NEURAL NETWORKS IN IONOSPHERIC WEATHER RESEARCH

Lj.R. Cander

CLRC Rutherford Appleton Laboratory, Chilton, Didcot, Oxon OX11 0QX, Great Britain
fax: +44 (0)1235 44 6140, e-mail: l.cander@rl.ac.uk

ABSTRACT

It is the aim of this paper to show by most recent examples that modern development of numerical models for ionospheric daily hourly short-term forecasting may proceed successfully applying the artificial neural networks. The performance of these techniques is here illustrated with an artificial neural network developed to predict 1-hour in advance temporal variations of ionospheric F2 layer critical frequency, foF2, during two great ionospheric storms in 1986. Comparisons between results obtained by the proposed approach and observed foF2 data provide prospects for future applications of the artificial neural networks in ionospheric weather research.

Keywords: Ionosphere, ionospheric storms, short-term forecasting, artificial neural networks.

1. INTRODUCTION

The ionosphere of Earth exhibits considerable changes with different spatial and temporal scales related to the mechanisms of creation, decay and transport of space ionospheric plasma. In spite of numerous studies of modelling electron density profiles through entire ionosphere (Ref.1), there remain several unresolved problems. Fluctuations associated with irregular ionospheric structures which correspond to the ionospheric weather are an important scientific issue concerned ionospheric short-term forecasting. New way to address this problem is by applying artificial intelligence methodologies to current large amount of solar-terrestrial and ionospheric data (Ref. 2). This paper presents details of the artificial neural network used for 1-hour in advance foF2 forecasting and results obtained in case of two great ionospheric storms.

2. ARTIFICIAL NEURAL NETWORK

Fig. 1 shows a schematic diagram of the hybrid time-delay multi-layer percepton neural network used with inputs as follows:

f(t) - foF2 at time t; Mf(t) - mean foF2 at t; Mf(t-1) - mean foF2 at t-1; Mf(t-23) - mean foF2 at t-23; Mf(t-47) - mean foF2 at t-47; Mf (t+1) - mean foF2 at t+1; Delta f(t)=f(t)-Mf(t); Delta f(t-1)=f(t-1)-Mf(t-1); Delta f(t-23)=f(t-23)-Mf(t-23) and Delta f(t-47)=f(t-47)-Mf(t-47). Mf values have been calculated using only the learning set of data to produce the background daily variations of foF2**.** There is one neural network output value: f (t+1) - predicted foF2 values at t+1. More detailed description of this type of neural network, has been presented recently by Cander et al. (Ref. 3).

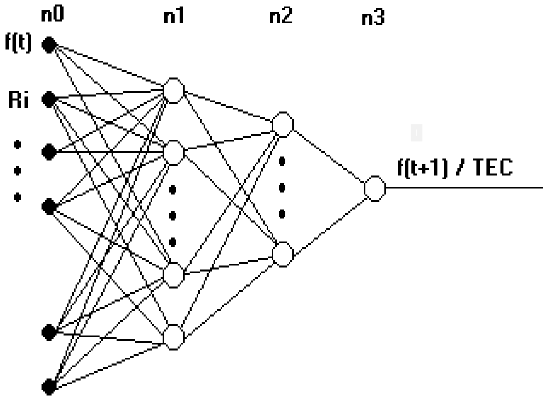

Figure 1. *A schematic diagram of artificial neural network.*

Table 1 introduces the matrix of sensitivity which gives quantitatively the relative importance of each input in determining the output of the proposed neural network. It is defined as a mathematical expectation of the absolute values of the first partial derivative of output under each input.

Table 1. *Matrix of sensitivity when inputs are only ionospheric parameters*

INPUT/ OUTPUT	FEB 1986	FEB 1986	MAY 1986	MAY 1986
M f(t+1)	20.82		19.38	
Delta f(t)	25.76	25.78	23.54	25.99
M f(t-47)	8.05	13.43	8.59	21.08
f(t)	16.33	15.30	19.65	16.84
M f(t-23)	16.76	28.27	17.12	23.90
Delta f(t-23)	8.93	11.23	10.43	13.39
Delta f(t-1)	5.16	4.31	6.37	5.29
Delta f(t-47)	3.62	5.35	2.66	5.60
M f(t-1)	5.70	6.72	6.92	7.29
M f(t)	2.27	2.60	2.88	5.80
relative error	8.86 (0.64 MHz)	9.03 (0.66 MHz)	6.06 (0.44 MHz)	6.17 (0. 45 MHz)

From close inspection of Table 1 it is clear that the neural network is equally effective at forecasting the test data set with and without Mf(t+1) as input parameters, which represents background ionosphere at forecasting time t+1.The main influence is of background mean daily variation of foF2 before time t, the latest available measurement and then foF2 data from 24 and 48 hours before.

3. FORECASTING RESULTS

Hourly foF2 values from Slough (51.5 N, 359.4 E) ionospheric station for 1986 have been used to train and test a neural network. Two storms that occurred on 6 February 1986 and 2 May 1986 were found suitable to show that ionospheric storms are complex phenomena (Ref. 4) and proposed neural network can describe the observed features adequately with prediction horizon of one hour. Geomagnetic activity associated with the period 6-14 February 1986 is illustrated by the variations of the Dst index in Figure 2. This exhibited very large changes in all geomagnetic activity indices showing that a great geomagnetic and consequently ionospheric storm was in progress. The second example of a geomagnetic storm occurred on 2 May and the Dst index variations are given in Figures 3. The F2 layer response observed at the ionospheric station Slough is described by foF2 variations in Figures 4 and 5.

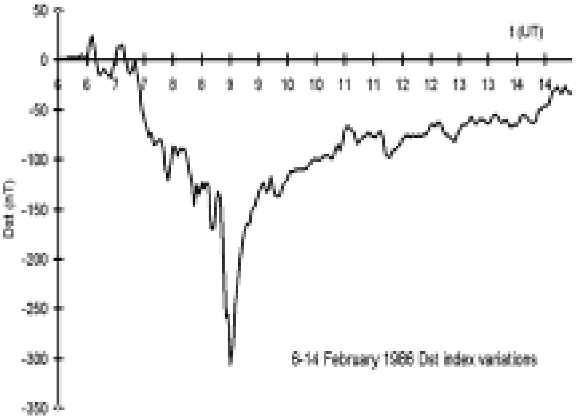

Figure 2. *Dst variations during 6-14 February 1986.*

Figure 4 shows the hourly foF2 values observed at Slough ionospheric station (dashed line) and predicted by neural network using the prediction horizon of one hour (solid line) for five days of test set starting from 6 February 1986. At Figure 5 the same pattern is given for the case of storm started at 2 May 1986. Close examination of the Figures 4 and 5 shows that there is an excellent agreement between observed and predicted foF2 values for prediction horizon of one hour. Relative mean square errors for the whole test set in February and May 1986 are around 9% and 6%, respectively.

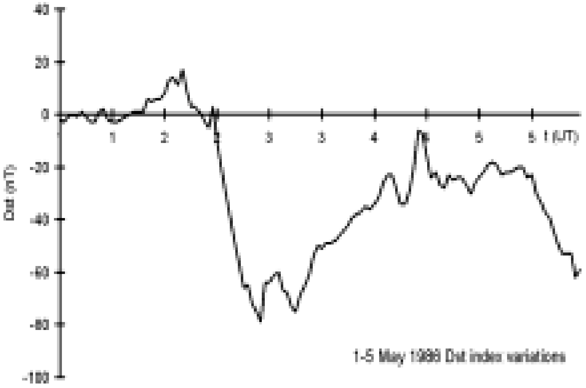

Figure 3. *Dst variations during 6-14 February 1986.*

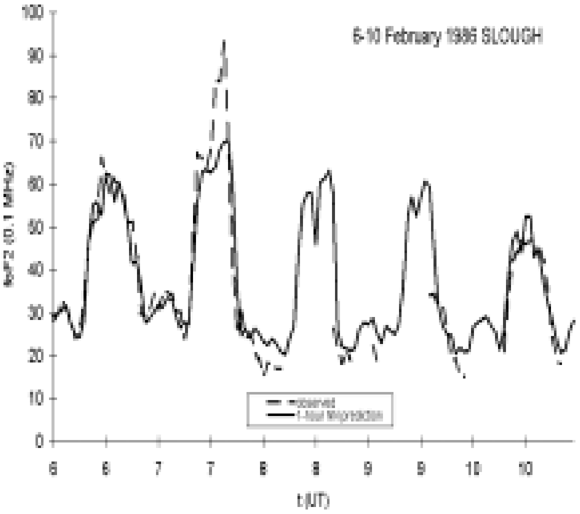

Figure 4. *1 hour ahead forecasting of foF2 for Slough station during February 1986 storm.*

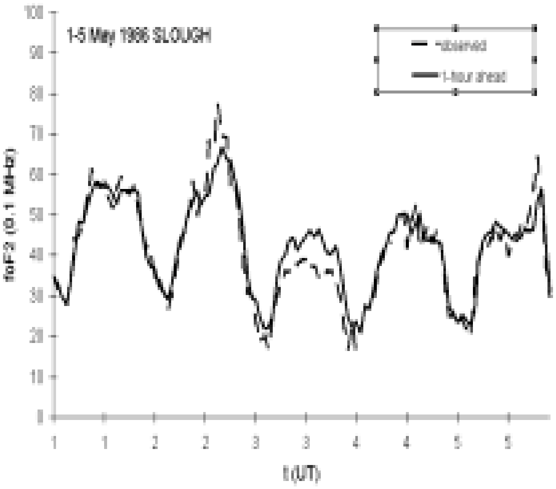

Figure 5. *1 hour ahead forecasting of foF2 for Slough station during May 1986 storm.*

4. CONCLUSIONS

There can be two different approaches to the ionospheric weather problem. The first can be focused upon efforts to improve significantly existing theoretical, parameterised and empirical ionospheric models beyond their climatological level, i.e. the average conditions observed during the forecast period. The second is associated with the real-time use of data resulting from improving techniques for solar-terrestrial monitoring and developing specification or nowcasting models as operational tools under the auspices of cooperative international projects. Furthermore, more effective use can be made of current ionospheric data and knowledge by employing artificial intelligence methodologies and neural network computation techniques.

Having this in mind an artificial neural network has been trained and tested using the hourly values of the critical frequency of F2 ionospheric layer at Slough station. The results show that proposed hybrid time-delay Multi-Layer Percepton neural network is capable to forecast the diurnal variations of foF2 values successfully during great ionospheric storms when the prediction horizon is one hour. This is an important result because of the well-known fact that the ionospheric variability during geomagnetic storms is highly non-linear process that has no general analytical and/or numerical model so far. This work supports the author's idea that neural networks techniques offer an excellent opportunity to finally develop the successful ionospheric short-term forecasting model as a part of the ionospheric weather prediction scheme.

5. ACKNOWLEDGEMENT

This work has been funded by the Radiocommunications Agency of the DTI as part of the National Radio Propagation Program at Rutherford Appleton Laboratory.

6. REFERENCES

1. Cander, Lj R & al 1998, Ionospheric models including the auroral environment, *this Proceedings.*

2. Haykin, S 1994, Neural networks - a comprehensive foundation, *Macmillan Collage Publishing Company*, New York.

3. Cander, Lj R & al 1998 Ionospheric forecasting technique by artificial neural networks, *Electronic Lett.*, 34, 16, 1573-1574.

4. Cander Lj R & Mihajlovic S J 1998, Forecasting ionospheric structure during the great geomagnetic storms, *J. Geophys. Res.*, 103, A1, 391-398.