Doğrusal Olmayan Bazı Süreçler İçin
Sinirsel Ağ Tabanlı Yaklaşımlar

Yurdanur Tulunay(1), Ersin Tulunay (2), A. Türker Kutay(2), Erdem Turker Senalp(2)

1) İstanbul Teknik Üniversitesi
Uçak ve Uzay Bilimleri Fakültesi
Maslak, İstanbul
ytulunay@itu.edu.tr

2) Orta Doğu Teknik Üniversitesi
Elektrik ve Elektronik Mühendisliği Bölümü
Balgat, Ankara
ersintul@metu.edu.tr, senalp@metu.edu.tr

Özet: *Yer'e yakın uzay süreçleri, yüksek derecede karmaşıktır ve doğrusal değildir. Bunların matematiksel benzeklenmesi çoğunlukla zor, ya da olanaksızdır. Bu durumlar için veri sürüşlü benzekleme yöntemleri, matematiksel benzeklemeyle koşut kullanılır. Burada, Sinirsel Ağ tabanlı yaklaşım gibi veri sürüşlü benzeklerin bu süreçlerin davranışının öngörümü, ya da kestiriminde başarılı olduğu gösterilmiştir. Bu makalede iki durum çalışması Sinirsel Ağ benzeklemeyi gösterecektir. İlk çalışmada iyonosferik kritik frekans – foF2 – değerleri bir ve 24 saat ileri öngörülerde bulunulmuştur. İkinci çalışmada Slough UK "ionosonde" dan elde edilen foF2 değerlerini öngörüde bulunma ile gezegen manyetik alanı (IMF) Bz polarite dönmelerinin yüksek frekans yayılım ortamındaki olası etkisi araştırılmıştır.*

Abstract: *Near Earth space processes are highly complex and nonlinear. Mathematical modeling of those is usually difficult or impossible. For those cases data driven modeling methods are used in parallel with mathematical modeling. It is demonstrated here that the data driven models, such as the models based on the neural network based approach are promising to forecast or predict the behavior of those processes. In this paper two case studies will demonstrate the neural network modeling. In the first case the ionospheric critical frequency – foF2 – values are forecast one and 24 hours in advance. In the second case the possible influence of the interplanetary magnetic field (IMF) Bz polarity reversals on the high frequency propagation medium is investigated in terms of the forecast of the foF2 values obtained by the Slough UK ionosonde.*

1. Introduction

Ionospheric processes are highly complex including nonlinearities and time-varying parameters for which obtaining exact mathematical models is impossible. In such cases it has been demonstrated by the authors and others that the data driven modelling approach such as neural network based modelling is very promising [1, 2,3,4, 5, 6]. The only basic requirement for this is the availability of representative data for the phenomena. For illustrating the process of modelling by using neural networks the following case studies are considered.

I. prediction of three orbit parameters, a, e, i, of a geostationary satellite;
II. forecasting of the foF2 values in order to study the effect of the IMF Bz turnings.

Neural network based orbit prediction for a geostationary satellite

A modular and general purpose computer program is developed to simulate a Multi Layer Perceptron type Neural Network [6]. The parameters that define the structure of the network: the number of inputs (maximum 20) the number of hidden layers (maximum 5), the number of neurons in each hidden layer (maximum 20) can be adjusted. Back propagation (Steepest Descent) algorithm is employed.

2. Discussion

After constructing the NN model ATKNN, a simulation is preformed with the parameters presented in Table 1 and the estimations for the orbit parameters a. E and i are obtained. The curves obtained for a. e. and i versus time for the 14 days period are presented in Figure 1 Figure 2 and Figure 3 respectively in comparison with the METUAEE1 results. The rms error for the semi-major axis turned out to be 21.28 m which was 29.91 m in the first run.

Table 1. shows the optimal parameters obtained for the NN.

N	2
n	4
Number of hidden layers	1
Number of neurons in thehidden layer	10
Number of iterations	60

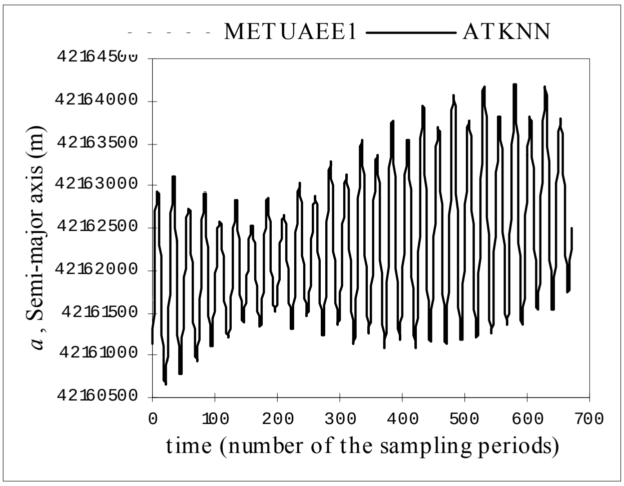


Figure 1. Variation of the semi-major axis in 14 days calculated by METUAEE1 and estimated by ATKNN

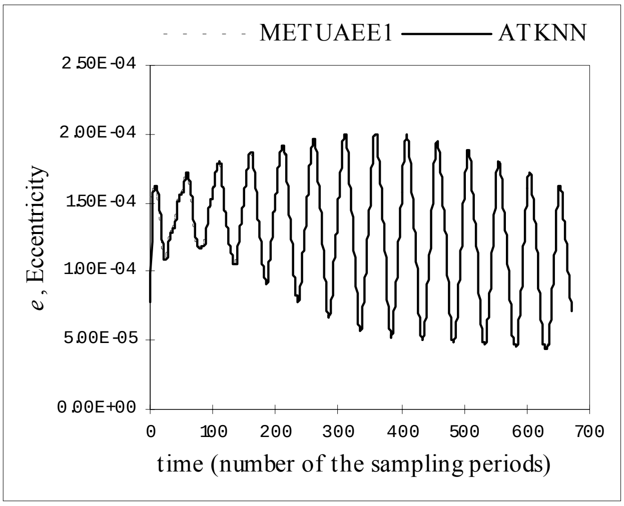


Figure 2. Variation of the eccentricity in 14 days calculated by METUAEE1 and estimated by ATKNN

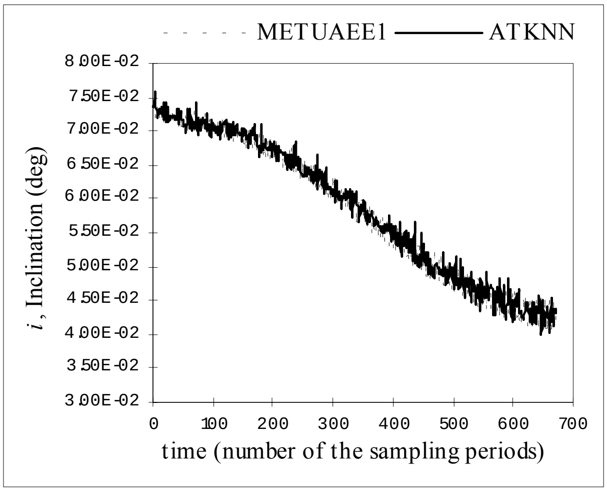


Figure 3. Variation of the inclination in 14 days calculated by METUAEE1 and estimated by ATKNN

Table 2. The rms errors, the normalized rms errors and the correlation coefficients in the estimation of a,e and i.

Orbit parameter	rms error	Normalized rms error	Correlation coefficient
a	21.28 m	$5.05*10^{-7}$	0.9996837
e	$3.24*10^{-6}$	$2.17*10^{-2}$	0.9970946
i	$2.09*10^{-3}$ deg	$3.54*10^{-2}$	0.9892513

In all of the simulations performed in this work the synthetic data of the TÜRKSAT 1B satellite generated by the METUAEE1 code were used. With the use of the real orbital data of a spacecraft more realistic results could be obtained.

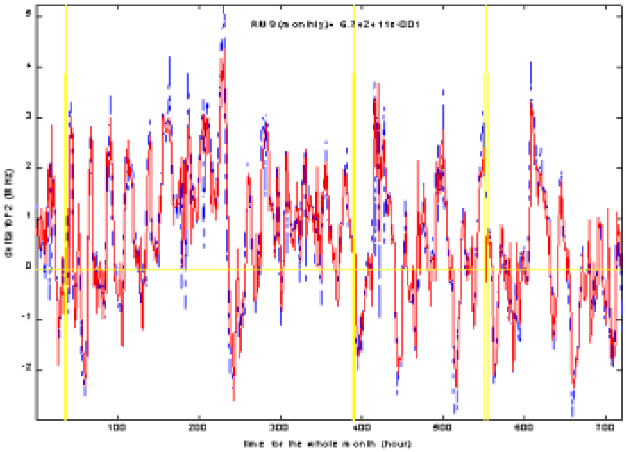
Neural network modelling of the effect of the IMF Bz polarity changes on the HF propagation medium

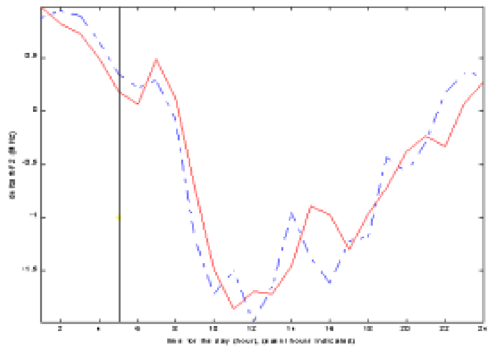
The possible effects of the orientation of the IMF Bz and By on the mid-latitude ionosphere were investigated in the past. The regular diurnal, seasonal and solar cycle variations in the foF2 data had been removed by subtracting the mean of foF2 for the same UT on all magnetically quiet days (Ap<6) within 15 days. This yields deviation δfoF2 from the average quiet time value. In order to study the effects of IMF Bz polarity changes the major events i.e., ΔBz greater than or equal to 11.5 nT/h are considered. The hourly variation of δfoF2, within the time intervals around the key dates, is modelled by using neural network trained, with April 1979 data, which forecast δfoF2 values one hour in advance for April 1982. It has been demonstrated that learning a process, rather than modelling it is a promising approach. That is the neural network based model is promising to forecast foF2 values during disturbances characterized by IMF B polarity changes. A neural network based model is developed which models time variations of foF2 for a single station during the IMF Bz southward polarity changes. The model forecasts δfoF2, during these disturbed conditions one hour in advance. The neural network system developed has one input layer with 12 inputs, one output layer with one output and one hidden layer. There are 12 neurons in the hidden layer. The twelve inputs used for the neural network are: four component coded hour of the day, normalized day (day/31), normalized month (month/12), normalized year [(year-50)/50], the present value δfoF2(k) of the time variations of the critical frequency foF2 observed at present time k, first difference, second difference, relative difference, all related to δfoF2, event occurance parameter. The output and the inputs of the neural network based model are shown in Table 3.

Table 3. The output and the inputs of the neural network based model.

Output	Inputs
Forecast of the δfoF2 value δfoF2(k+1) to be observed (determined) one hour later	Four component coded hour of the day, day/31, month/12, (year-50)/50, present value δfoF2(k) of δfoF2, first difference, second difference, relative difference, event occurance parameter (+1 for event occurring, -1 for no event case)

This method has the capability to be generalized to cover the other stations of interest. However in this paper an attempt for Slough station is made to introduce the model to possible users. Some sample results are presented for the forecast of δfoF2 one-hour in advance during IMF Bz polarity changes. Monthly rms error = 0.67, Monthly absolute error = 0.47 MHz.





Time for the day (hour) (event hours indicated)

Figure 4 . a) Monthly variation of δfoF2 values for Slough station for April 1982. Observed (dotted), Forecast (solid), Events: vertical solid (yellow) lines. b) Variation of δfoF2 for 17 th day of April 1982

The preliminary results reported here indicate that the neural net based method for modelling of the effect of IMF turnings on the variability of HF propagation medium is a promising one via forecasting of δfoF2 and thus foF2 values one hour in advance.

3. Conclusions

Summarizing, the main contributions reported herewith are:

i) neural network based modelling of a complex nonlinear process;
ii) preparation of significant data for teaching complex processes;
iii) demonstration of learning capability by calculating cross-correlation coefficients and demonstration of reaching a proper operating point by calculating errors.

References

[1] Kutay, A.T., *Modeling and Simulation of the Türksat 1B Satellite Using Artificial Neural Networks*, MS Thesis, Dept of Aeronautical Engineering, Middle East Technical University, Ankara, Turkey, (1999).

[2]. Tulunay, E., Introduction to neural networks and their applications to process control, in Neural Networks: *Advances and Applications*, ed. by E.Gelenbe, pp.241-273, Elsevier, New York, (1991).

[3]. E.Tulunay, C. Ozkaptan, Y. Tulunay, Temporal and spatial forecasting of the foF2 values up to twenty four hour in advance, *Physics and Chemistry of the Earth,* **25**, No.4, pp. 281-285, (2000).

[4]. A.Kumluca, E.Tulunay, İ.Topalli, Y.Tulunay, Temporal and spatial forecasting of ionospheric critical frequency using neural networks, *Radio Science* **, 34**, issue 6, pp.1497-1506, (1999).

[5]. Cander, L.R., Lamming, X., Neural networks in ionospheric prediction and short term forecasting, *in 10th International Conference on Antennas and Propagation*, IEE Conf. Publ., 436, 2.27-2.30, (1997).

[6]. Williscraft, L.A., Poole, A.W.V., Neural networks foF2, sunspot number and magnetic activity, *Geophys. Res. Lett.,* **23**, 3659-3662, (1996).

[7]. C. Sakaci, *Two Simulation Models: Low Altitude Flows and the TURKSAT Satellite Orbit*, MS Thesis, Department of Aeronautical Engineering, Middle East Technical University, Ankara, Turkey, (1996).

[8]. A. Cichocki, R. Unbehauen, *Neural Networks for Optimization and Signal Processing*, JW & Sons, (1992).