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ПРЕДВАРИТЕЛЬНЫЕ РЕЗУЛЬТАТЫ ОЦЕНКИ ПЭС В ЗОНЕ ЯКУТСКА С ИСПОЛЬЗОВАНИЕМ НЕЙРОННОЙ СЕТИ

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PRELIMINARY RESULTS OF NEURAL NETWORK ESTIMATION OF TEC IN THE YAKUTSK REGION

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Аннотация. Серии данных ПЭС с низким временным разрешением моделировались для ст. Якутск с использованием Нейронной сети. Предварительные расчеты показали удовлетворительные результаты моделирования, но требуется улучшение модели.

Ключевые слова: ионосфера, ПЭС, нейронная сеть.

Abstract. TEC series of low time resolution in 2018 were modeled for station Yakutsk using Neural Network (NN). The preliminary results showed satisfactory NN performance, but the improvement of the model is needed.

Keywords: ionosphere, TEC, neural network.

INTRODUCTION

Artificial Neural Network (NN) is a computing system, inspired in the biological neural networks, that uses a set of interconnected processing units called neurons [Haykin, 2009]. NNs are used in the cases of unknown relationships between variables (phenomena) because of their basic ability to “learn” and “recognize”. In the ionosphere studies NN are applied for the tasks of classification of radar sounding data, modeling and forecasts of the critical frequencies of F2 and Es layers as well as Total Electron Content (TEC) behaviour. The advantage of the NN use for modeling and parameters prediction is that, unlike the traditional methods of forecast, NNs are not tied to a specific ionosphere model as dependences are established during network training. There is a number of works dedicated to TEC modeling with NN use, for instance [Cander, 2019 and references therein]. In this study we use the NN model developed by [Ferreira et al., 2017]. TEC values used in the analysis were reconstructed from data of GNSS receiver (RINEX files) employing “TayAbsTEC” method [Yasyukevich et al., 2015]. TEC estimations were performed during 2018 which is the period of low (almost minimum) solar activity when TEC values are lower comparing to other parts of solar cycle. Moreover, the estimation was made for the high latitude GNSS receiver station YAKT located in Yakutsk (62.03° N, 129.68° E). TEC values at high latitudes are lower than at other latitudes [Afraimovich, Perevalova, 2006]. Therefore, a small peak-to-peak variation is to be modeled (10–15 TECU). To note, Yakutsk region is characterized by the presence of the ionospheric electron density anomaly (Yakutsk anomaly) [Klimenko et al., 2013].

NEURAL NETWORK

The model used in this work is based on [Ferreira et al., 2017], but with differences in purpose and application. This present work focuses on TEC estimation using single station approach in order to perform TEC estimations with a view to nowcasting activities. In contrast to the present experiment, previously the network ran for low latitudes during the ascending part of the solar cycle (higher TEC values). Furthermore, the initial time resolution of TEC data was rather high (15 or 30 s). In this work we perform calculations with the much lower time resolution. This is a challenge we put in order to understand if the NN can be applied for the nowcasting purposes in the future. Short-term- and now-casting are based on the near real time data arrays. TEC maps are calculated by different Space Weather services every 10–30 min. This time is needed to download and process GNSS data and calculate the corresponding TEC values. 30 min data was chosen for this work. We also changed the number of days whose data was used for NN training from 10 to 27 days. First, it was partially to compensate the decrease of data samples because of the low time resolution. Second, 27 days data has a physical meaning as it represents TEC monthly variation. The option to exclude some days from training or estimation process was added, because some days the data was not of good quality or not “complete”. The input parameters for the NN are: a) solar radio flux (F10.7 index); b) geomagnetic field variations represented by K_p index; c) TEC seasonal variation represented by doy; d) monthly (training set length) and diurnal (hour of the day) variations. The aim of the study was to check the NN performance under the described conditions and make the conclusions if the improvements are needed.

PRELIMINARY RESULTS AND CONCLUSIONS

In general, the modeling of TEC was satisfactory. The plotted curves of modeled TEC (TECNN) and experimental (observed) TEC that serves a reference (TECRef) were similar in most cases. Let us consider the cases of the largest differences between TECNN and TECRef, which means not well NN performance.

First, it was noted that in winter months (Jan, Feb, Nov, Dec) the lowest values during the day were underor overestimated. Example is given in Fig.1. May be the inclusion of thermospheric winds in the model can improve these estimates.

Second, though in general NN captured the tendency of TEC change during geomagnetic disturbances of different intensity, the level of TEC increase/decrease sometimes required improvement. Figures 2 and 3 show examples for June and August. The positive TEC disturbance on June 18th was predicted by model, but underestimated. This was the day of the weak geomagnetic disturbance (Dstmin = – 35nT). The bad results for June 2–3 and June 26 were also observed during-after the weak disturbances. This means that may be K_p index is not good enough or not sufficient as a representative of geomagnetic field changes.

As for August 2018, the intense geomagnetic storm (Dst_{min} = – 174 nT) occurred on August, 25–28 provoked a light positive TEC disturbance on day 26th and negative disturbance of the following two days. TECNN followed this pattern but the accuracy of estimation needs improvement as in the previous case.

To sum up, the first results of the NN performance were satisfactory. In general, NN showed better estimation than the simplest forecast with median value. At the same time, there is still room for performance improvement, especially during geomagnetic disturbed days. It can be achieved through the introduction of new input parameters and/or NN configuration change. Dst data inclusion probably could help to improve TEC modeling during geomagnetic storms days. These improvements make part of our future work.

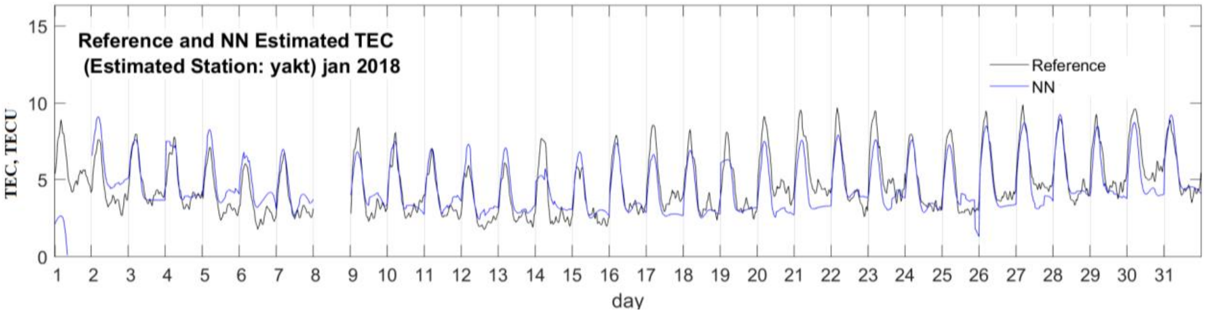

Figure 1. Modeled (NN) and experimental (Reference) TEC values in January 2018

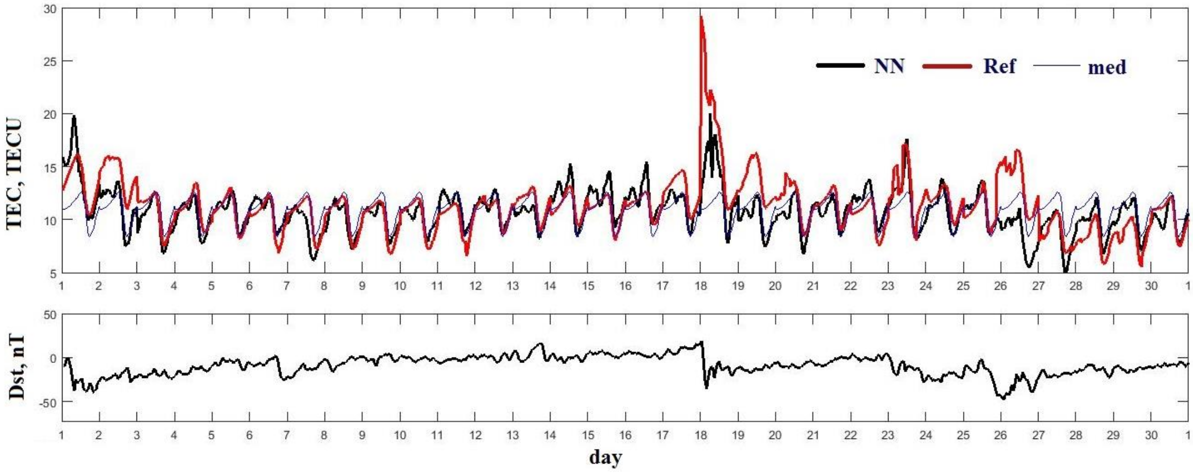

Figure 2. Modeled (NN) and experimental (Ref) and median TEC (med) values (upper panel) and *Dst* index (lower panel) for June 2018

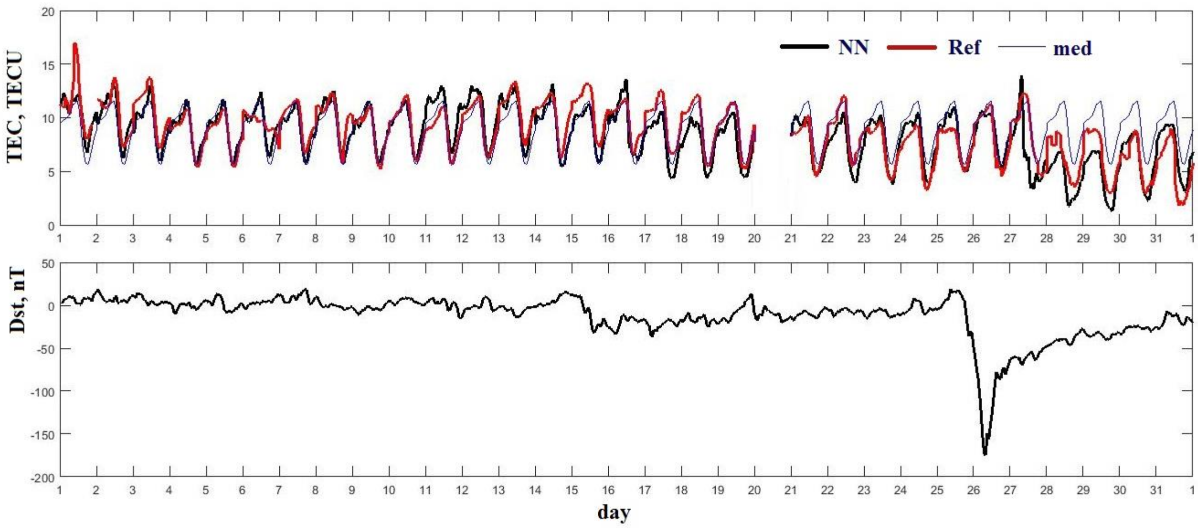

Figure 3. Same as in Figure 2, but for August 2018

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