and forecast ionospheric Total Electron Content (TEC) [3]. These machine learning methods have

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shown their capabilities in extracting valuable information from the data and revealing ionospheric features by exploring previously unknown relationships between input and output parameters [4 - 5]. These approaches leverage the power of machine learning algorithms to capture complex patterns and dependencies within the ionospheric data, leading to improved forecasting accuracy and a deeper understanding of ionospheric behavior.Long Short-Term Memory (LSTM) networks, on the other hand, offer a solution to these problems [6]. LSTMs are an extension of RNNs, and they are designed to overcome the limitations of traditional RNNs by effectively extending their memory. Memory blocks within LSTM networks replace the self-connected hidden units found in RNNs, allowing them to better capture long-term dependencies and retain information over longer periods [7 - 9]. This property enables LSTMs to fully exploit the benefits of training on long-term TEC time series data, leading to more accurate and meaningful predictions of ionospheric behavior. As a result, LSTMs are well-suited for forecasting ionospheric TEC, making them a preferred choice in many research applications. On the other hand, the "tanh" activation function regulates the flow of values throughout the LSTM network [10]. It allows the cell state to forget obsolete or less relevant memory information, facilitating the retention of essential information while discarding less important details [11 - 13]. These two activation functions together enable the LSTM to effectively manage memory and handle long-term dependencies, making it particularly suitable for capturing patterns in time series data, such as ionospheric TEC time series [14].

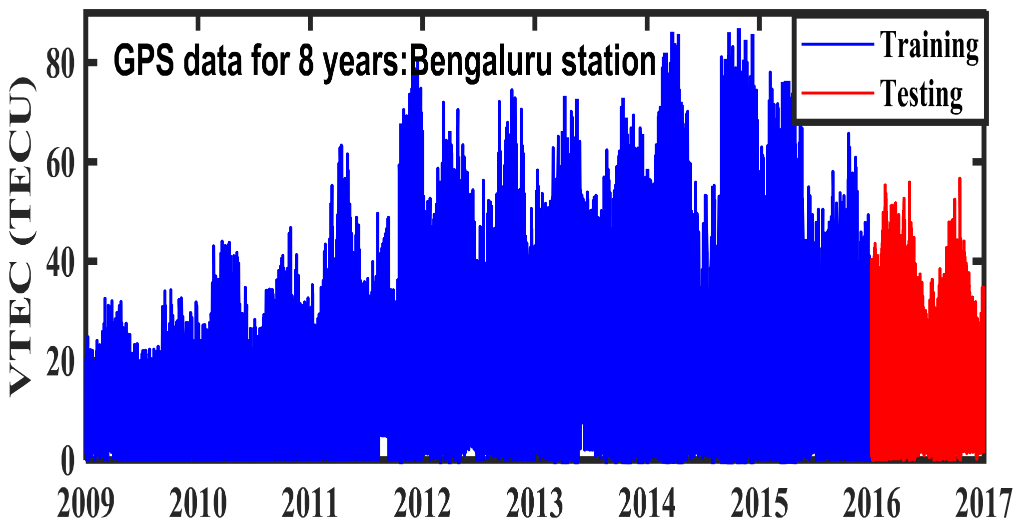

Figure 2 shows experimental data for deep learning forecasting that tests the descending phase using the LSTM TEC model.

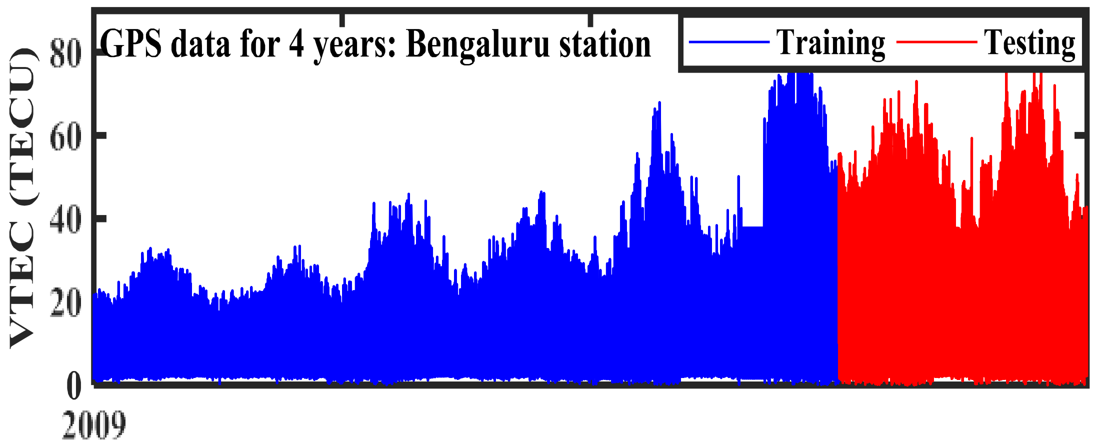

Fig. 3 shows Using the LSTM TEC model to assess ascending phase, experimental data for deep learning forecasting.

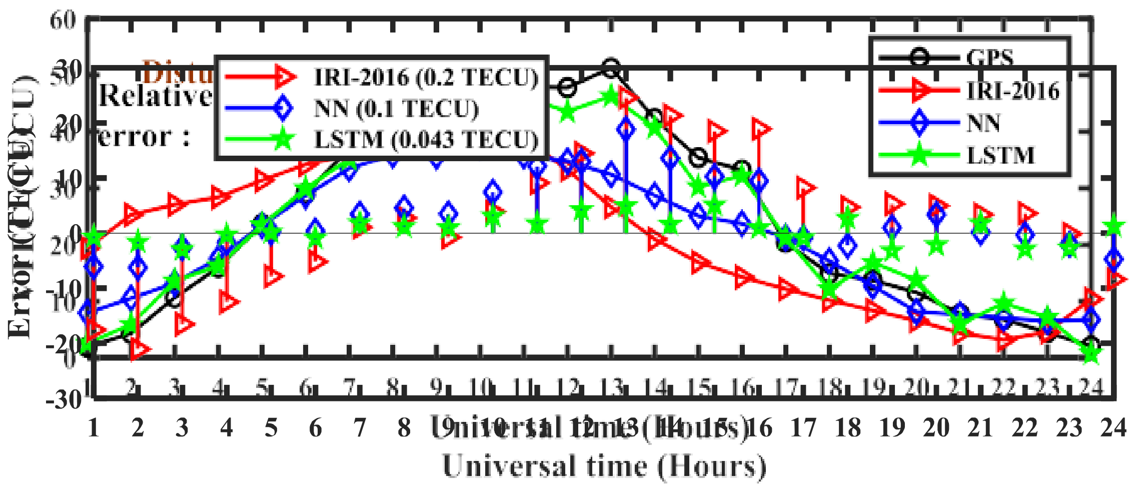

Figure 4 shows the performance of the LSTM TEC model, the NN model, and the IRI-2016 model on November 19, 2016, a geomagnetic quiet day, and (bottom) its forecasting errors.

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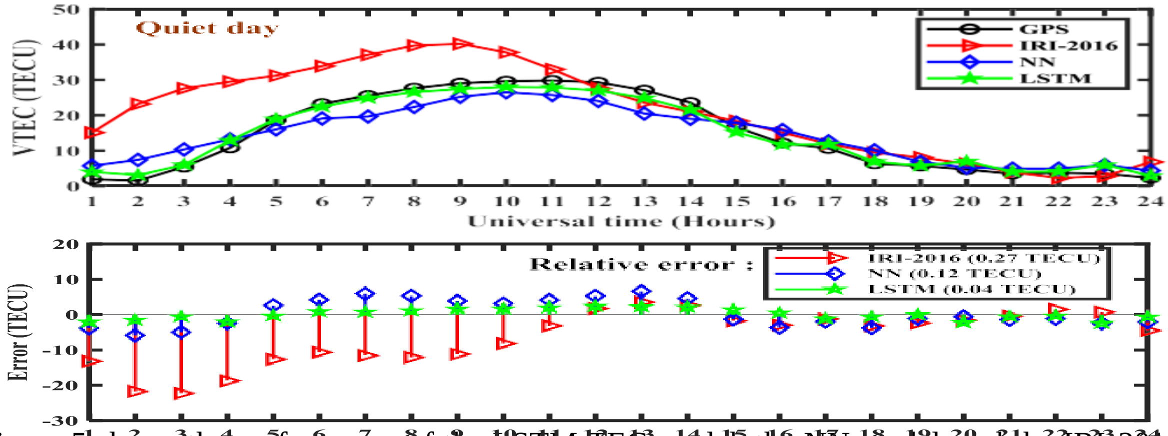

Figure 5 shows the performance of the LSTM TEC model, the NN model, and the IRI-2016 model on the May 8, 2016, geomagnetic disturbance day, and the forecasting errors for each model.

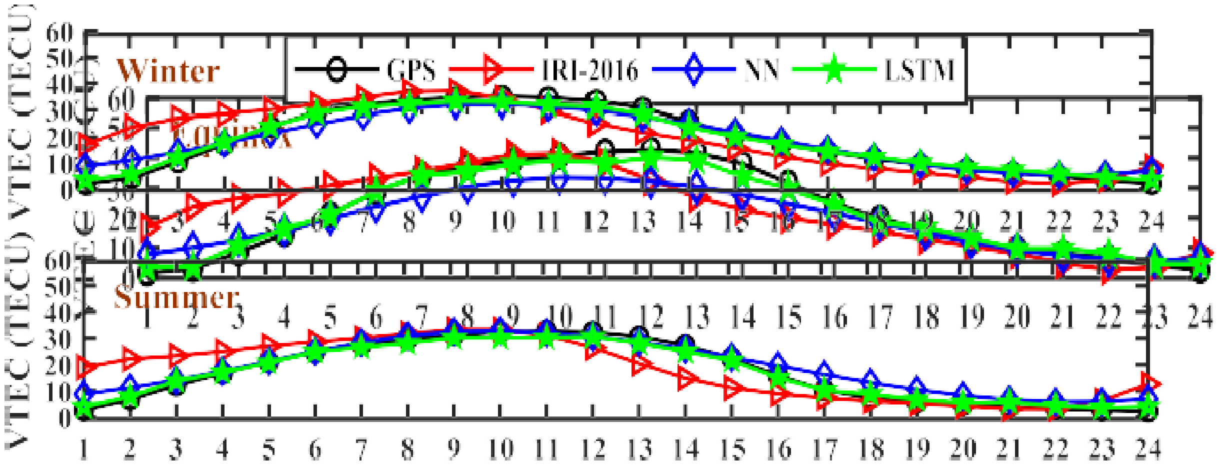

Fig. 6. Seasonal fluctuations of GPS-measured VTEC and predicted VTEC using LSTM TEC model, NN model, and IRI-2016 model, including (Top) equinox, (Middle) winter, and (Bottom) summer.

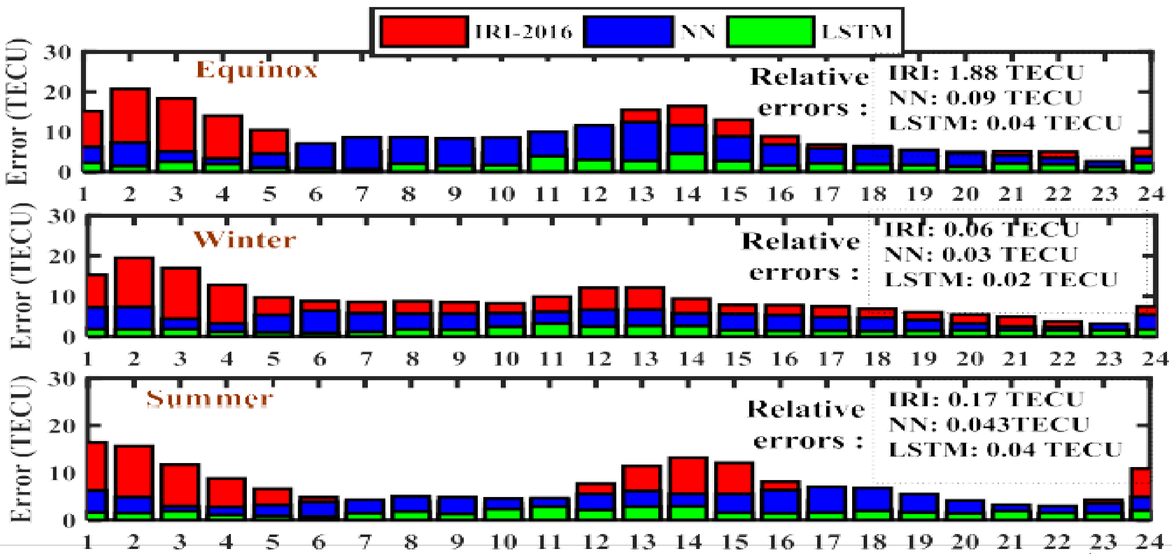

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Fig. 7. RMSE bar plots for (Top) equinox, (Middle) winter, and (Bottom) summer to forecast TEC using LSTM, NN, and IRI-2016 models.

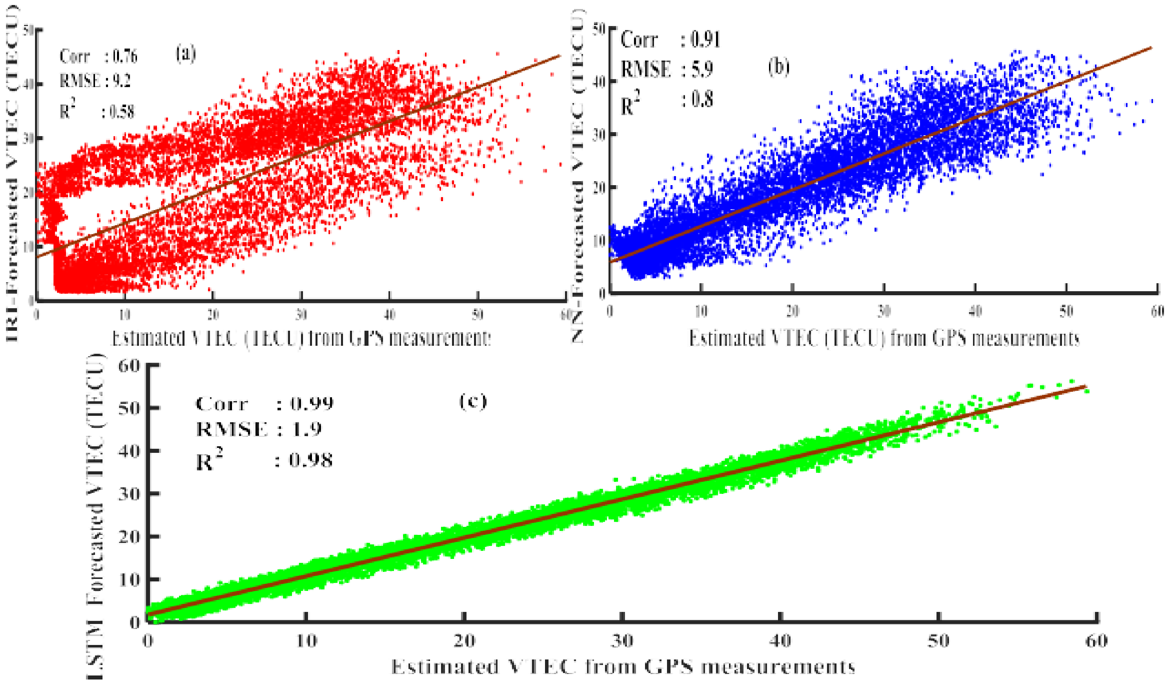

Figure 8 shows scatterplots of GPS-measured VTEC in 2016 against the IRI-2016 model, the NN model, and the LSTM TEC model.

CONCLUSION

To assess its performance, the LSTM TEC model is compared with both the conventional neural network (NN) and the IRI-2016 models during the testing period of 2016. The comparison is carried out over the Bengaluru IGS station, a low-latitude GNSS station. The LSTM TEC model's forecasting capabilities are tested to capture the effects of solar activity on ionospheric TEC variations during geomagnetic quiet and disturbed conditions, as well as seasonal variations.The experimental forecasting results, spanning eight years of data during the 24th solar cycle, demonstrate that the LSTM model is well-suited as a deep learning technique. It achieves high correlation coefficients of 0.99 and coefficient of determination (R2) of 0.98, with relatively low Root Mean Squared Error (RMSE) values of 1.9 TECU. These results indicate the LSTM TEC model's proficiency in accurately capturing variations in VTEC corresponding to both solar and geomagnetic activity effects.Considering the successful performance of the LSTM model, it is deemed a suitable forecasting model for ionospheric

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TEC variations. The model shows promise in addressing the complex and dynamic nature of the ionosphere, making it a valuable tool for future research and applications in different geographical regions with ionospheric TEC data.

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