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The Analysis of Current Neural Network Configuration Used to Predict the Critical Frequency foF2 of the Ionosphere*

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Abstract. Ionosphere is the ionized part of the upper atmosphere containing free electrons and ions. The critical frequency (foF2) is one of the most important parameters of the ionospheric electron density, which affects the functionality of radio communication and navigation equipment. This frequency is a very variable parameter, which depends on various geophysical parameters. Therefore, improving the accuracy of predicting the critical frequency foF2 of the ionosphere is of great importance for the proper operation of radio communication and navigation equipment. Various physical and empirical models are used to predict this parameter. The large amount of observational data and development of modern machine learning algorithms make it possible to use new approaches for predicting ionospheric parameters. In the paper we analyzed a neural network created for predicting foF2 measured by Irkutsk Digisonde, as a function of various geophysical parameters. We studied the contribution of these parameters to the predicted foF2 frequency. It was shown that the critical frequency of foF2 most strongly depends on 10.7 cm solar radiation and on the local solar time.

1 Introduction

The characteristics of the ionosphere are of significant practical importance for radio communications. Prediction of these characteristics allows one to work more reliably with radio communication and navigation equipment. Many methods have been developed for predicting the ionospheric characteristics [1]. These methods can be divided into techniques based on physical models and techniques based on empirical models. One of the novel widely studied methods is the use of machine learning for building empirical models. The method is mathematically formulated as the detection of hidden patterns in numerical series and the construction of approximation schemes based on these patterns. The large amount of

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available measurement data and the growth of computational capabilities allow one to use very complex empirical prediction models - artificial neural networks.

One of the key ionospheric parameters is the foF2 frequency. The critical frequency foF2 is the maximal frequency of a radio wave propagating vertically and reflecting from the ionosphere [2]. If the frequency of the radio wave exceeds the critical frequency the wave penetrates the ionosphere. The foF2 critical frequency is frequently used for predicting the radio wave propagation characteristics. So the knowledge of this frequency is of practical importance for radio communications.

The foF2 dependence on the indices of solar and geomagnetic activity is well known [3]. The dependence of foF2 on the solar radiation intensity at the wavelength of 10.7 cm is especially significant. The physical reason of such a dependence is an increase in atmospheric ionization with an increase in solar radiation intensity, which can be detected by an increase in solar radio emission flux. The dependence of foF2 on the geomagnetic activity (for example on ap-index) is also known. In this paper, we use Dst, ap and Kp geomagnetic activity indices for predicting foF2. The planetary index Kp describes the geomagnetic disturbance in the three-hour interval. The initial data for the calculation of the Kp index is the K-index data of the twelve observatories located between 63 ˚ and 48 ˚ north and south of the geomagnetic latitudes. The K-index takes values from 0 to 9, where 0 corresponds to undisturbed conditions and 9 corresponds to a very strong geomagnetic disturbance [4].

The index ap is calculated from the Kp-index data. It represents the change in the most disturbed geomagnetic field component D or H over the 3-hour time interval at mid-latitude stations and is calculated in units of 2γ. The ap index is refered as the planetary amplitude in the 3-hour interval. The Dst-index characterizes the intensity of the symmetric ring current, which is typically observed in the recovery phase of a geomagnetic storm. Dst-index is the average value of the geomagnetic disturbance over the hourly interval, calculated over the network of low-latitude geomagnetic stations separated by longitude. The unit of measurement for the Dst-index is γ. To calculate the Dst-index, the data from 4 geomagnetic stations are used [4].

For analysis we use measurements of the foF2 critical frequency near Irkutsk, made with the DPS-4 digisonde from 2009 to 2016. The DPS-4 digisonde has two 150W transmitters, four receiving antennas and a "crossed vertical rhombs" transmitting antenna system. The digitization module has the ability to simultaneously register in the automatic mode the following radio signal parameters: amplitude, frequency, height (range), angles of arrival, phase, polarization, and Doppler frequency shift of the radio waves reflected by the ionosphere [5]. Observations of the digisonde are obtained from the ISTP database [6]. Solar and geomagnetic indices for the same period are obtained from publically available databases (OMNI database [7]).

2 Model development and input data

To take into account the periodicity of foF2 changes, in addition to the solar and geomagnetic indices mentioned above, a periodic function is used that depends on the day number in a year. The periodic functions that depend on the hour of the day have also been used.

$$cosDOY(LST) = \cos\left(\frac{2\pi \cdot DOY}{365.25}\right) \tag{1}$$

$$cosHOD(LST) = \cos\left(\frac{2\pi \cdot HOD}{24}\right) \tag{2}$$

$$sinHOD(LST) = \sin\left(\frac{2\pi \cdot HOD}{24}\right) \tag{3}$$

where HOD is the ordinal hour number of the day (from 0 to 23, we use local solar time), DOY is the ordinal day number of the year (from 1 to 365 or 366).

We train our foF2 prediction algorithms based on the following dataset: cos_DOY (LST), cos_HOD (LST) and sin_HOD (LST), f10.7 solar index, Dst, Kp, ap geomagnetic indicies, foF2.

The resulting dataset is divided into two subsets: the training dataset and the test dataset in a ratio of 80 to 20%, respectively. The whole experimental data set consists of 61675 elements.

An artificial neural network is a collection of interconnected perceptrons (neurons) aggregated into layers. Each perceptron in the neural network converts its input to its output by making a linear combination of input values and using it as an argument for some ('activation') function:

$$OutN(w, x) = \sigma(w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + \ldots + w_n \cdot x_n + b) \tag{4}$$

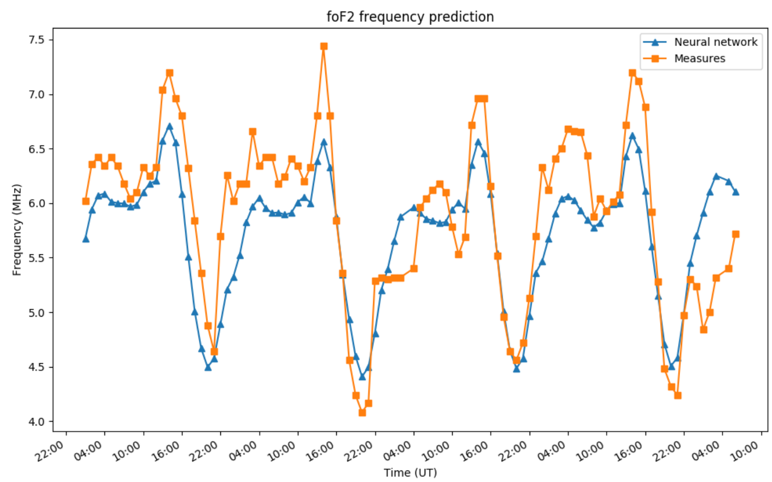
where $\{x_i | x_{2,} x_{3,} x_{4,} x_5, \ldots, x_n\}$ - is a set of input attributes, w_i, b - weights, and $\sigma(x)$ is an activation function.

For prediction of foF2 we trained a neural network with two hidden layers with 11 and 5 neurons in each, and a sigmoid activation function. The model was built on the basis of the Python scikit-learn software library and the Perceptron Multi-layer class [8], with "adam" solution algorithm, and a regularization coefficient of 0.001. We used an algorithm with back propagation of an error for training the neural network [9].

3 Discussion

An example of the forecast over test dataset is shown in Figure 1. The prediction over test dataset provides a Pearson correlation coefficient of 0.89, a root mean square error of 0.84MHz and a mean absolute percent error of 14.7%. A high correlation coefficient and a rather small root-mean-square error indicate that the model is of sufficient quality to predict the ionospheric critical frequency.

Fig. 1. Neural network forecast values compared with experimental data



To estimate the degree of influence of various input parameters on the final result we made an analysis of the weights inside each neuron.

Table 1. The weights in the neurons of the first layer of the neural network

Neuron	Kp_index	Dst-index(nT)	ap_index(nT)	f10.7_index	cos_HOD(LST)	sin_HOD(LST)	cos_DOY(LST)	ABS_SUM
10	-0,054	-0,336	-0,083	0,088	-5,389	3,258	-2,847	12,055
11	0,069	-0,197	-0,049	0,324	-3,618	-1,991	-4,058	10,306
1	0,795	-0,106	-0,761	0,012	0,244	-2,911	-4,56	9,389
6	0,118	-0,21	-0,346	4,781	-1,968	0,669	-0,473	8,565
2	0,181	0,248	-0,027	-0,202	-3,496	-1,388	-2,874	8,416
9	-0,137	0,344	-0,23	-0,094	-2,171	3,1	-0,552	6,628
7	0,269	-0,022	-0,385	2,149	-0,01	-0,875	-2,329	6,039
3	0,286	-0,233	-0,142	-0,201	-3,436	-0,814	0,035	5,147
8	-0,026	-0,255	0,094	3,333	0,335	0,534	-0,282	4,859
4	0,131	-0,301	-0,137	-0,304	-0,737	0,426	-1,534	3,57
5	0,03	0,048	0,086	-0,305	0,774	0,607	-1,546	3,396

Table 1, 2, and 3 show the weights values inside each neuron in the first layer (see Table 1), second layer (see Table 2) and output layer (see Table 3). The last column of the Table 1 and Table 2 corresponds to the sum of the absolute values of the weight coefficients in each neuron. The rows of the table are sorted in descending order by this parameter, allowing us to find the neurons of higher importance.

As one can see from Table 1, the first three most influential neurons (marked by color) of the first layer have significant prevalence of weights corresponding to

Table 2. The weights in the neurons of the second layer of the neural network

Neuron	Neuron out 1	Neuron out 2	Neuron out 3	Neuron out 4	Neuron out 5	Neuron out 6	Neuron out 7	Neuron out 8	Neuron out 9	Neuron out 10	Neuron out 11	ABS_SUM
3	-1,522	1,016	-2,01	1,172	-4,614	1,944	1,508	1,437	1,493	-5,129	-3,106	26,558
4	-0,091	2,578	-0,416	-4,699	-3,057	2,292	-2,229	1,704	1,265	0,086	-0,098	19,906
2	0,173	-0,813	1,675	-1,246	3,007	2,07	4,023	-0,308	-1,337	1,815	0,556	16,917
5	0,069	2,653	0,942	-3,453	-0,784	-0,18	-0,639	2,541	1,847	0,511	0,376	18,013
1	0,75	-0,249	1,704	-3,85	0,529	-0,176	1,492	1,883	-0,402	-0,148	1,905	18,612

Table 3. Output layer of the neural network

Neuron	Neuron out 1	Neuron out 2	Neuron out 3	Neuron out 4	Neuron out 5
1	2,09	1,941	-3,122	3,378	4,599

local time and date (cos_HOD (LST), sin_HOD (LST), cos_DOY (LST)), showing the importance of regular daily and seasonal variations in foF2 dynamics.

As one can see from Table 2 the first most influential neuron (marked by color) of the second layer contains large coefficients (-5.139 and 3.106) at the outputs of the tenth and eleventh neurons of the first layer (which are the most influential in the first layer). At the same time, the coefficients at the output of the sixth, seven and eighth neurons of the first layer are also significant (1.944, 1.508 and 1.437). These neurons of the first layer have the greatest weights corresponding to the index f10.7 (solar radiation flux at a wavelength of 10.7 cm).

The output layer (see Table 3) has coefficients of approximately the same order. This allows us to ignore the output neuron and to limit the analysis of the most influential neurons to analysis of the first two layers. From this we can conclude that the main contribution to the neural network output is produced by solar radiation index f10.7 and solar local time and date.

4 Conclusion

In this paper we described our experience in creating and training a neural network for predicting the critical frequency foF2 using data obtained at Irkutsk with the DPS4 Digisonde for the period 2009-2016, as well as solar and geomagnetic indices for the same period. It is shown that average model accuracy is about 0.84MHz and Pearson correlation coefficient is 0.89.

We analyzed the structure of the network and showed that variations in the ionospheric critical frequency foF2 are mostly caused by f10.7 index and periodical daily and seasonal variations. The dependence of foF2 on the geomagnetic indices Dst, ap, and Kp is much weaker. This result corresponds well with physical mechanisms of formation F2 layer in the ionosphere and can be explained by an increase in the ionospheric ionization intensity with the solar radiation intensification and the daily and seasonal dynamics of the solar zenith angle.

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