

# Application of deep learning methods to predict ionosphere parameters in real time

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**Abstract.** In this paper, the previously obtained results on recognition of ionograms using deep learning are expanded to predict the parameters of the ionosphere. After the ionospheric parameters have been identified on the ionogram using deep learning in real time, we can predict the parameters for some time ahead on the basis of the new data obtained. Examples of predicting the ionosphere parameters using an artificial recurrent neural network architecture long short-term memory are given. The place of the block for predicting the parameters of the ionosphere in the system for analyzing ionospheric data using deep learning methods is shown.

## 1 Introduction

In [1-9, etc.], various approaches are proposed for predicting mainly the foF2 parameter of the ionosphere. In this paper, the previously obtained results on recognition of ionograms using deep learning are expanded to predict the parameters of the ionosphere in real time. In papers [10-11], it is proposed to apply deep learning for recognition of ionograms and to further distinguish ionospheric parameters based on recognized layers. An outstanding feature of the new method proposed by the authors in [10] is the use of deep learning to recognize traces of reflections from different layers of the ionosphere. Deep neural network learning is realized on the basis of reference markings created by operators. The operators mark ionospheric parameters on the ionograms and detect, when possible, reflection traces from E, F1 and F2 layers of the ionosphere.

Currently, the following basic characteristics are determined by ionograms[12](Figure 1):

- fmin is the lowest frequency at which traces of reflections from the ionosphere are observed on the ionogram;

- foE is the critical frequency of the O-component of the lowest thick layer in region E;

- foF1 is the critical frequency of the O-component reflected from the F1 layer;

- foF2 is the critical frequency of the O-component reflected from the F2 layer;

- fxF2 is the critical frequency of the X-component reflected from the layer F2;

- fbEs is the screening frequency of the sporadic layer Es, that is, the lowest frequency at which first-order reflections of the O-component from the overlying region are observed;

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- foEs is the limiting frequency of the O-component reflected from the Es layer;
- h'E is the minimum effective height of the region E;
- h'Es is the minimum effective trace height of reflections from Es used to determine foEs;
- h'F is the minimum effective height of the trace of reflections of the O-component from the region F taken as a whole;
- h'F2 is the minimum effective height of the layer F2.

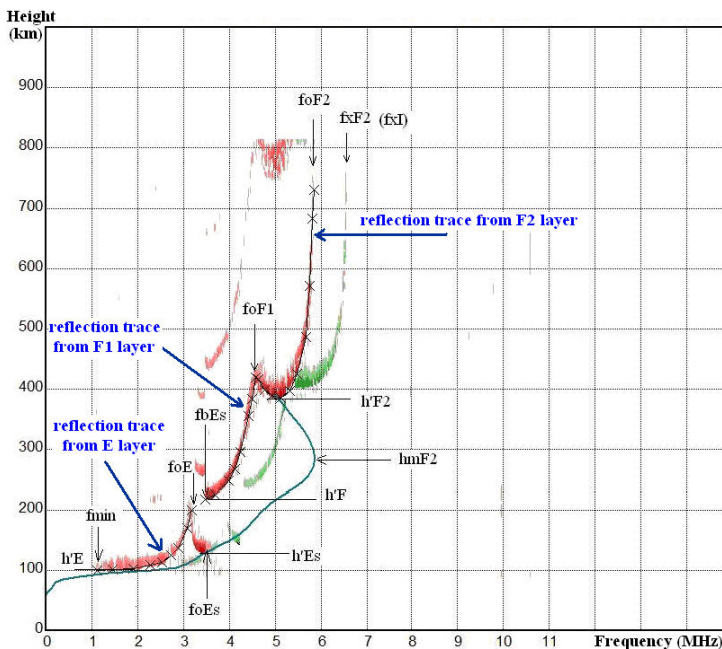
Using the noted parameters of the ionosphere and / or the traces of reflections from different layers of the ionosphere, the electron concentration profile  $N(h)$  is constructed, based on which the heights hmF2, hmF1 and hmE of the main maximum of the electron concentration of the F2, F1 and E layers are determined, respectively.

Dimensionless characteristics are also determined by ionograms [12]:

- M3000 (F2, F1) is a coefficient showing the ratio of the maximum applicable frequency (MUF) to the critical frequency of a given layer with oblique incidence at a jump distance of 3000 km;
- types of sporadic layers by which reflections from Es are classified. There are eleven special categories by which reflections from sporadic Es layers are classified;
- types of F-scattering - classification of the type of scattered reflections.

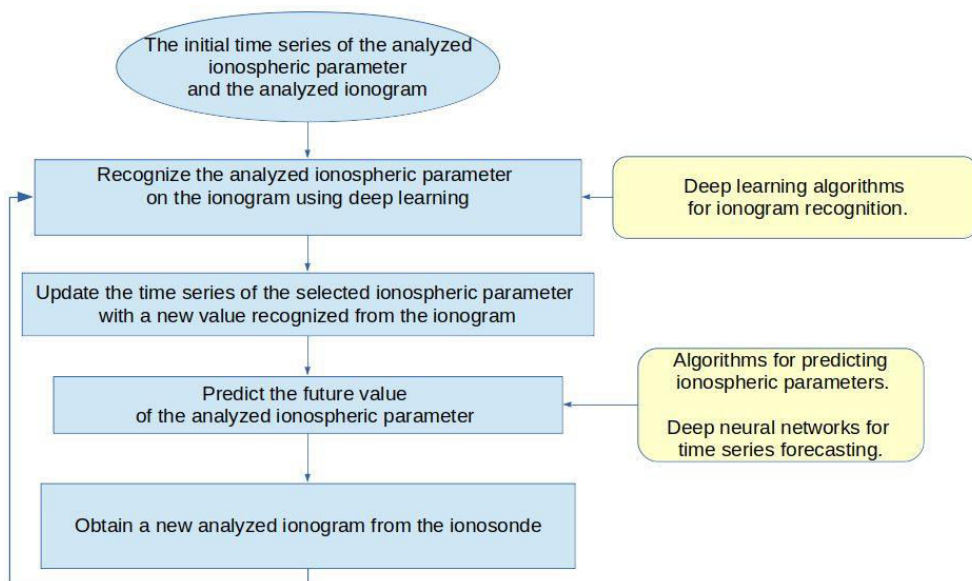
The determination of ionospheric characteristics by ionograms is often difficult, and sometimes completely impossible for various reasons (ionospheric or instrumental). Therefore, to explain the difficulties of characterization and classification of phenomena adopted by the international system of letter designations [6].

Based on the selected traces of reflections from different layers of the ionosphere [10], we are able to determine at least the following of the above parameters of the ionosphere [11]: foF2, foF1, foE, h'F2, h'F, h'E. Based on the selected parameters and based on the selected traces of reflections from different layers of the ionosphere, we are able to construct the electron concentration profile  $N(h)$  and then determine the heights hmF2, hmF1 and hmE.



**Fig. 1.** Example of vertical sounding ionogram with main measurable parameters [6].

After the ionospheric parameters have been identified on the ionogram using deep learning [10,11] in real time, we can predict the parameters for some time ahead on the basis of the new data obtained. The place of the block for predicting the future value of the analyzed ionospheric parameters is shown in Figure 2. For example, consider using long short-term memory (LSTM) to predict foF2 and foE ionosphere parameters.



**Fig. 2.** System for analyzing ionospheric data using deep learning methods.

## 2 The use of long short-term memory to predict foF2 and foE ionosphere parameters

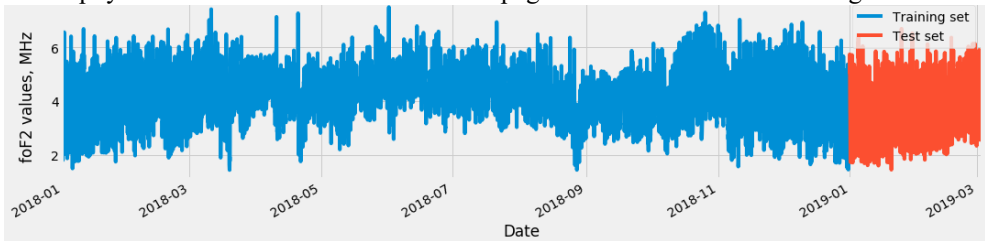
LSTM is an artificial recurrent neural network (RNN) architecture used in the field of deep learning [13]. Previously we used long short-term memory and gated recurrent unit (GRU) for predicting the values of geomagnetic indices [14]. In [14], it was shown that more accurate value predictions are provided by the selected LSTM architecture compared to the selected GRU architecture. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the exploding and vanishing gradient problems that can be encountered when training traditional RNNs. Relative insensitivity to gap length is an advantage of LSTM over RNNs, hidden Markov models and other sequence learning methods in numerous applications [15].

Based on the application of Keras library [16], a program was written to predict ionospheric parameters. We used this LSTM architecture [17]:

```
regressor = Sequential()
# First LSTM layer with Dropout regularisation
regressor.add(LSTM(units=50,return_sequences=True,
input_shape=(X_train.shape[1],1)))
regressor.add(Dropout(0.2))
# Second LSTM layer
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
```

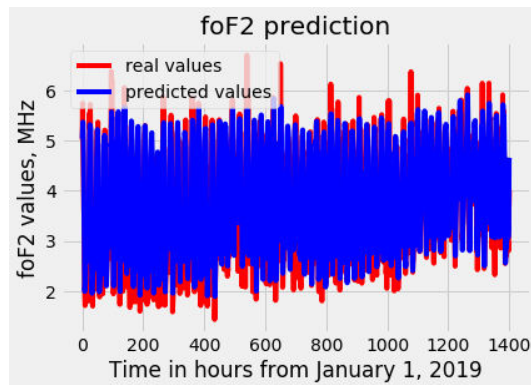
```
# Third LSTM layer
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
# Fourth LSTM layer
regressor.add(LSTM(units=50))
regressor.add(Dropout(0.2))
# The output layer
regressor.add(Dense(units=1))
# Compiling the RNN
regressor.compile(optimizer='rmsprop',loss='mean_squared_error')
# Fitting to the training set
regressor.fit(X_train,y_train,epochs=50,batch_size=32)
```

We used Tesla K80 video card to train LSTM network. As an initial data for training the LSTM network to predict foF2 ionosphere parameter we used hourly data for 2018 (Figure 3) from ionosonde “Parus-A” [18], which has been operated at the Institute of Cosmophysical Research and Radio Wave Propagation in Kamchatka since August 2015.



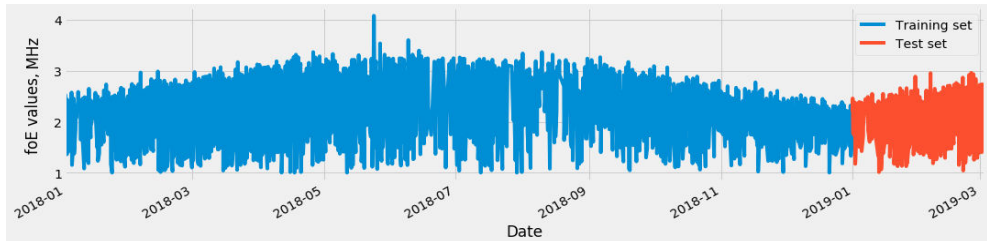
**Fig. 3.** Training and test set for foF2 ionosphere parameter prediction.

We used mean squared error loss function (LF) and after 50 training iteration we get LF result = 0.0044. The training time on the Tesla K80 video card of LSTM network took 2578 seconds. Figure 4 shows the results of predicting the next foF2 ionosphere parameter value based on a series of known previous values. The root mean square error of prediction is 0.4281.



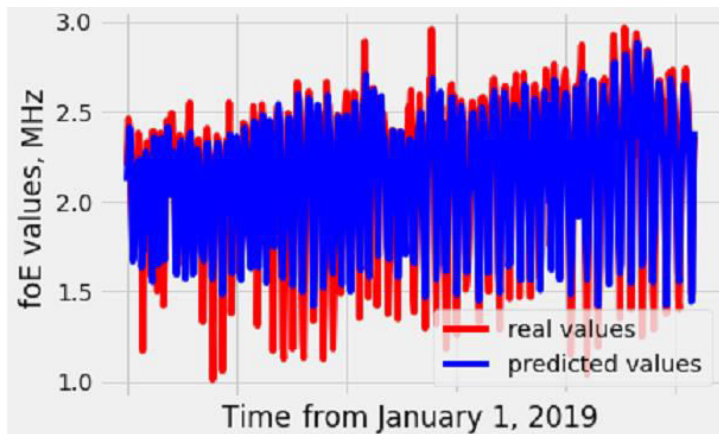
**Fig. 4.** Prediction results using the LSTM network for the next foF2 ionosphere parameter value based on a series of known previous values.

As an initial data for training the LSTM network to predict foE ionosphere parameter we used hourly data for 2018 (Figure 5) from ionosonde “Parus-A”.



**Fig. 5.** Training and test set for foE ionosphere parameter prediction.

We used mean squared error loss function (LF) and after 50 training iteration we get LF result = 0.0103. The training time on the Tesla K80 video card of LSTM network took 983 seconds. Figure 6 shows the results of predicting the next foE ionosphere parameter value based on a series of known previous values. The root mean square error of prediction is 0.2100.



**Fig. 6.** Prediction results using the LSTM network for the next foE ionosphere parameter value based on a series of known previous values.

### 3 Conclusion

The paper presents the application of deep learning at various stages of the analysis of ionospheric data. Initially, deep learning is used to recognize the traces of reflection from different layers of the ionosphere in the ionogram [10], which makes it possible to extract some ionospheric parameters [11] and update the time series to predict in real time the future value of the analyzed ionospheric parameter. The above examples of using long short-term memory to predict foF2 and foE ionosphere parameters have shown the promise of end-to-end application of deep learning at various stages of ionospheric data analysis. It should be noted that further research is needed to improve the accuracy of forecasting ionospheric parameters. This should include the application of various predictive architectures of deep neural networks, the use of physical models and additional data on the state of the ionosphere, integration with existing results of forecasting the state of ionospheric parameters, and much more.

## Acknowledgments

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## References

1. B.G. Barbashov, O.A. Maltseva, *Proceedings of universities. North Caucasian region. Natural Sciences*, **2**, 33-38, (2003), in Russian
2. O.V. Mandrikova, V.V. Bogdanov, *Collection of reports of the VI international conference «Solar-Terrestrial Relations and Physics of Earthquake Precursors»*, 142-145, (2010), in Russian
3. O.V. Mandrikova, N.V. Glushkova, I.V. Zhivetiev, *Collection of reports of the VI international conference «Solar-Terrestrial Relations and Physics of Earthquake Precursors»*, 119-123, (2013), in Russian
4. D.B. Rozhdestvenskii, V.A. Telegin, V.I. Rozhdestvenskaia, “*Physics of Auroral Phenomena*”, *Proc. XLI Annual Seminar*, 139-142, (2018), in Russian
5. Hendy Santosa. *Modeling and prediction of ionospheric characteristics using nonlinear autoregression and neural network. Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor Of Engineering at The University of Electro-Communications*
6. Andong Hu, Kefei Zhang, *Remote Sensing*, **10(10)**, 1658-1671 (2018)
7. Hongmei Bai, Haipeng Fu, Jian Wang, Kaixue Ma, Taosuo Wu, Jianguo Ma, *Radio Science, Technical Reports: Methods*. **53(10)**, 1292-1301 (2018)
8. P. Wintoft, Lj.R Cander, *Part C: Solar, Terrestrial & Planetary Science*, **25(4)**, Pages 267-273 (2000)
9. Elijah O. Oyeyemi, L.A. McKinnell, A.W.V. Poole, *Journal of Atmospheric and Solar-Terrestrial Physics*, **68(16)**, 1807-1818 (2006)
10. V.A. Mochalov, A.V. Mochalova, *Proceedings, XXVI Russian open conference RWP*, 477-479 (2019)
11. V. A. Mochalov, A. V. Mochalova, *E3S Web Conference*, **127**, (2019)
12. *Instructions for ionospheric, magnetic and heliophysical observations. Part I. Ionospheric observations* (2015), in Russian
13. Hochreiter S., Schmidhuber J., *Neural Computation*, **9(8)**, 1735–1780 (1997)
14. V.A. Mochalov, A.V. Mochalova, *Proceedings of the III International Conference on BioGeoSciences* (to be published).
15. Long short-term memory, URL: [https://en.wikipedia.org/wiki/Long\\_short-term\\_memory](https://en.wikipedia.org/wiki/Long_short-term_memory)
16. Keras – Python Deep Learning library, URL: <https://keras.io>
17. Intro to Recurrent Neural Networks LSTM | GRU, URL: <https://www.kaggle.com/thebrownviking20/intro-to-recurrent-neural-networks-lstm-gru>
18. G.V. Givishvili, I.V. Krasheninnikov, L.N. Leshchenko, Yu.M. Vlasov, A.V. Kuz'min, *Heliogeophysical investigation*, **4**, 68-74, (2013) in Russian