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Deep Learning-Based Ionospheric TEC Prediction Approach

İsmail DEMİRYEGE*[1], Mustafa ULUKAVAK [1]

[1]Harran University, Engineering Faculty, Department of Geomatics Engineering, Şanlıurfa, Turkey

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ABSTRACT

The ionosphere layer is an environment that causes a time delay depending on the frequencies of the radio waves of the Global Positioning System (GPS) satellites. Most ionospheric studies are performed using total electron content (TEC) changes obtained from GPS signals. Today, studies on the physical structure of the ionosphere continue in many areas such as the prediction of space weather conditions, positioning, navigation, and communication. This study aims to create a deep learning-based model for the prediction of ionospheric TEC. Artificial Neural Networks (ANN) method was used to create this model. The artificial neural network and related properties designed for this method have been prepared in the MATLAB® environment using the Deep Learning Toolbox. In this study, HRUH permanent station which is located in Harran University Campus was registered Turkey Continuously Operating Reference Station' (CORS-TR) RINEX observations are used. TEC variations were obtained from GPS observations between the years 2016 and 2019 with two hours of temporal resolution. In this study, the determination of the optimum parameters was investigated which aims to forecast ionospheric TEC variations for the first six months of 2019. In the created model, the number of iterations is selected as constant (i = 100). The minimum RMSE value is ±0.28704 TECU with parameters where the number of hidden layers is selected as 50. The RMSE value of the forecasting model which is calculated in 1 hidden layer is ± 0.47298 TECU.

1. INTRODUCTION

The global positioning system (GPS) is a positioning and navigation system based on satellite technology. Although GPS is widely used in various fields such as air, sea, and land navigation, it is also used in daily life, industry, research, and education. A large part of the atmospheric effects encountered in positioning caused by ionospheric effects on GPS signals. Disruptions in the ionosphere; In particular, changes caused by space weather conditions damages the radio communication system and propagation (S.-S. Tan, 2008). Therefore, it may negatively affect the communication of radio signals such as communication, navigation, and radar (S. Tan, Zhou, Guo, & Liu, 2011). Since the ionosphere plays an important role in radio communication, applications should be carried out by considering ionospheric conditions.

Total Electron Content (TEC) is defined as the total number of electrons (10^{16}el/m^2) obtained in a cross-sectional area of 1 square meter along the signal path from GPS satellites to the GPS receiver, and its unit is expressed as the total electron content unit (TECU) (Abdullah, Strangeways, & Walsh, 2009). TEC is an indication of ionospheric variability obtained from GPS signals corrected by free electrons (Yaacob, Abdullah, & Ismail, 2010). TEC is an important parameter that provides information about disturbances in the ionosphere (Chakraborty, Kumar, De, & Guha, 2014; Schmidt, Bilitza, Shum, & Zeilhofer, 2008). Complex physical interactions between the geomagnetic field and solar activities make it difficult to model and predict ionospheric effects (Xu, 2007). GPS observations, along with navigation and positioning applications, are also used to investigate the effects of ionospheric space climatic conditions (Hofmann-Wellenhof, Lichtenegger, & Collins, 1993).

In this study, the performance of the LSTM Estimated TEC model for the GPS-TEC data mentioned above for the TEC time series estimation will be evaluated. Artificial Neural Networks (ANN) models will be used to model and predict ionospheric TEC

* Corresponding Author

*(demiryege@hotmail.com) ORCID ID 0000-0003-3836-3328
(mulukavak@gmail.com) ORCID ID 0000-0003-2092-3075

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differences using the TEC time series measured by GPS. Although NNs perform better than statistical methods, the necessity of large-input training data including TEC samples of many years and the complexity in determining synaptic weights in the training process, and the lack of standard mathematical background limiting the application of the NN model for short-term TEC estimation have been identified (Leandro & Santos, 2007; Tulunay, Senalp, Radicella, & Tulunay, 2006). For this reason, recurrent neural networks (RNNs) are designed for time series in deep learning. Long Short-Term Memory (LSTM) is a specific recurrent neural network (RNN) architecture designed to model time series and long-range dependencies (Hochreiter & Schmidhuber, 1997). From the past time series data consisting of TEC values, forward-looking GPS-TEC predictions can be made with the LSTM network model. In short, forward-looking time series and the relationship between these series can be found. In this study, the LSTM network model is applied to predict 3.5-year sequential GPS-TEC data during the 24th solar cycle.

2. METHOD

2.1. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a method developed by simulating the cognitive learning process of the human brain (Karahan, 2015). ANN is similar to the human brain in two ways (Ataseven, 2013; Gülpınar, 2015): first, the information in ANN is obtained by the network through the learning process, then the ANN uses it to store the information of the relationship between neurons known as synaptic weights. The general purpose of ANN is the learning process. ANN learns by training and testing similar to the human brain (Karymshakov & Abdykaparov, 2012). ANN; It can reveal the relationship between learning, memorizing, and data (Özkan, 2012). ANN imitates the working principle of the human brain; It has many important features such as being able to learn from examples (learning), generalize, work with missing information, complete pattern, establish relationships (associate), perform one or more of the classification and optimization processes (Aydemir, Karaatlı, Yılmaz, & Aksoy, 2014; Öztemel, 2006).

2.1.1. Long Short-Term Memory (LSTM) TEC Model

The proposed LSTM network architecture for the prediction of the TEC time series consists of 4 layers as input layers, LSTM layers, hidden layers, and output layers (Figure 1).

Each element of the input layer are vectors obtained from TEC values. LSTM has input layer [$x_t = (x_1, x_2, x_3, ..., x_n)$] and hidden layer output [$h_t = (h_1, h_2, h_3, ..., h_n)$] in the peered order. The process of these operations is done according to the following equations:

$$i_t=\sigma\ (W_{ix}x_t + W_{ih}h_{t-1} + b_i) \quad (1)$$
$$f_t= \sigma\ (W_{fx}x_t + W_{fh}h_{t-1} + b_f) \quad (2)$$
$$o_t= \sigma\ (W_{ox}x_t + W_{oh}h_{t-1} + b_o) \quad (3)$$
$$c_t= f_t * c_{t-1} + i_t*\tanh\ (W_{ox}x_t + W_{ch}h_{t-1} + b_c) \quad (4)$$
$$h_t= o_t*\tanh(c_t) \quad (5)$$

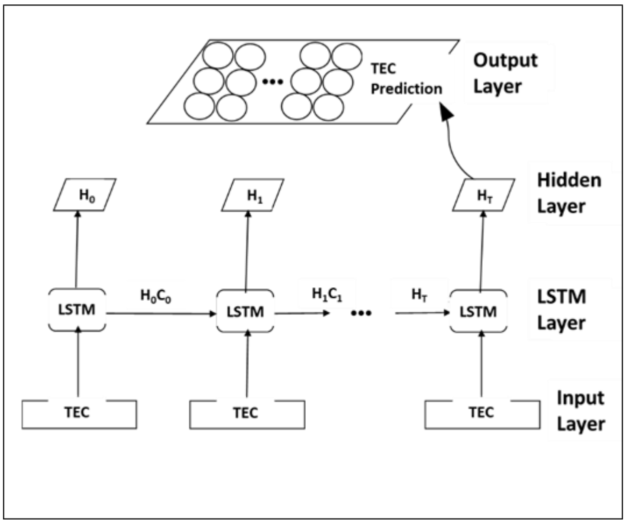

Figure 1. LSTM Network Architecture

The i in the formula is the input gate controlling how much of the input to each hidden unit is written into the inner state vector (c_t). f is the discharge gate that determines how much of the previous internal state (c_{t-1}) is maintained. The combination of write and drain ports enables the network to control what information needs to be stored and overwritten at each step. It is the output gate and controls how much of each unit's update is preserved and is involved in storing non-relevant information of the LSTM cell. c_t is the cell that learns the long dependencies of time series data. The last latent case h represents the predicted values of time series data (Sun et al., 2017).

3. RESULTS

In this study, an application was carried out to predict the TEC values for the first half of the year 2019 by using the TEC values obtained by using GPS observations of the HRUH station 3-years TEC changes data were used as training data in the established LSTM network. To train 3 years of data in a deep learning environment; the main parameters of the deep learning model such as the initial learning rate, the number of hidden layers, and the number of iterations were determined. The information was updated with the sigmoid function and it was ensured that the data were associated with the preceding data for the convolution of the network. Then, the training of the network was provided according to the determined parameters, and the standardization of the test data was made. Estimates of ionospheric TEC changes and squared mean errors (RMSE) were obtained for the first six months of the year 2019. The 6-month estimated TEC values were obtained through the deep learning process and these data were compared with the test data of the year 2019. After this encounter, the RMSE values were reduced by updating again over the estimated-TEC values.

In this study, the number of hidden layers was chosen as 50, and the number of iterations selected as 100. Separate and sequential deep learning processes were made 1 to 50 hidden layers. RMSE values obtained from the solutions are shown in Figure 2.

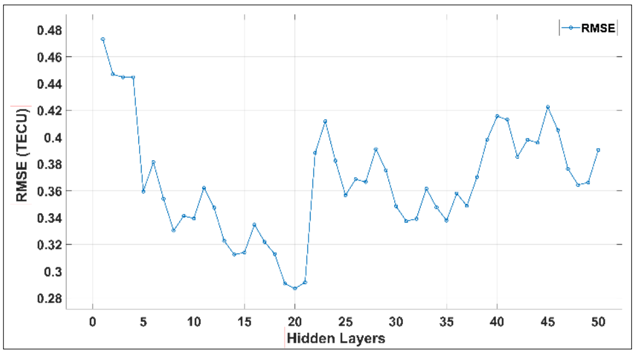

Figure 2. RMSE values calculated based on the number of hidden layers

In Figure 2, it is seen that as the number of hidden layers is increased, there is a decrease in the RMSE values, but there is an increase again after the 20th hidden layer value (RMSE = ±0.28704 TECU). The comparison of the estimated data with the test data and the errors between are shown in Figure 3.

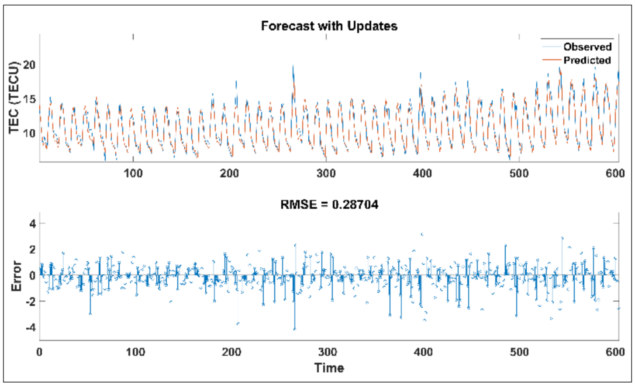

Figure 3. Plots of the 2019's first 48 days TEC validations

4. CONCLUSION

The time-series data in the installed model consists of the TEC changes between 2016-2019 with a two-hour temporal resolution. Based on these 3-year TEC data, the forecast of the TEC changes for the first 6 months of the year 2019 was investigated. In other words, the relationship between the 6-month estimated TEC time series data was investigated over the past 3-year TEC time series data.

In order to use the Deep Learning Toolbox customized in the MATLAB® environment, the computer hardware (such as video card, ram) must have the ability to perform high-capacity processing. In addition, the solution method of the selected network should be chosen to better represent the time series values. The use of the stochastic gradient descent momentum (SGDM) method for data with very long inputs is suggested as the findings of this study. The other solution method, adaptive momentum estimation (ADAM), is recommended to be used in the analysis of fewer data. The mathematical formulas and analysis forms of these 2 solution methods can be accessed from the MATLAB® Deep Learning Toolbox.

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REFERENCES

Abdullah, M., Strangeways, H. J., & Walsh, D. M. A. (2009). Improving ambiguity resolution rate with an accurate ionospheric differential correction. *Journal of Navigation*. doi:10.1017/S0373463308004979

Ataseven, B. (2013). YAPAY SİNİR AĞLARI İLE ÖNGÖRÜ MODELLEMESİ. *Öneri Dergisi*. Marmara Üniversitesi. doi:10.14783/od.v10i39.1012000311

Aydemir, E., Karaatlı, M., Yılmaz, G., & Aksoy, S. (2014). 112 Acil Çağrı Merkezine Gelen Çağrı Sayılarını Belirleyebilmek için Bir Yapay Sinir Ağları Tahminleme Modeli Geliştirilmesi. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*. Pamukkale Üniversitesi. doi:10.5505/pajes.2014.98608

Chakraborty, M., Kumar, S., De, B. K., & Guha, A. (2014). Latitudinal characteristics of GPS derived ionospheric TEC: a comparative study with IRI 2012 model. *Annals of Geophysics*, *57*(5). doi:10.4401/ag-6438

Gülpınar, V. (2015). YAPAY SİNİR AĞLARI VE SOSYAL AĞ ANALİZİ YARDIMI İLE TÜRK TELEKOMÜNİKASYON PİYASASINDA MÜŞTERİ KAYBI ANALİZİ. *Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi*. Marmara Üniversitesi.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. doi:10.1162/neco.1997.9.8.1735

Hofmann-Wellenhof, B., Lichtenegger, H., & Collins, J. (1993). *Global Positioning System. Theory and practice. Global Positioning System. Theory and practice.*

Karahan, Y. D. D. M. (2015). TURİZM TALEBİNİN YAPAY SİNİR AĞALARI YÖNTEMİYLE TAHMİN EDİLMESİ. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*. Süleyman Demirel Üniversitesi.

Karymshakov, K., & Abdykaparov, Y. (2012). Forecasting stock index movement with artificial neural networks: The case of Istanbul Stock Exchange. *Trakya University Journal of Social Science*, *14*, 231–242.

Leandro, R. F., & Santos, M. C. (2007). A neural network approach for regional vertical total electron content modelling. *Studia Geophysica et Geodaetica*, *51*(2), 279–292. doi:10.1007/s11200-007-0015-6

Özkan, F. (2012). Döviz Kuru Tahmininde Parasal Model ve Yapay Sinir Ağları Karşılaştırması. *A Comparison of the Monetary Model and Artificial Neural Networks in Exchange Rate Forecasting. (English)*, *3*(2), 27–29.

Öztemel, E. (2006). *Yapay Sinir Ağları*. *Papatya Yayıncılık*. İstanbul.

Schmidt, M., Bilitza, D., Shum, C. K., & Zeilhofer, C. (2008). Regional 4-D modeling of the ionospheric electron density. *Advances in Space Research*, *42*(4), 782–790. doi:10.1016/j.asr.2007.02.050

Sun, W., Xu, L., Huang, X., Zhang, W., Yuan, T., Chen, Z., & Yan, Y. (2017). *Forecasting of ionospheric vertical total electron content (TEC) using LSTM networks*. In *Proceedings of 2017 International Conference on Machine Learning and Cybernetics, ICMLC 2017*. doi:10.1109/ICMLC.2017.8108945

Tan, S.-S. (2008). Development and thought of compass navigation satellite system. *Yuhang Xuebao/Journal of Astronautics*, *29*, 391–396.

Tan, S., Zhou, B., Guo, S., & Liu, Z. (2011). Research on COMPASS navigation signals of China. *Zhongguo Kongjian Kexue Jishu/Chinese Space Science and Technology*, *31*, 9-14+29. doi:10.3780/j.issn.1000-758X.2011.04.002

Tulunay, E., Senalp, E. T., Radicella, S. M., & Tulunay, Y. (2006). Forecasting total electron content maps by neural network technique. *Radio Science*, *41*(4). doi:10.1029/2005RS003285

Xu, G. (2007). *GPS: Theory, algorithms and applications*. *GPS: Theory, Algorithms and Applications*. doi:10.1007/978-3-540-72715-6

Yaacob, N., Abdullah, M., & Ismail, M. (2010). GPS Total Electron Content (TEC) Prediction at Ionosphere Layer over the Equatorial Region. In *Trends in Telecommunications Technologies*. doi:10.5772/8474