Use of deep learning methods for processing and analysis of ionospheric data

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1. Motivation

An interface between processes in space and on Earth is formed by the very dynamic environment continuously influenced by solar radiation and space weather from above and by atmospheric weather and electrical discharges from below. This region consists also of ions and electrons called the **ionosphere**. The ionosphere is the most critical atmospheric layer for transmission of the radio signal between space-based missions and ground-based stations. All the disturbances that occurre in the ionosphere can rapidly modify the amplitude and phase of the radio waves. Such modifications are called **ionospheric scintillations**. They represent a high-risk effect for the signal from Global Navigation Satellite System (GNSS).

2. Problem

The importance of knowing when ionospheric scintillations occur is highlighted by many studies, which, however, predominantly focus on predicting amplitude scintillations. Therefore, we have decided to focus on a different, less explored type – **phase ionospheric scintillations**. Our main goal is the automatic prediction of their occurence. The expected output is a binary value: will scintillation occur or not?

3. Data

To study phase ionospheric scintillations, we focused on the phase ionospheric scintillation intensity parameter $\boldsymbol{\sigma_\phi}$. We used data measured in high-latitude regions by the Canadian High Arctic Ionospheric Network (**CHAIN**) from 2013 to 2021. These data represent time series, which we transformed into time windows. Using the **sliding window approach**, we created training and testing datasets. Each record represents a time window with a defined size and a prediction value with a specified time shift. Based on the ANOVA analysis, we selected the most relevant parameters for prediction. The final selection consisted of geomagnetic indices: **PC(N) index**, **ASY/H**, **Bz GSE**, and **Ap index**.

4. Methodology

From the experiments, we found that classifying predicted values using only a simple threshold method results in a high number of FP or FN. Therefore, we decided to apply post-processing techniques to the predictions. The problem and its solution were then divided into three main steps:

1. **Deep learning approach** – using reccurent neural networks such as LSTM and Bi-LSTM for regression problem. We tested various approaches:
   - **Autoregressive models** *(input: previous values σ_ϕ)*
   - **Base Multivariate models** *(input: previous values σ_ϕ + previous values of a single added parameter)*
   - **Extended Multivariate models** *(input: previous values σ_ϕ + previous values of each added parameter)*
2. **Post-processing** applied to predictions and true values. We used **coefficient of variance** (CoV) to distinguish between values indicating scintillation and those not indicating scintillation
3. **Binary classification** Determined a threshold value of CoV for phase ionospheric scintillation detection.

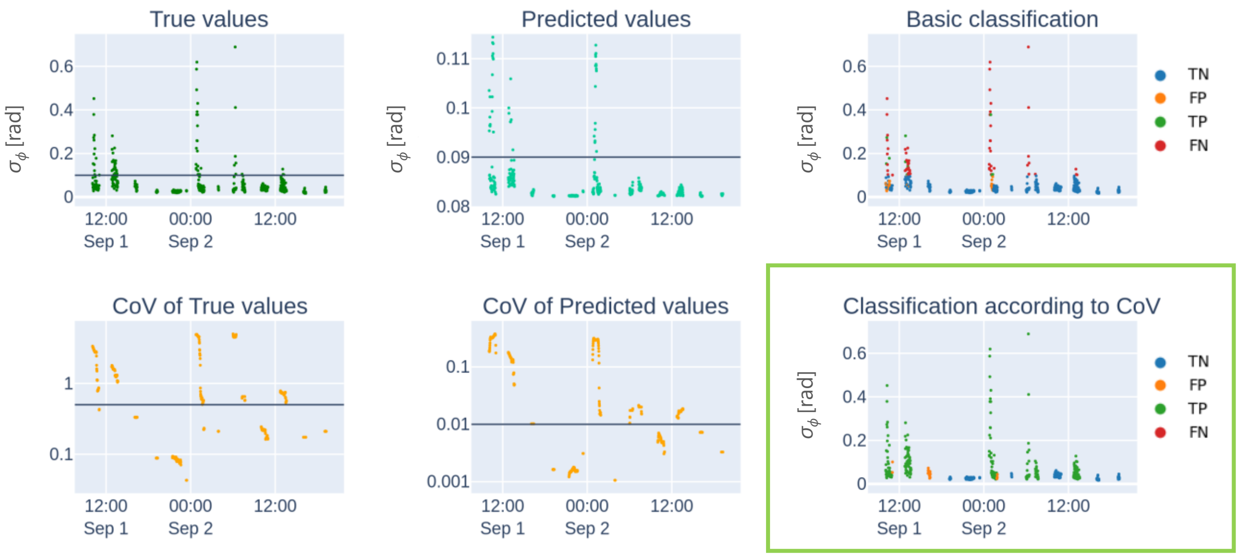

Figure 1.

Comparison of two approaches. Final result from proposed solution (autoregressive model) is highlited in green.

5. Results

Model	CoV	P	R	F1	TSS
Autoregressive	0,01	0,63	0,76	0,69	**0,70**
Base multivariate PC	0,10	0,50	0,78	0,61	0,68
Extended multivariate	0,05	0,31	0,82	0,45	0,59

Here are the results and comparison of the best models for predictions 15 minutes ahead, based on 45-minute time windows. Higher precision and recall are reflected by many TP and TN points, as shown in the highlighted plot in Figure 1.

6. Contributions

- Contribution to ESA PECS project ASPIS (*Autonomous Service for Prediction of Ionospheric Scintillations*)
- The proposed solution was also used in the development of https://aspis.services/#/