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Enhanced Prediction of Ionospheric Total Electron Content Using Deep Learning Model Over Equatorial Kenya: A Review of Literature

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Abstract: This study explores the emergence of deep learning approach in predicting ionospheric total electron content (TEC); which is pivotal for space weather forecasting. Total electron content variability has profound implications for satellite communications and navigation systems, especially in regions with unique ionospheric characteristics such as equatorial Kenya. Traditional TEC prediction models which are rooted in empirical or physics-based methods, often encounter challenges in capturing the complex, non-linear behaviors inherent in equatorial ionospheric dynamics. A systematic literature review (SLR) was performed to extract and synthesize the algorithms and features that have been used in long short-term memory networks (LSTMs) techniques to model and predict the ionospheric TEC, with a focus on the unique characteristics of the geomagnetic equator at low latitudes. Several articles on ionospheric TEC prediction using deep learning were obtained from research databases where few were selected based on the inclusion/exclusion criteria used in the study. The outcome of the review from several studies embarked on deep learning using LSTMs architectures, they highlighted the importance of feature selection and feature engineering in enhancing prediction accuracy. The study also explored hybrid machine learning techniques models which showed improved forecast performance. Additionally, the suggestion on addressing data gaps and considering additional parameters which could further enhance the accuracy and reliability of TEC predictions.

Keywords: Deep Learning; Predictions; LSTM; Ionospheric; Total Electron Content; Space Weather Forecasting

1. INTRODUCTION

The introduction highlights the description of ionospheric layers, ionization of the electron population and its impact on the trans-ionospheric radio transmissions, including those from GPS satellites which experience a time delay as a result of the ionized layer's role as a dispersive medium for electromagnetic waves (Garner et al., 2008). The importance of using machine learning techniques such as LSTM for prediction of total electron content, where Goodfellow et al. (2016) state that the LSTM approach is a well-known and potent subset of artificial neural networks that is renowned for its ability to solve time series data. Recently, LSTMs have been used to forecast many characteristics related to space weather.

1.1 TEC Variability at Low Latitudes

According to Kumar and Singh (2009), due to existence of the huge background TEC values, there may be a greater likelihood of signal degradation over the low-latitude zones due to substantial changes in TEC. It is well recognized that the temporal and geographical characteristics of TEC at low latitudes and the equatorial regions vary according to solar activity, season, and time of day. They further explain that large TEC and irregularities in electron density of the ionized layer can have adverse effects on transmission of signals. These effects include: (1) Signal Degradation; where high TEC levels and electron density irregularities can lead to signal degradation in communication systems, particularly in satellite communications and Global Navigation Satellite Systems (GNSS). This degradation can result in signal loss, interference, and reduced signal quality, affecting the reliability of communication links and navigation accuracy. (2) Scintillation Irregularities in electron density that is referring to acute variability in the amplitude and phase of high frequency signals passing through the ionized layer. Scintillation can degrade communication signals, leading to signal fading and loss of signal lock in GNSS receivers. (3) Ionospheric Perturbations; Large TEC values and electron density irregularities can create ionospheric perturbations that introduce errors in positioning and timing information provided by GNSS systems. These perturbations can affect the accuracy of location-based services, navigation applications, and timing synchronization. (4) Geomagnetic Storm Effects; During geomagnetic storms, the ionosphere experiences strong perturbations in TEC, which can further exacerbate the adverse effects on communication and navigation systems. Geomagnetic storms can lead to increased ionospheric disturbances, causing disruptions in signal propagation and navigation services.

1.2 Satellite Signals

Shenvi and Virani (2023) explain further that the essential component in the transmission of radio waves is the ionosphere, which is located in the upper atmosphere of the earth. Positioning accuracy can be reduced by variations in the ionosphere's electron density, which can affect the radio signals' speed and delay as they travel from GNSS satellites to receivers. The ionosphere's impact on satellite communications is closely correlated with the TEC statistic. Radio waves traveling through the ionosphere are delayed by the TEC. Therefore, it is a significant cause of mistake in GNSS and other navigation systems. As a result, high frequency communications, navigation, and positioning systems all depend on the forecast of ionospheric TEC. Correcting location inaccuracies brought on by the ionosphere will be made easier with the help of a successful TEC forecast.

In the studies of ionospheric variables, the ionospheric total electron content, is a crucial parameter. Precise TEC prediction is essential in the development of satellites and ground-based systems. Thus, it is essential to understand the space weather fluctuations in TEC and create precise TEC models

1.3 Empirical Models

Various models such as the NeQuick model (Nava et al., 2008), the Bent model (Bent et al., 1975), the International Reference Ionosphere (IRI) model (Bilitza, 2018; Bilitza et al., 2022) for ionospheric parameter prediction, and global empirical models are currently preferred. These models offer substitute platforms for TEC estimate, including long-term forecasting.

Nonetheless, it is still necessary to estimate the TEC instantly. As a result, estimated TEC values need to accurately capture the characteristics of visible ionosphere phenomena. Thus, in an effort to investigate ionospheric variability, numerous research has developed regional TEC forecasting models. There are two main types of approaches used to forecast regional TEC: empirical methods (Cesaroni et al., 2020) and physics-based methods

However, the physics-based techniques which are now used to predict regional TEC are predicated on quite straightforward theoretical frameworks. Time-series forecasting, auto-regressive moving average (ARMA) (Zhang et al., 2017), EXtreme Gradient Boosting over Decision Trees (Zhukov et al., 2021) and different deep learning models have recently been created to predict regional temperature extremes (Tebabal et al., 2019).

Physical models are parameterized using simplifying assumptions and might not function worldwide, as well as because empirical data might not be available for all geographic regions, physical models are also not strictly physical. In addition, space weather activities and signal transmission process all contribute to the formation of the ionosphere. The majority of research primarily rely on data assimilation methods for simulating the ionospheric total electron content (Zewdie et al., 2021).

1.4 Machine Learning Techniques

Machine learning techniques offer a viable alternative. These techniques are well-known for their ability to learn from data and retrieve pertinent information. When a nonlinear system cannot be well described by linear approaches like least squares regression, they are especially well-suited for issues requiring a suite of variables. Many industries are now using machine learning and deep learning techniques, which have produced some amazing results (Camporeale, 2019)

2.0 OBJECTIVE

In the study of ionospheric variables, the ionospheric total electron content, is a crucial parameter. Precise TEC prediction is essential for the development of satellite and ground-based systems. Thus, it is essential to comprehend the space weather fluctuations in TEC and create precise TEC models (Xiong et al., 2021).

Long Short-Term Memory (LSTM) model simulates time-based data structures and their long-range dependencies. Many time-series prediction and time-series labeling applications, including recognition of speech and handwriting production have shown remarkable effectiveness with the LSTM (Goodfellow et al., 2016)

Goodfellow et al., 2016 state further that the LSTM approach is a well-known and potent subset of artificial neural networks that is renowned for its ability to solve time series data. Recently, LSTMs have been used to forecast many characteristics related to space weather. Hence, this systematic review of literature is an attempt to identify methods, features, evaluation metrics and existing gaps in the prediction of ionospheric total electron content using LSTM models.

3.0 LITERATURE REVIEW

The review of literature was able to explores the LSTM techniques, ionospheric features, evaluation metrics for predicting the total electronic content. Also, future research gaps are highlighted as stipulated below:

3.1 Deep Learning and Ionospheric Parameters

Several studies have explored advanced machine learning methods to improve the accuracy of TEC forecasting. Zewdie et al. (2021) utilized Long Short-Term Memory (LSTM) networks, leveraging parameters from both solar wind and geomagnetic storm variables to predict low-latitude TEC. Shenvi and Virani (2023) also applied LSTM models, incorporating a comprehensive set of exogenous parameters such as Proton Density (Np), Planetary Index (AP and KP), Interplanetary Magnetic Field Component (Bz), Solar Radio Flux (F10.7), Disturbance Storm Time Index (Dst), Plasma Speed (Vp), and Time. Sulungu and Uiso (2019) took a different approach, using a multi-layer perceptron neural network with inputs including Year, Day of the Year, Hour of the Day, Geographic Latitudes, Geographic Longitudes, Sunspot Number (SSN), and IRI-NmF2. Additionally, Jeong et al. (2024) explored deep learning models, such as LSTM and Convolutional LSTM (ConvLSTM), incorporating synthetic TEC maps generated by a Deep Convolutional Generative Adversarial Network (DCGAN) to enhance data representation.

3.2 Evaluation Metrics

The performance of TEC forecasting models is typically evaluated using various error metrics. Shenvi and Virani (2023) assessed their LSTM model using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) to measure forecast accuracy. Similarly, Sulungu and Uiso (2019) evaluated their multi-layer perceptron neural network using RMSE. Jeong et al. (2024) compared the performance of their LSTM and ConvLSTM models by calculating RMSE values between the predicted TEC values and the ground truth TEC maps generated by DCGAN.

3.0 METHODOLOGY

It is important to conduct a thorough SLR in a particular field in order to formulate research questions and provide support for further studies in that field (Torres-Carrion et al., 2018). The research methodology in this study, adopted the systematic literature review techniques developed by Kitchenham and Charters (Wen et al., 2012). A review procedure was developed during the planning stage. The procedure involves six main stages: the research questions, definition, search strategy design, study selection, quality assessment, data extraction, and data synthesis which are the six primary steps of this review technique.

3.1 Planning Review Phase

This phase involves formulating research questions, developing a procedure, and ultimately validating the protocol to determine the viability of the strategy. Publication databases, first search keywords, and criteria for choice of publication are defined. The protocol is reworked once more to determine whether it now reflects an appropriate review protocol after all of this information has been defined. The internal processes of the plan review phase include; (1) research question definition, (2) search protocol definition, (3) database selection, (4) search strings definition, (5) publication selection criteria definition and (6) revision of search protocol consecutively

3.2 Conducting the review

In conducting the review, all of the target databases were searched in order to choose the publications. After the data was extracted, more details about the research topics as well as information about the authors, year and type of publication, were saved. Following accurate extraction of all relevant data, the data was synthesized to produce a summary of the pertinent publications that have been published to date as follows: (1) finding publications, (2) data extraction and (3) synthesizing data

3.3 Reporting the review

In reporting the review, the two major steps were carried out during conduction of the actual review: (1) showing the results and (2) answering the research questions

3.4 Research Questions

The four research questions (RQs) below have been established to define the main objective of this SLR study.

RQ1: Which deep learning algorithms have been used in the literature for ionospheric TEC prediction?
RQ3: Which features have been used in literature for prediction of ionospheric TEC?
RQ3: Which evaluation metrics and evaluation approaches have been used in literature for ionospheric TEC prediction?
RQ4: What are challenges in the field of ionospheric TEC prediction using machine learning?

4.0 DISCUSSION AND FINDINGS

This study highlights the various long term short term neural network techniques used by researchers including multi variate deep learning LSTM, hybrid deep learning where RNN-LSTM and ConvLSTM were combined. Different combinations of number of layers and neurons were trained respectively, the studies showed different results when these combinations were deployed. Features included in modelling were Year, Day of the Year, Hour of the Day, Geographic Latitudes, Geographic Longitudes, Sunspot Number (SSN), IRI-NmF2, F10.7 (Solar Radio Flux), Dst (Disturbance Storm Time Index, Vp (Plasma Speed), Bz (Interplanetary Magnetic Field Component) and Time where the inclusion and exclusion of some of the features showed different results both in prediction and performance. The most common evaluation metrics across the studies were Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2), these metric managed to evaluate the performance of the LSTM models which were in accordance with the prediction outcomes. Hence, with more studies it is clear that LSTM can be used to enhance the prediction of ionospheric total electron content over Kenya.

5.0 CONCLUSION

In conclusion, this paper has provided a comprehensive overview for the utilization of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, for predicting ionospheric Total Electron Content (TEC) over Equatorial Kenya. The study systematically reviewed existing literature, synthesizing findings from various studies to explore the effectiveness of LSTM models in capturing the complex dynamics of equatorial ionospheric variability.

The review revealed that traditional TEC prediction models often face challenges in accurately capturing the nonlinear behaviors inherent in equatorial ionospheric dynamics. However, deep learning approaches, particularly LSTM networks, have emerged as promising tools for addressing these challenges. Various studies showcased the application of LSTM architectures in predicting TEC variability, also demonstrating their effectiveness in capturing seasonal variations in TEC with the potential for real-time prediction.

5.1 Future Work

For future work, the discussion highlighted the importance of feature selection, feature engineering and model architecture in enhancing prediction accuracy, as well as the need for further research to explore advanced machine learning techniques or hybrid models to improve forecast performance. Additionally, addressing data gaps and considering additional parameters could further enhance the accuracy and reliability of TEC predictions

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