

## ОЦЕНКА ПЭС ДЛЯ СРЕДНЕ-ВЫСОКОШИРОТНОЙ СТАНЦИИ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННОЙ СЕТИ: УСЛОВИЯ СОЛНЕЧНОГО МИНИМУМА

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## TEC ESTIMATION FOR MID-HIGH LATITUDE STATION USING NEURAL NETWORK: SOLAR MINIMUM CONDITIONS

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**Аннотация.** Вариации ПЭС для средне-высокоширотной ст. Светлое в период минимума солнечной активности моделировались при помощи Нейронной сети. Использовались данные с низким временным разрешением. В целом результаты моделирования удовлетворительные. Однако требуется доработка модели.

**Ключевые слова:** Ионосфера, ПЭС, Нейронная сеть, средневысокие широты

**Abstract.** TEC variations for mid-high latitude station Svetloe under solar minimum conditions were modeled with use of Neural Network (NN). Data of low time resolution was used. The general NN performance was satisfactory. However, the improvement of the model is needed.

**Keywords:** Ionosphere, TEC, Neural Network, mid-high latitude

### INTRODUCTION

During the last decades, a new applied area of mathematics, artificial neural networks (NN), has been developed intensively around the world. The NN concept suggests the brain model as a set of neurons of the same structure. The advantage of NN model is the ability to “study” (instead of being programmed) and perform generalization. Consequently, NN can find complex relationships between the input and output data, combining the computer's ability to process large amounts of data and the brain's ability to generalize and recognize. Usually, NNs are applied if the theory of phenomena is absent or not well-developed [Golovko, 2001]. They can be used to solve the task of estimation and forecast of the ionosphere parameters [Cander, 2019], in particular for Total Electron Content (TEC) estimation. This study is the attempt to analyze the NN performance for the mid-high latitude station Svetloe (SVTL) (60.53° N, 29.78° E) under the solar minimum conditions. Though the solar cycle 24 minimum is still on the way, the conditions of 2018 can be considered as solar minimum due to the low solar activity in 2018: a) 61 % of the spotless days during the year; b) no major flares occurred; c) only one intense geomagnetic storm. TEC values were calculated with “TayAbsTEC” method [Yasyukevich et al., 2015].

It is known that ionospheric electron density variation is dependent on solar activity variations. In the low activity periods TEC values are also low (if compare to ascending, descending and maximum parts of cycle). Moreover, TEC values at high latitudes are low themselves (if compare to other latitudes). This means that TEC variations to be modeled are of very small peak-to-peak amplitude. This can be the additional challenge for our modeling task.

### NEURAL NETWORK USED FOR THE STUDY

Initially, the NN used in this work was developed for the low latitudes (Brazil) and was validated with data of the ascending part of the present cycle [Ferreira et al., 2017]. The obtained results were well. We refer the reader to [Ferreira et al., 2017] for more details. The aim of this study was to check the possibility of TEC modeling with this particular NN under different conditions. In contrast to the previous test (for low latitudes), the physical factors impacting on TEC can be different at mid-high latitudes. Thus, one of the tasks was to test the idea if the consideration of only geomagnetic field (GF) and solar flux variations is sufficient when solar and geomagnetic activity dominates less in the day-to-day ionosphere variations. Another task was to check if the NN performance is acceptable when using the data of much lower time resolution than 15 or 30 second (as

previously). This is due to the fact, that eventually NN modeling is expected to be used for nowcasting purposes. Usually, the near real-time TEC maps are calculated every 10–30 min as the time for downloading and processing of data is needed. We chose 30 min TEC data for this work. As the time resolution was changed, the time period used for training was also modified. The data of 27 days previous to the day of estimation was used to train the NN. This provides a median pattern of TEC monthly variation which will be taken into account. As sometimes the data was not of good quality or some day was not “complete”, the possibility to exclude some days from training or estimation process was added.

To sum up, solar radio flux, GF variations, TEC seasonal (day), monthly (training set length) and diurnal (hour of the day) variations were taken into account for the NN estimation.

**PRELIMINARY RESULTS**

In general, the modeling of TEC was satisfactory in 2018. Both the series of TEC modeled by NN (TECNN) and the experimental “reference” TEC series (TECRef) followed the same pattern of increase/decrease of daily maximum TEC value, except for some particular days. The largest differences appeared at night time. The statistics of one year is not sufficient to make conclusions on the seasonal dependence of NN performance, but it

should be noted that the worse nighttime TEC estimation corresponded to winter months (Jan, Feb, Nov, Dec).

Figure 1 shows the example of results for March 2018. TECRef are the experimental values observed (measured) at SVTL. The correlation coefficient  $r$  between TECNN and TECRef was  $r = 0.8884$ , which means a high correlation between data. More or less,  $r$  was similar in other months of the year. TECNN was closer to TECRef than the monthly median TEC values which are the simplest way to predict quiet time TEC. No intense geomagnetic disturbances occurred in March. The same was true for February. Thus, it was fortunate for NN training. The largest difference between the model and observations is seen on March 10-11 and March 19–20. Both periods were characterized by moderate Dst decreases. We recall that GF changes in NN are represented by  $K_p$ , therefore they should have been taken into account. It is possible, that the not very well result for March 10–11 was due to a weak  $K_p$  index change. The results for March 19–20 are probably due to the influence of other physical factor on TEC (not considered within the input parameters of NN). For instance, the moderate GF disturbances of these days were accompanied by the significant decrease of thermospheric ratio O/N2, or it could be another unconsidered factor.

The worst NN results were for August 2018 (Figure 2), the month of the intense magnetic storm. In contrast, July

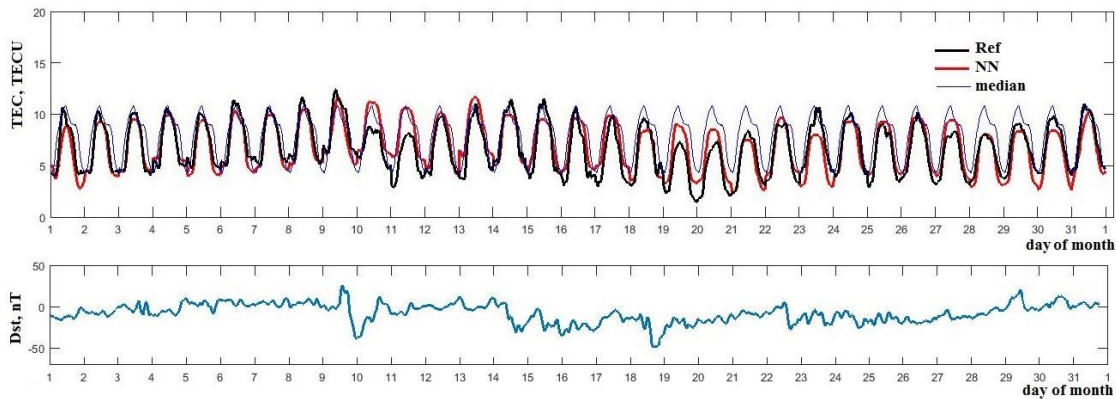


Figure 1. Modeled (NN), experimental (Ref), median TEC values (upper panel) and Dst index (lower panel) for March 2018

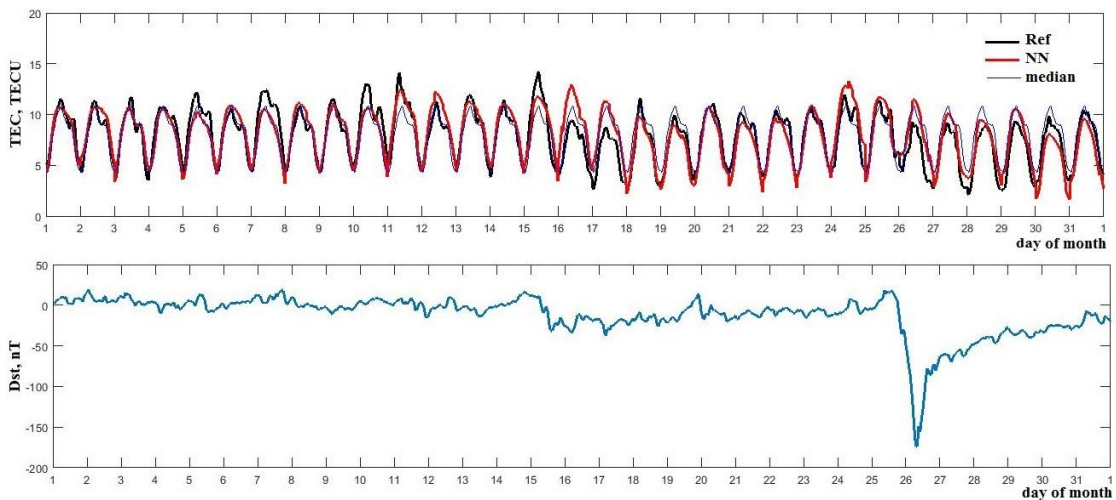


Figure 2. Same as in Figure 1, but for August 2018

(used for NN training) was a quiet month in terms of GF variations. Still the correlation was high  $r = 0.8775$ . On the geomagnetic storm day August 26<sup>th</sup> the NN estimation was not very well. First, it was the only storm of such intensity in 2018, thus NN could not be trained appropriately. Second, some unconsidered physical reason could have its impact. As a possibility, may be O/N2 inclusion into NN input could help, as its drastic decrease (not shown for the economy of space) could be favorable for TEC decrease. At the same time, the modeling result was not totally bad. This is probably due to a not very significant TEC change itself on August 26<sup>th</sup>. The worst result is seen for August 16–17 because of some unconsidered input factors.

## CONCLUSIONS

The possibility of TEC estimation by NN was tested for mid-high latitude station under solar minimum conditions. Low time resolution TEC data was used by intention as a step towards the future TEC nowcasting with NN. The preliminary results were satisfactory during the whole year 2018: correlation between modeling and experimental results was high.

Some nighttime effects (e.g. short-time night TEC enhancements in winter) were not modeled well. This means that the data on the responsible physical cause was not introduced to NN (e.g. the possible F2-layer parameters change). During some days, the diurnal TEC variation was under/overestimated. This mostly occurred during moderate GF disturbances. Thus, may be  $K_p$  is not sufficient in our case. The NN performance should be tested with  $Dst$  and other new input data included (e.g.  $AE$  index, absorption data, etc.). The following NN model improvement both in the part of input parameters and in the NN structure itself are the subjects of our future work.

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