PREDICTIVE METHODS FOR MAJOR GEOMAGNETIC DISTURBANCES

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Abstract. The goal of this paper is to analyse the frequencies, intensity and time of occurrence of geomagnetic storms and the associated spectrum of geomagnetic field. Also, we set out to analyse the possibility of predicting these geomagnetic storms. The data used in this paper are acquired within the Surlari Observatory, and we obtained additional information to characterize the analysed geomagnetic storms analysed from specialized sites such as www.intermagnet.org and www.noaa.gov. Information about geomagnetic data from other observatories, as well as planetary physical parameters allowed us to perform comparative studies between the data recorded in different observatories. We have used a series of filtering algorithms, spectral and wavelet analysis with different mother functions at different levels. The numerical experiments presented in this paper are part of different methodological categories, with the same purpose, but with different approaches. The common goal is the prediction of geomagnetic disturbances and the methodologies used comparatively are Fourier spectral deconvolution, autoregressive models on time series and recurrent Long Short-Term Memory (LSTM) neural networks that are capable of long-term dependence.

Keywords: Geomagnetic disturbances, Autoregressive models, Long and Short Term time-series Network, Neural networks.

Rezumat. Metode predictive pentru perturbațiile geomagnetice majore. Scopul acestei lucrări este de a analiza frecvențele, intensitatea și timpul de apariție a furtunilor geomagnetice și spectrul asociat al câmpului geomagnetic. De asemenea, ne-am propus să analizăm posibilitatea de a prognoza aceste furtuni geomagnetice. Datele utilizate în această lucrare sunt achiziționate în cadrul Observatorului Surlari și am obținut informații suplimentare pentru a caracteriza furtunile geomagnetice analizate de pe site-uri specializate precum www.intermagnet.org și www.noaa.gov. Informațiile despre datele geomagnetice de la alte observatoare, precum și parametrii fizici planetari ne-au permis să realizăm studii comparative între datele înregistrate în diferite observatoare. Am folosit o serie de algoritmi de filtrare, analize spectrale și wavelet cu diferite funcții mamă la diferite niveluri. Experimentele numerice prezentate în această lucrare fac parte din diferite categorii metodologice, cu același scop, dar cu abordări diferite. Scopul comun este predicția perturbațiilor geomagnetice, iar metodologiile utilizate comparativ sunt deconvoluția spectrală Fourier, modelele autoregresive pe serii de timp și rețelele neuronale recurente de memorie pe termen lung si scurt (LSTM) care sunt capabile de dependență pe termen lung.

Cuvinte cheie: perturbații geomagnetice, modele autoregresive, rețeaua de serii temporale pe termen lung și scurt, rețele neuronale.

INTRODUCTION

A geomagnetic storm is a temporary disturbance of the Earth's magnetosphere caused by solar coronal mass ejections, coronal holes or solar flares. Solar wind shock waves typically strike the Earth's magnetic field 24 to 36 hours after the event. This only happens if the shock wave travels in a direction toward Earth. The solar wind pressure on the magnetosphere will increase or decrease depending on the Sun's activity. These solar wind pressure changes modify the electric currents in the ionosphere.

Solar wind is a stream of charged particles ejected from the upper atmosphere of the Sun. It mostly consists of electrons and protons and varies in temperature and speed over time. Magnetic storms usually last 24 to 48 h, but some may last for many days. These geomagnetic disturbances occur at the level of the entire planet, but with different intensities depending on the latitude of the location of the observatory in which we measure.

These geomagnetic storms or substorms may damage many technological or critical systems, depending on the intensity of the geomagnetic activity. Thus, the predictability analysis of geomagnetic storms becomes very important.

The Sun is a sphere of hot gas (plasma) with loop-like structures on the solar surface which are associated with the magnetic field of the Sun. When one of these loops becomes unstable, it breaks off from the surface of the Sun and creates a solar flare. The biggest flares can be hundreds of times the size of the Earth. Five categories are used to rank solar flashes associated with solar flares based on their intensity (A, B, C, M and X). A-class flashes are the weakest, while X-class flashes are the most energetic. Solar flares are seen by the photons (or light) released across the spectrum. X-rays are the primary wavelength monitored in the classification of solar flares. Flares also contribute to the acceleration of protons and other charged particles that may accompany a significant event.

METHODOLOGIES

Multivariate time series forecasting is an important machine learning problem across many domains, including predictions of solar and geomagnetic storms. Temporal data arise in these real-world applications and often involve a mixture of long-term and short-term patterns, for which traditional approaches such as Autoregressive models and Gaussian Process may fail.

Deep neural networks have received an increasing amount of attention in time series analysis. Also, Recurrent Neural Networks RNN architectures have been studied for extracting informative patterns from geomagnetic sequential data and classifying the data with respect storm's categories. RNN has also been applied to mobile data, for classifying the input sequences with respect to geomagnetic activity and Convolution Neural Network CNN models have also been used in recognition and extraction of shift-invariant local patterns from input sequences as the features of classification models.

Deep neural networks have also been studied for time series forecasting, i.e., the task of using observed time series in the past to predict the unknown time series in a look-ahead horizon and the larger the horizon, the harder the problem. Efforts in this direction range and the hybrid models combining the use of Auto Regressive Integrated Moving Average ARIMA and a deep learning framework designed for the multivariate time series forecasting, namely Long- and Short Term time-series Network (LSTNet), as illustrated in figure 1.

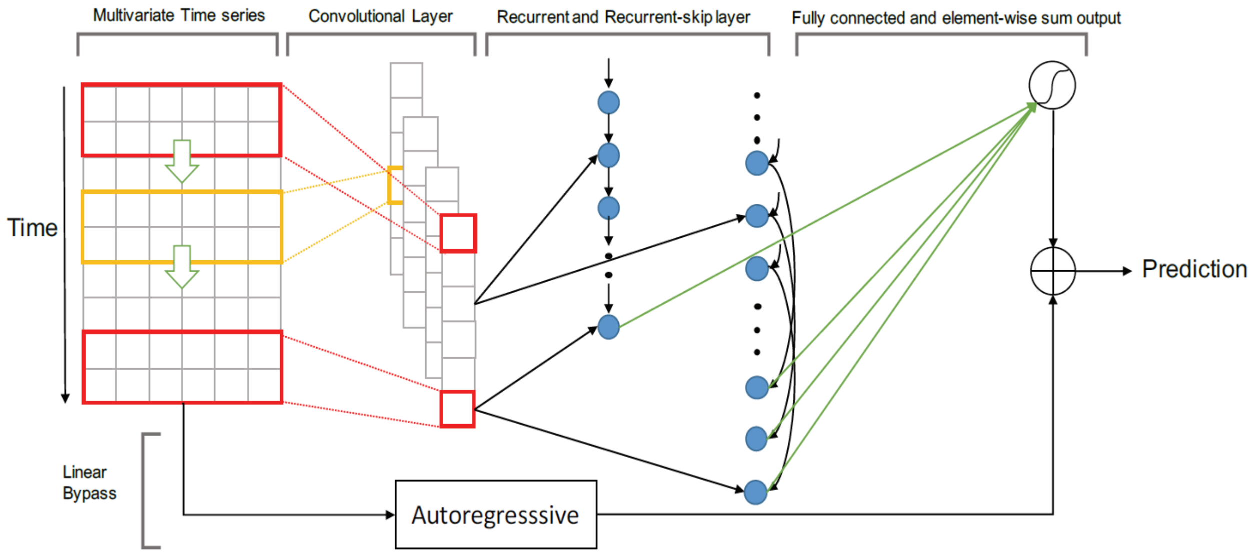

Figure 1. An overview of the Long- and Short-term Time-series network (LSTNet) (GUOKUN et al., 2018).

It leverages the strengths of both the convolutional layer to discover the local dependency patterns among multi-dimensional input variables and the recurrent layer to captures complex long-term dependencies.

A novel recurrent structure, namely Recurrent-skip, is designed for capturing very long-term dependence patterns and making the optimization easier as it utilizes the periodic property of the input time series signals. LSTNet incorporates a traditional autoregressive linear model in parallel to the non-linear neural network part, which makes the non-linear deep learning model more robust for the time series with scale changing.

The geomagnetic time series datasets, consistently outperforms the traditional linear models and GRU Gated Recurrent Unit.

Estimation of geomagnetic field disturbances is similar to the standard problem of estimating a signal disturbed by signal theory.

The term noise refers to any modification that changes the periodic or quasi-periodic characteristics of the original signal.

The Dst index is used to assess the severity of geomagnetic storms and to determine the effects of the solar wind on space and terrestrial infrastructures and is very important to be able to predict the effects of the geomagnetic storm.

In the field of geomagnetism, papers have been published on numerical developments of time series for data acquired in the Surlari Geomagnetic Observatory (ASIMOPOLOS N.S. – 2019 a, b).

Auto Regressive Integrated Moving Average (ARIMA) has many variations AR (Auto Regressive) and MA (Moving Average) that has demonstrated its outperformance in precision and accuracy of predicting of time series for linear and stationary processes (BOX G.E.P.et al, 2016; BISGAARD S., KULAHCI M., 2011).

$$y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) - \cdots - (Y_{t-d+1} - Y_{t-d}) \qquad (1)$$
$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots \theta_q\varepsilon_{t-q} \qquad (2)$$

where y_t denotes a smooth time series obtained after d-differentiating from the non-stationary data, and d is a non-seasonal difference order in (1). After the data is differentiated, it is subjected to an autoregressive moving average process (2), which contains AR and MA processes. Between them, the positive terms are AR processes, while the negative terms are MA processes. The corresponding non-negative integer p is the autoregressive order, and q is the moving average order. $\varphi 1 \ldots \varphi p$ are the regression coefficients, $\theta_1 \ldots \theta_q$ are the moving average coefficients, and εt is a Gaussian white noise. According to the settings of the parameters p, d, and q, the original ARIMA model can be applied to different forms of time series predictions.

However, the ARIMA method is essentially a linear model so that it is not capable of accurate prediction for large observational time series datasets with strong nonlinearity (YI et al., 2017) used transportation big data to build the nonlinear prediction model of traffic conditions by deep learning neural network which can obtain very high accuracy, around 99%. (WANG et al., 2017) used big system data to build a nonlinear deep learning model for spatiotemporal in cellular network.

(ZHANG et al., 2018) made a survey to study the nonlinear modeling technique of deep learning for various big data applications. In this regard, deep learning algorithms hold great potential to improve the prediction performance.

Gaussian Processes (GP) are a method designed to forecast time series data (inclusive geomagnetic recordings from observatories) and solve regression and probabilistic classification problems. The prediction interpolating the observations is probabilistic (Gaussian) so that one can compute empirical confidence intervals and decide based on those if one should refit (online fitting, adaptive fitting) the prediction in some region of interest.

Long and Short-Term time-series Network (LSTNet) is a recurrent neural network (RNN) that enables support for time series and sequence data in a network. LSTNet performs additive interactions, which can help improve gradient flow over long sequences during training (KIM, 2017). LSTNet is best suited for learning long-term dependencies.

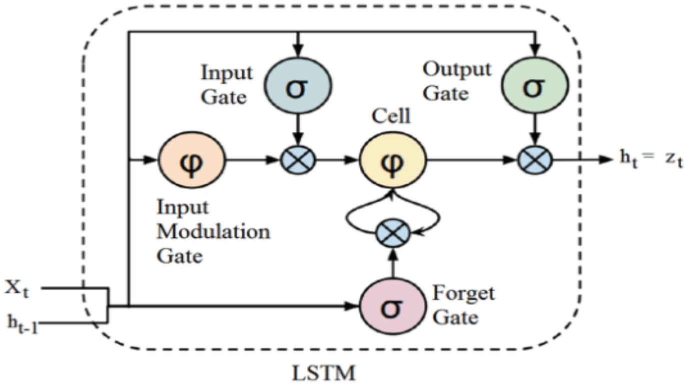

Figure 2. The architecture of an LSTNet cell.

Conceptually, a recurring LSTNet unit tries to "remember" all the past knowledge about the network is seen so far and to "forget" the irrelevant data. This is done by introducing different layers with activation functions called "gates" for different purposes. Each recurrent LSTNet unit also maintains a vector called an "internal cell state" that conceptually describes the information that was chosen to be retained by the previous recurrent unit. An LSTNet network comprises four different gates for different purposes, as described in figure 2.

• Forget gate: determines the extent to which previous data can be forgotten.
• Input gate: determines the information to be written in the internal cell state.
• Input modulation gate: it is considered as a part of the input gate and is used to modulate the information that the input gate will write on the internal cell state internally, adding nonlinearity to the information and normalizing the information. This is done to reduce learning time, ensuring faster convergence. Although the actions of this gate are less important than the others and are often treated as a concept that offers finesse, it is good practice to include this in the structure of the LSTNet unit.
• Output gate: determines which output (next hidden layer) is generated from the internal state of the LSTNet unit.

Within the SAFESPACE project we developed a web-based interactive platform JupyterLab notebooks for codes and data. Its interface allows users to configure workflows in data science, such as geomagnetic data. This platform has a modular design and extensions to enrich functionality.

The component that manages computational and storage resources for data processing and analysis is SAFESPACE Core, being implemented by using the ICIPRO cloud infrastructure (http://www.icipro.ro) and based on the use of Docker containers that are managed using the Kubernetes resource manager [https://www.mathworks.com].

This structure stores data that is transferred from the specialized components of the platform and also provides computing resources for the execution of applications and services.

CASE STUDY AND RESULTS

Using the JuytherLab instance deployed on the SAFESPACE platform, many studies were developed for the forecast of the Dst geomagnetic index, which is computed using data provided by low-latitude geomagnetic observatories using 1-hour average values of the horizontal component of the Earth's magnetic field.

The Dst index is used to assess the severity of geomagnetic storms and to determine the effects on critical infrastructures such as: long power transmission networks, long pipeline networks for the transport of petroleum products, satellite communications, civil and military aviation.

For the geomagnetic storm analysis, we present a major event (30 May – 2 June 2013).

For predicting the value of Dst index from 1 hour ahead to 6 hours ahead, we implemented a predictive model (i.e., a model for 1 hour ahead prediction, a different model for 2 hours ahead prediction, and so on).

Specifically, for training the ARIMA model, we extend the period that included the first geomagnetic storm such that a total of 11 days was considered as training data. The ARIMA model was implemented with the following parameters: p=5, d=1, q=0.

For a 3 hour ahead prediction, the model was tested on the 30 May – 2 June 2013 geomagnetic storm (Fig. 3) and had a Correlation Coefficient (CC) of 0.84 and Root Mean Square Error (RMSE) of 21.61.

However, more advanced Deep Learning algorithms such as Recurrent Neural Networks like LSTNet have been proven to provide better results for time series forecasting. In this regard, we implemented an LSTNet network to model the Dst forecasting and compared the results to the ARIMA model (Figure 4 and Table 1). The LSTM model obtained a CC of 0.85 and an RMSE of 19.97.

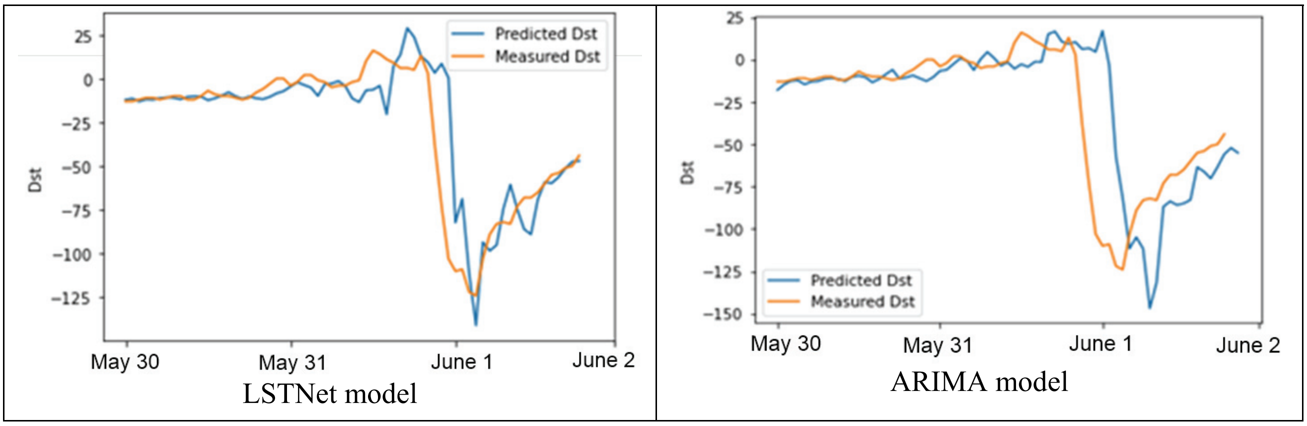

Figure 3. Comparison of LSTNet and ARIMA models for 3 hours ahead Dst forecasting (after STANCIU et al., 2021).

Furthermore, we experimented an LSTNet model for each 1 hour ahead to 6 hours ahead forecasting, and the results are shown in the Table 1 and Figure 4.

Table 1. Comparison of LSTNet models' performance for 1 hour ahead to 6 hours ahead forecasting.

	1h	**2h**	**3h**	**4h**	**5h**	**6h**
CC	0.96	0.93	0.85	0.72	0.62	0.44
RMSE	9.62	14.11	19.97	28.41	32.31	35.58

In addition, for each LSTNet model we can implement a Gaussian Process (GP) in order to obtain probabilistic forecasting and calculate empirical confidence intervals.

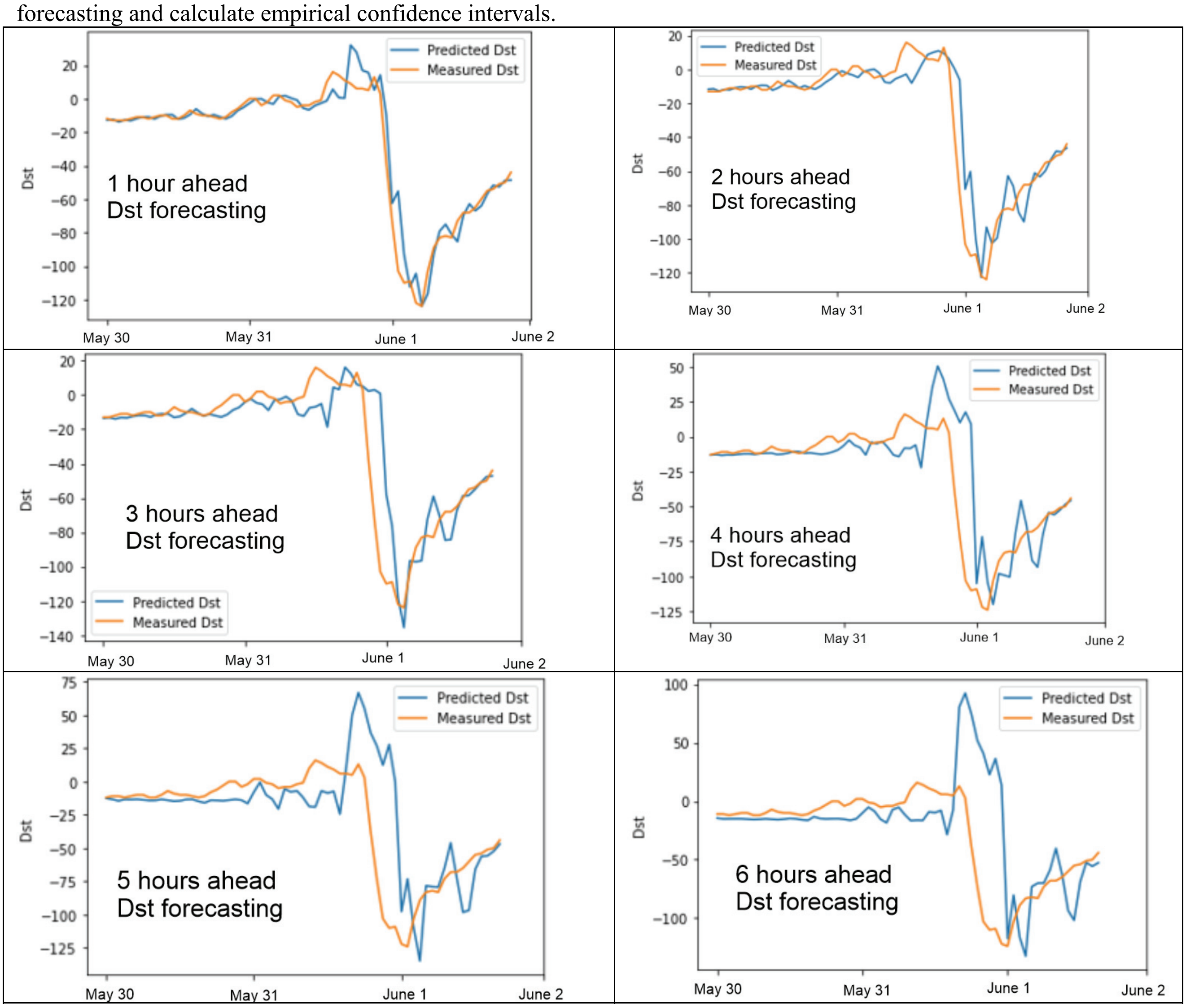

Figure 4. 1 hour to 6 hours ahead Dst forecasting using LSTNet models (after STANCIU et al., 2021).

For instance, the 3 hours ahead LSTNet model can be used as a mean for a GP with an RBF kernel, as depicted in Figure 5.

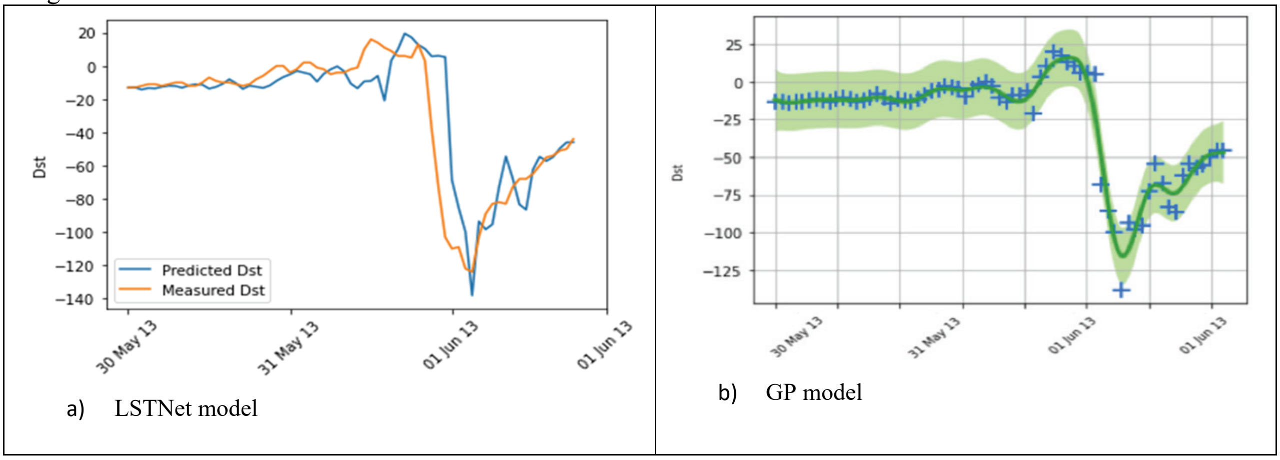

Figure 5. Gaussian Process (GP) based on the LSTNet model.

Based on the LSTNet model we can create a classifier for the geomagnetic storms. For instance, storms in which Dst has a value < -100 nT can be classified as intense, whereas for -100 < Dst < -50, we can consider moderate storms.

The ROC curve provides useful information regarding the classifier's selection, and the reliability diagrams show how good forecast probabilities correspond to the actual frequency of the event; for instance, an event predicted with probability *p* is observed with the same probability.

CONCLUSIONS

Stationary time series have the property that average and standard deviation are constant over time. The series of geomagnetic observations do not meet these conditions and are non-stationary signals. These signals can only be approximated with the help of a linear trend. Therefore, they must be differentiated as many times as necessary to obtain stationary series, whose variation and predictability characterize the signal source.

In terms of predictability, the identification and characterization of the behaviour of a signal source is reduced to the determination of a probability space and its nature.

A time series is called stationary if its variation as a stochastic process is not affected by a constant increment in the time parameter, i.e., if the output **y [n]** or **y (t)** of the signal generating source does not depend on any parameter of type α **n** or α**t**, $\forall\alpha\in$ **R**, respectively.

A time series is called stationary if its statistical properties depend on time. The evolution of non-stationary time series cannot be estimated beyond a linear regression only over portions and over the short term, and only if the probability distribution of the signal generating source has a slow variation over time. The most common approximations of non-stationary series are linear self-regressive (AR) models. The ARIMA method is widely used in predicting linear and stationary time series. However, it can also give results in nonlinear, quasi-periodic processes.

We used the hourly mean of the DST index, representing the axially symmetric disturbance magnetic field at the dipole equator on the Earth's surface (data from http://www.noaa.gov), which are negative, i.e. decreases in the geomagnetic field, for major disturbances in Dst. These are produced mainly by the ring equatorial current system in the magnetosphere. Positive DST indexes are caused by the compression of the Earth's magnetosphere make due to increases in solar wind pressure.

The training data is an important factor affecting the performance of deep learning methods, especially in different regions. However, geomagnetic storms are always hard to be captured, which may be due to the fact that the number of extreme storm events in training data are too few, so that their features are hard to be learned by the deep learning models. The prediction performance of the main phase in some geomagnetic storms is still limited.

Long and Short Term time-series Networks that perform additive interactions can help improve gradient flow over long sequences during training. This method is the best suited for learning long-term dependencies in case of geomagnetic disturbances, such as geomagnetic storms and sub-storms.

Also, Gaussian Processes (GP) are a method designed for forecasting time series data and solving regression and probabilistic classification problems. Gaussian Processes can compute empirical confidence intervals and decide, based on those, if one should refit (online fitting, adaptive fitting) the prediction in some region of interest.

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