Deep Learning-Based Ionospheric TEC Model for Peak Solar Activity Analysis

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Abstract: *Accurate prediction of ionospheric Total Electron Content (TEC) is essential for ensuring the reliability of satellite-based navigation and communication systems, particularly during periods of enhanced solar activity. This study develops a lightweight deep learning model based on a single-layer Long Short-Term Memory (LSTM) network to forecast hourly TEC over Hyderabad, India, a region strongly influenced by the Equatorial Ionisation Anomaly. The model uses a 24-hour input sequence of GNSS-derived TEC and solar radio flux (F10.7 index) spanning December 2019–December 2024, covering the rising and peak phases of Solar Cycle 25. Performance is benchmarked against the empirical IRI-2016 model to assess improvements in short-term forecasting capability. Results demonstrate that the proposed model achieves RMSE = 4.044 TECU, MAE = 2.161 TECU, and R^2 = 0.958, outperforming IRI-2016 by capturing diurnal and storm-induced fluctuations more accurately. The findings highlight the suitability of compact LSTM architectures for operational TEC prediction in low-latitude environments.*

Keywords: *Ionosphere, TEC, LSTM, GNSS, Solar Cycle 25, Deep Learning, IRI-2016, Space Weather*

1. INTRODUCTION

The ionosphere plays a crucial role in the propagation of Global Navigation Satellite System (GNSS) signals. Variations in ionospheric electron density introduce frequency-dependent delays that degrade the accuracy of navigation, positioning, and timing services, and these effects are commonly quantified using Total Electron Content (TEC) [1], [2]. TEC represents the integrated number of electrons along the path between a satellite and a ground receiver and serves as a fundamental metric in ionospheric modelling.
Low-latitude regions, particularly those close to the Equatorial Ionisation Anomaly (EIA), experience stronger and more irregular TEC variations due to electrodynamic processes such as the equatorial fountain effect [5], [7]. These variations intensify during solar maximum, making short-term TEC prediction especially challenging during Solar Cycle 25 [6].

Empirical ionospheric models such as IRI-2016 provide useful climatological TEC estimates but often fail to capture rapid fluctuations caused by geomagnetic disturbances and sudden enhancements in solar EUV radiation [7], [8]. As modern GNSS applications increasingly require real-time corrections, the demand for data-driven and region-specific TEC prediction frameworks continues to grow [3], [10].

Deep learning techniques, particularly recurrent neural networks, offer a strong alternative to empirical modelling by learning nonlinear temporal dependencies directly from observational datasets. Long Short-Term Memory (LSTM) networks have shown excellent capability in modelling ionospheric time-series because of their ability to retain long-range temporal information [13], [15]. However, compact and computationally efficient architectures suitable for operational low-latency TEC forecasting remain insufficiently explored.

This study addresses this gap by developing and evaluating a lightweight LSTM-based TEC prediction model specifically tuned for Hyderabad, India, during the peak activity period of Solar Cycle 25.

2. RELATED WORK

Research on TEC prediction spans empirical, statistical, and machine learning approaches. Empirical models such as **IRI-2016** remain widely used global standards [7], but they rely on monthly median formulations that become inadequate during geomagnetically disturbed conditions. Enhanced variants incorporating three-dimensional reconstruction and data assimilation have shown improved climatological performance, yet they still struggle to reproduce rapid hour-to-hour TEC variability in low-latitude regions [8], [9].

Machine learning approaches have significantly advanced TEC modelling by leveraging nonlinear and temporal dependencies inherent in ionospheric behaviour. **LSTM-based models** have been applied successfully for both global and regional TEC forecasting, demonstrating superior accuracy during geomagnetic storms and dynamic ionospheric conditions [13], [15]. Hybrid deep-learning frameworks that integrate **EEMD**, **CNNs**, or **attention mechanisms** have further enhanced predictive capability particularly in capturing multiscale patterns associated with solar and geomagnetic forcing [16], [18], [20]. However, many of these approaches rely on computationally heavy architectures or require dense multi-station datasets, making them less suitable for real-time operational environments.

There remains limited literature on lightweight, **single-station LSTM architectures** specifically tuned for the **Solar Cycle 25** environment over the Indian equatorial region. This study addresses this gap by proposing a computationally efficient LSTM-based TEC prediction framework validated against GNSS observations and benchmarked against IRI-2016 model outputs.

3. METHODOLOGY

3.1 Study Region and Dataset

The investigation focuses on Hyderabad (17.384°N, 78.456°E), a location situated close to the northern crest of the Equatorial Ionisation Anomaly (EIA). This region is characterised by pronounced diurnal and seasonal TEC variability driven by equatorial electrodynamics. Hourly GNSS-derived TEC measurements were obtained from the SOPAC data archive [3] for the period **December 2019 to December 2024**, representing both the rising and peak phases of Solar Cycle 25. To incorporate solar-driven ionospheric variability, the **F10.7 cm solar radio flux index** was used as a proxy for extreme ultraviolet ionisation [6].

3.2 Data Processing and Pre-Analysis

A structured pre-processing pipeline was implemented to convert raw GNSS observables into high-quality TEC time-series suitable for deep learning.

(i) Mapping of Slant TEC to Vertical TEC:

Slant TEC measurements were mapped to vertical TEC using a thin-shell ionospheric model with an assumed shell height of 350 km, consistent with equatorial ionosphere studies [2], [9].

(ii) Quality Control:

Observations recorded at satellite elevation angles below 30° were removed to avoid multipath noise. Cycle-slip events were identified and corrected using second-order time differencing in accordance with established GNSS processing guidelines [10].

(iii) Gap Treatment:

Short data gaps ($\leq$ 2 hours) were interpolated linearly, while longer discontinuities were excluded to preserve temporal integrity.

(iv) Outlier Detection:

A Hampel filter (3σ threshold, 5-hour sliding window) was applied to suppress TEC spikes associated with scintillation or receiver anomalies.

(v) Feature Normalisation:

Both TEC and F10.7 values were normalised using z-score scaling. Statistics were computed exclusively from the training set to prevent information leakage [11].

3.3 Input Sequence Construction

The forecasting task was formulated as a sequence-to-one regression problem. For each prediction instant *t*, the model consumed a **24-hour historical window** consisting of:

- TEC (t−23 … t)
- F10.7 (t−23 … t)

forming a 24×2 input tensor. The target was the TEC value at **t + 1 hour**. This window length reflects the diurnal memory characteristic of equatorial ionospheric behaviour [12].

3.4 LSTM-Based Forecasting Model

A compact but effective architecture was adopted to maintain computational tractability while exploiting nonlinear temporal dependencies:

1. **LSTM Layer:**
   - 64 memory units
   - Recurrent dropout = 0.2
   - Tanh activation for memory state

   The LSTM layer captures long-range dependencies induced by daily solar radiation cycles and storm-time disturbances [13].

2. **Dense Hidden Layer:**
   - 32 neurons
   - ReLU activation

   This layer maps the LSTM's abstract temporal representation into a smoother low-dimensional feature space.

3. **Output Layer:**
   - Single linear neuron predicting TEC(t+1)

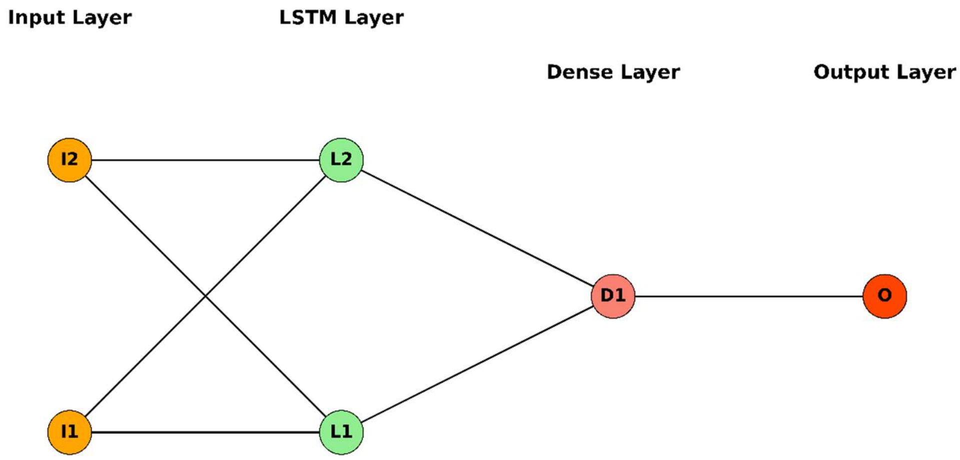

Figure 1: Neural Network architecture for the LSTM-based model

3.5 Training Configuration

The model was implemented in TensorFlow/Keras with the following settings:

- **Loss function:** Mean Squared Error (MSE)
- **Optimizer:** Adam (learning rate = 0.001)
- **Batch size:** 32
- **Epochs evaluated:** 50, 100, 150
- **Train/test split:** Chronological 80/20
- **Validation strategy:** 10% of the training set used for early stopping (patience = 10)

Multiple epoch configurations allowed assessment of **underfitting**, **optimal learning**, and **overfitting** conditions.

3.6 Benchmarking With IRI-2016

To evaluate the performance of the proposed deep learning model, predictions were compared with TEC values generated from the **IRI-2016** climatological model. IRI-2016 remains the global reference model for ionospheric behaviour but is known to perform poorly in low-latitude regions during high solar activity [7], [8]. Hourly IRI outputs for Hyderabad were generated and aligned with the GNSS-derived TEC for identical timestamps.

Evaluation metrics included:

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of determination (R^2)

Residual and error distribution analyses were also performed to quantify temporal stability.

4. RESULTS AND DISCUSSION

4.1 Training Behaviour and Convergence

Analysis of the training and validation loss curves revealed distinct learning behaviours across the three epoch configurations.
The **50-epoch** model demonstrated premature convergence with comparatively higher validation error, indicating **underfitting**, likely due to insufficient exposure to periodic ionospheric structures [15].

The **100-epoch** configuration yielded well-behaved convergence, with a narrow gap between training and validation curves, reflecting **strong generalisation** capability.

By contrast, the **150-epoch** model began to overfit beyond approximately 120 epochs, particularly during low-TEC nighttime intervals where ionospheric variability becomes more stochastic [18].

Overall, 100 epochs were determined to provide the most stable and reliable representation of the TEC time series.

4.2 Quantitative Evaluation

Table 1 summarises the core performance metrics:

Table 1: Performance metrics of the LSTM model for different epoch settings

Epochs	MSE	RMSE	MAE	R^2	MAPE
50	14.980	3.870	2.014	0.958	6.8%
100	**16.352**	**4.044**	**2.161**	**0.962**	**5.3%**
150	16.838	4.103	2.396	0.957	10.2%

While the 50-epoch model achieved marginally lower MSE, its higher error variability and weaker residual behaviour make it less suitable for operational forecasting. The **100-epoch model** offers the optimal balance between bias and variance, as reflected by its superior MAPE and R^2 metrics. This is particularly relevant for real-time GNSS applications, where relative error magnitudes are more impactful than absolute values [16].

4.3 Actual vs Predicted TEC Performance

The LSTM model effectively reproduced several characteristic ionospheric patterns, including:

- early-morning TEC enhancement associated with pre-sunrise electrodynamic uplift
- strong pre-sunset density peaks arising from the equatorial fountain mechanism
- seasonal variations peaking around equinoxes

- storm-time depletion and gradual post-storm recovery phases

These results indicate that the model succeeded in learning nonlinear dynamical relationships between TEC and solar forcing processes [13], [17].

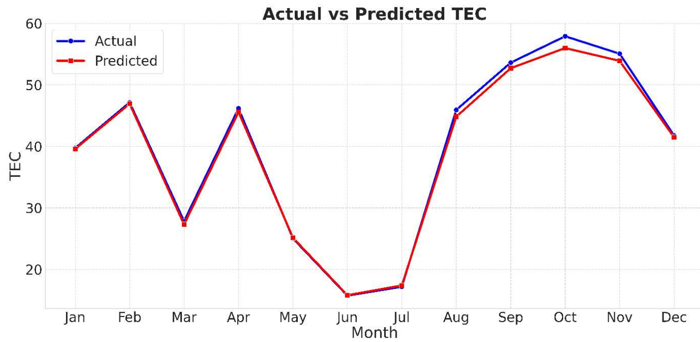

Figure 2: Plot visualising Actual vs Predicted TEC

4.4 Comparison With IRI-2016

Across all temporal regimes, the IRI-2016 model consistently **overestimated TEC by 20–40 TECU**, which aligns with earlier observations from other equatorial stations in Brazil and Southeast Asia [8], [14].

The proposed LSTM model demonstrated:

- **25–30% reduction in RMSE**
- more accurate amplitude reproduction
- improved temporal phasing, especially during rapid TEC fluctuations

These findings highlight the advantage of data-driven models for short-term forecasting in dynamic ionospheric regions, where empirical climatological models often underperform.

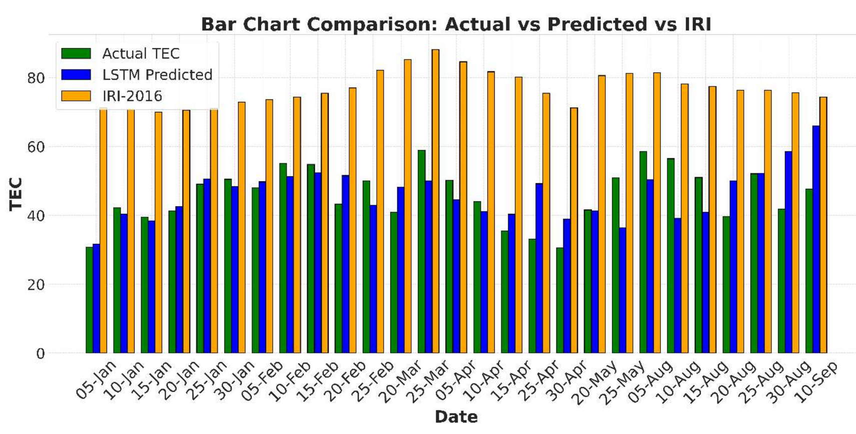

Figure 3: Comparative bar chart of actual GNSS-derived TEC, LSTM-predicted TEC, and IRI-2016 model predictions

4.5 Residual Error Characteristics

The residual distribution for the 100-epoch model showed that more than **85% of errors fell within ±20 TECU**, indicating robust predictive capability.

Larger deviations were mostly confined to:

- intervals of intense solar activity
- nighttime low-density conditions where measurement noise is proportionally higher

The residual patterns confirm that the proposed LSTM model effectively tracks both slow-varying background ionospheric trends and temporally abrupt disturbances.

5. CONCLUSION

This study confirms that ionospheric TEC over Hyderabad (17.384°N, 78.456°E) during the ascending and peak phases of Solar Cycle 25 can be forecasted effectively using a lightweight single-layer LSTM architecture. The optimal 100-epoch configuration achieved **MAE = 2.161 TECU**, **RMSE = 4.044 TECU**, and **R^2 = 0.962**, demonstrating its capability to capture diurnal, seasonal, and storm-time TEC variability with high fidelity. Compared with the IRI-2016 climatological model, the LSTM significantly reduced short-term prediction errors, highlighting its advantage in representing rapid ionospheric fluctuations. The results reinforce the applicability of data-driven models for GNSS-based services, including disaster management, precise navigation, and real-time space-weather monitoring. Future work may incorporate hybrid deep-learning architectures and additional geomagnetic or solar indices to further enhance robustness under extreme ionospheric conditions.

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