

FORECASTING IONOSPHERIC TOTAL ELECTRON CONTENT MAPS WITH DEEP NEURAL NETWORKS

Noëlie Cherrier, Thibaut Castaings, Alexandre Boulch

ONERA, The French Aerospace Lab,
Chemin de la Hunière, 91123 Palaiseau, France

ABSTRACT

Satellite telecommunications and Global Navigation Satellite Systems (GNSS) would benefit from an early prediction of the ionospheric activity. The Total Electron Content (TEC) values of the ionosphere are already locally predicted by models from previous studies, but no model exists to our knowledge for worldwide prediction. A large amount of data for world TEC maps is available from the Center for Orbit Determination in Europe (CODE). With Deep Neural Networks (DNN), we propose a method to forecast a sequence of global TEC maps following past given TEC maps, without introducing any prior knowledge. By combining several state-of-the-art architectures, the proposed approach is competitive with previous works on TEC forecast, while predicting global TEC maps.

Index Terms— Ionosphere, TEC, forecast, deep learning, neural networks, sequence prediction

1. INTRODUCTION

Satellite telecommunication services and Global Navigation Satellite Systems (GNSS) are widely used services subject to perturbation due to the ionospheric activity. During high ionospheric activity, the path of transionospheric radio waves indeed changes, inducing significant bitrate reduction and positioning errors [1, 2]. As a consequence, forecasting the ionosphere state globally (*i.e.* worldwide) increases the ability of the users to evaluate, for example, data loss probabilities or margin of error in positioning planning.

The ionospheric activity is usually measured using Total Electron Content (TEC), which is the total number of electrons in the ionosphere integrated along a vertical path above a given location. It is expressed in TEC Units ($1 \text{ TECU} = 10^{16} \text{ el}/m^2$), usually ranging from a few units to one hundred TECU.

Several services exist to address TEC forecasting. They rely on measurements provided by GNSS ground networks [3] and aim at producing global TEC maps. CTIpe is an experimental tool implementing complex physics models [4] developed by the US Space Weather Prediction Center that produces global forecasts 30 minutes ahead of real-time. In

Europe, the ESA Ionospheric Weather Expert Service Center combines products from different national services to provide global and regional 1-hour TEC forecasts. However, the records of the input data and forecasts are not published.

A global analytical TEC model has been proposed in [5], using open source TEC data from the Center for Orbit Determination in Europe (CODE). This model is intended to apply to any temporal range, without relying on a record of TEC values.

The literature provides several methods using time series and statistical methods to predict TEC with various forecasting horizons from a few minutes to several days based on the previous state of the ionosphere. Most of these methods [6, 7, 8, 9, 10] provide predictions above specific stations. Among these, a few works aim at reconstructing the TEC on a small area [11, 12] with methods such as Bezier surface-fitting or Kriging. Some of them use machine learning, particularly neural networks [11, 13, 14], to infer the model parameters. However, they only focus on local stations and obtaining a regional or global prediction would require one model for each location and interpolation for not covered areas.

In this paper, we aim at predicting global TEC maps from 2 to 48 hours ahead of real-time. We propose a purely data-driven approach using deep convolutional recurrent networks. Deep Neural Networks (DNN) have the advantage to enable complex modeling of large input data, such as global TEC maps in this case, with little or no prior knowledge.

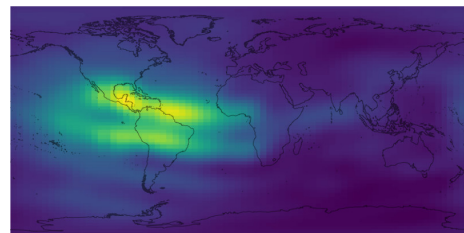


Fig. 1. TEC map example

This work is a supplementary study following the works published in [15] and investigates the possible improvement provided by an alternative neural network architecture. The paper is organized as follows: Section 2 presents the recurrent

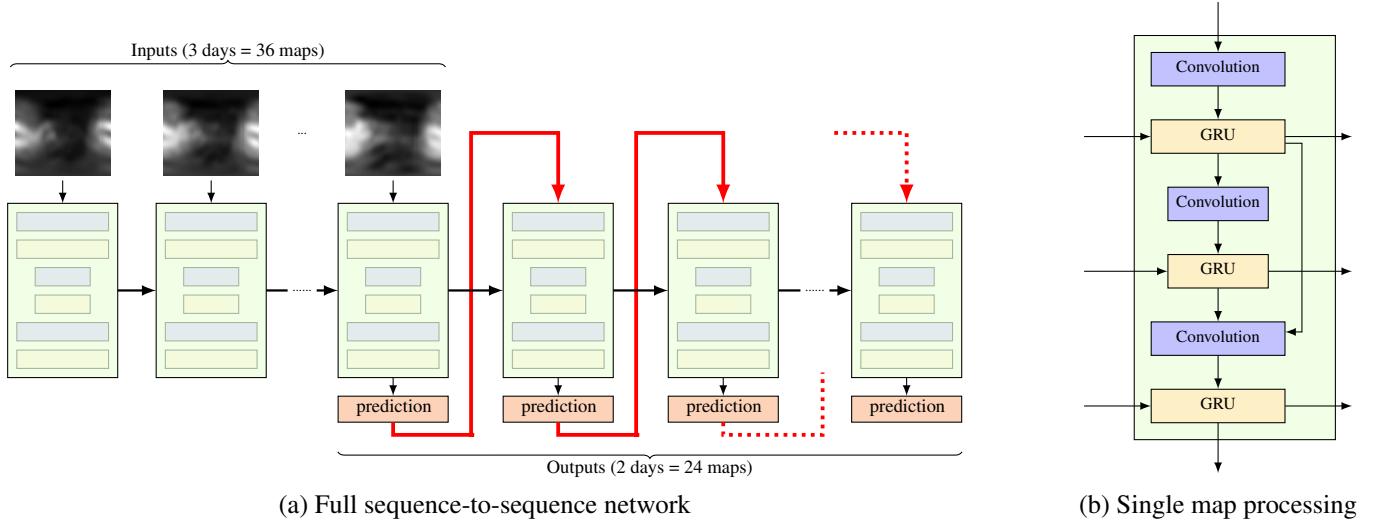


Fig. 2. Network architecture

U-net architecture and Section 3 shows quantitative results on TEC prediction.

2. METHOD

A neural network architecture is designed considering that we want to output a sequence of 48 hours of TEC maps given a number of past maps.

2.1. Data retrieving and preprocessing

Open source TEC data from the CODE is used in this study, the TEC maps having a $5^\circ \times 2.5^\circ$ resolution on longitude and latitude and 2-hour temporal resolution, covering all latitudes and longitudes (Fig. 1). One pixel in these maps represents the vertical TEC at this point. The study is conducted using the data from 1/1/2014 to 12/31/2016.

A 24-hour periodicity can be easily noticed while observing the data, due to the Sun heating the ionosphere during the day. There is no interest of having a neural network learn deterministic phenomena such as the day-night cycle. As in [15], we make the effect of Earth's rotation no longer visible to the neural network by changing the frame of reference to Heliocentric. Finally, the data is loaded as a sequence of 60 maps (one map every two hours): the first 36 maps (*i.e.* 3 days) are fed to the network, the last 24 maps (*i.e.* 48 hours) being the prediction targets.

2.2. Network architecture

The challenge of this study is to design a neural network able to handle a specific sequence prediction problem in which both the inputs and targets are a sequence of images (*i.e.* TEC maps).

Global architecture. The underlying idea of this paper is that a large part of future ionospheric activity can be inferred from its previous states. Particularly when looking at the temporal evolution of TEC maps, the main phenomena are continuous, which supports the possibility of predicting the next map sequence. This temporal trend is extracted via Recurrent Neural Networks (RNN), allowing temporal information to flow between processed maps and assist the prediction. The whole pipeline is presented in Fig. 2 (a). The sequence is processed frame by frame in the temporal order by a recurrent convolutional neural network (green block in Fig. 2 (a)), the temporal information being kept during the iterations of the process. The prediction process is achieved by recursively feeding the next column of the network with the last prediction (red arrows).

Computational block. The recurrent convolutional neural network used to process one temporal frame is presented in Fig. 2 (b). Convolutional Neural Networks (CNN) are used to handle the bidimensional structure of the TEC maps. Also, as we need to output TEC maps, an architecture similar to U-net [16] is exploited as an alternation of convolutional layers and recurrent units. Three Gated Recurrent Units (GRU) [17], a special kind of Recurrent Neural Network (RNN) are used to capture the temporal dependencies at different spatial scales.

Training For each predicted map, the individual cost function is defined as the sum of the relative error and the ℓ_1 loss with respect to the ground truth. The final cost function is summed over the maps produced by the successive prediction columns.

3. RESULTS

Once it has been trained, the network can be fed with any 3-day sequence from the test set and produce 2-day forecasts consecutive to this sequence. The Root Mean Square (RMS) error (1) is used to assess the performance of the model.

$$\epsilon_{RMS} = \sqrt{\sum_{t \in \mathcal{S}} \sum_{i \in \mathcal{M}^t} (P_i^t - T_i^t)^2} \quad (1)$$

with \mathcal{S} the sequence of TEC maps, \mathcal{M}^t the TEC map at t , P the predicted map and T the ground-truth map, where t indexes time and i is the map pixel index.

3.1. Comparison on sequence prediction

For benchmarking purposes, we set up three reference methods. The first one is a basic constant prediction: the mean over the input sequence. The next one is called periodic prediction, the predicted sequence is exactly the input of the last two days. Finally, the approach proposed in [15] is a less complex neural network relying on Long Short-Term Memory (LSTM) networks (an other type of RNN) and CNN. The overall data flow (Fig. 2 (a)) is similar, but the single map processing block (Fig. 2 (b)) is implemented by an Encoder-LSTM-Decoder cell.

Table 1 presents the results of our experiments. We evaluate the performance of our architecture against the three baseline models. We also add in the table the scores of our model where we replaced the convolutional GRU units by LSTM ones.

First column presents the best scores obtained over several trainings. The approach from [15] gets a mean RMS of 2.407 TEC units (the average TEC value being around 30 TEC units) while the proposed network RMS averaged over the predicted sequence is 2.373 TEC units. Comparing to periodic prediction and convolutional LSTM [15], the performance is improved by respectively more than 8% and more than 1% using the U-net and GRU cell.

To our interpretation, this improvement comes from the higher interdependence between recurrent maps. Our network uses three recurrent units against one in [15]. The temporal behavior is captured at different spatial scales. Particularly, details do not suffer from the high compression rate operated by the encoder in [15].

However, as shown in the second column, these networks have difficulties to converge and on several trainings they do not reach a satisfactory performance. The bad scores are mainly obtained in the 24-48 hours prediction range. As underlined by the third column (first 24 hours mean RMS errors), our networks perform very well for the first 24 hours predictions, overcoming [15] by 0.1 TEC unit. We understand the difficulty to predict the 24-48 hours range as a long-term dependency only understood by a few trainings (the best runs,

Table 1. Comparison with other methods. RMS are expressed in TEC units

Method	RMS 48h (best)	RMS 48h (mean)	RMS 24h (mean)
Constant	3.18	3.18	3.12
Periodic	2.59	2.59	2.59
LSTM [15]	2.407	2.69	2.56
Ours LSTM	2.38	2.67	2.45
Ours GRU	2.373	2.69	2.43

that outperform periodic prediction on the whole 2-48 hours range).

3.2. Comparison with literature

In Table 2, we compare the results for the proposed approach with results from state-of-the-art models. The presented RMS errors are computed by selecting the same latitude(s) of the station(s) studied in the cited paper, as well as the same period of study.

Table 2. Results of previous works

	Reference	RMS (ref)	RMS (proposed)
[6]	Chunli D., Jinsong P.	1.45	2.049
[13]	Huang, Z., Yuan, H.	≤ 2	1.936
[9]	Niu, R. <i>et al.</i>	3.1	0.800

The obtained results are competitive with state-of-the-art models (their RMS errors range from 1.5 to 3 TEC units) and the proposed approach provides global TEC map forecasting 2 to 48 hours ahead of real-time. However, the comparison with previous works on TEC forecast is only indicative since these works differ by their prediction horizons and since several studies focus on one or a few specific measuring stations instead of producing a worldwide TEC prediction.

4. CONCLUSION AND PERSPECTIVES

In this work, we extend the method of [15] for TEC sequence prediction given the previous TEC maps. By investigating a new network architecture based on multiple recurrent neural units, we show that using more interlinked spatial processing (convolutional layers) and temporal information passing (recurrent units) leads to improved results.

Among the future work, the convergence issues requiring several training will be investigated. We will also explore the inclusion of more input information. There are complex dependencies that may not depend on the previous states of the ionosphere. As an example solar particles may interfere with the ionosphere [18, 19]. The next step will consist in using

solar activity as an additional input to the network. Several information sources are considered such as multispectral solar images or solar wind.

5. REFERENCES

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