Pergamon

Phys. Chem. Earth (C), Vol. 24, No. 4, pp. 343–347, 1999

1464-1917/99/$ - see front matter

PII: S1464-1917(99)00009-4

Short-Term Prediction of foF2 using Time-Delay Neural Network

P. Wintoft[1] and Lj. R. Cander[2]

[1]Solar-Terrestrial Physics Division, Swedish Institute of Space Physics, Lund Observatory, Box 43, SE-22100 Lund, Sweden
[2]CLRC Rutherford Appleton Laboratory, Chilton, Didcot, Oxon OX11 0QX, U.K.

Received 5 June 1998; accepted 1 December 1998

Abstract. To test the ability and efficacy of neural networks in short-term prediction of ionospheric parameters, this study used the time series of the ionospheric foF2 data from Slough station during solar cycles 21 and 22. It describes different neural network architectures that led to similar conclusions on one-hour- ahead foF2 prediction. This prediction is compared with observations and results from linear and persistence models considered here as two special cases of the neural networks.

1 Introduction

Long time series of traditionally and in recent years automatically scaled data sets from ionosonde records has become an excellent example of time series data with which to test the abilities of neural networks in ionospheric studies. (Altinay et al., 1997; Cander and Lamming, 1997; Poole and McKinnell, 1998; Cander et al., 1998). With increased use of computers in the stages of ionospheric data collection and processing, these studies are now focused on real time analysis of ionospheric behaviour and its short-term prediction. In accord with standard theory, at least two parameters: the critical frequency of the F2 layer, foF2, and the propagation factor, M(3000)F2, are representative of the prevailing ionospheric structures seen by ionosonde records and used in electron-density height profile formulation. They can be measured unambiguously and have been monitored at a wide variety of ground stations. While an extensive research has been done on the long-term spatial and temporal changes of foF2 and M(3000)F2 and their prediction, seeking to establish empirical relationships in terms of solar activity indexes, the weight of effort is currently aimed on daily specification and hourly forecasting of foF2 and M(3000)F2.

Correspondence to: P. Wintoft

The purpose of this study is to investigate the abilities and efficiencies of different neural network architectures in one-hour-ahead prediction of foF2 for different geophysical conditions. The trained networks are analysed to determine the optimal input parameters for the desired output. The success of these techniques is compared with observations and other existing methods for predicting the near future behaviour of foF2.

2 Data

Hourly foF2 data from Slough station are used for the years of 1980, 1981, 1985 and 1986 to represent the ionospheric conditions during high (1980 and 1981) and low (1985, 1986) solar activities in solar cycle 21. The data set is divided into two separate sets: a training set which is used to train the network, and a test set which is used to determine the performance of the network. The training sets were foF2 values in the whole of 1980 and 1985, and the test sets the whole of 1981 and 1986, respectively. To investigate a possible neural network in ionospheric foF2 prediction during the minimum phase in solar cycle 22, Slough data for 1995 were chosen for training during the whole year except September and then prediction was tested at this month.

3 Neural network

For ionospheric application we have chosen a time-delay feed-forward neural network with backpropagation learning algorithm (Haykin, 1994). The concepts of time-delay line and backpropagation learning will be explained in the following. The time-delay line is used to transform the temporal signal into a spatial pattern, which is then fed forward through the network to produce the output. If the signal is $x(t)$ and the time-delay line extends over $n+1$ time steps then the input pattern becomes

$$x^{\mu} = (x(t - n\Delta t), \ldots, x(t)), \quad (1)$$

where μ is the pattern number and Δt is the length of the time step. The spatial pattern is fed forward through the network according to

$$y^\mu = \sum_i v_i g \left(\sum_j w_{ij} x_j^\mu \right), \tag{2}$$

to produce the output signal y^μ. The weight w_{ij} connects input unit j to hidden unit i, and the weight v_i connects hidden unit i to the output unit. The transfer function g should be a non-linear monotonic increasing function, and here we choose $g(a) = \tanh a$.

The free parameters of the network are the weights v_i and w_{ij} which are found through training with the back-propagation algorithm on known input-output patterns. The algorithm tries to minimise the summed squared error

$$E = \frac{1}{2} \sum_\mu (d^\mu - y^\mu)^2 \tag{3}$$

between the desired output d^μ and the network output y^μ by adjusting the weights. This is done by calculating the first derivatives of E with respect to the weights v_i and w_{ij}. The weights are changed in the direction of the negative gradient, i.e. in a direction so that E is decreased, until the error E does not decrease further.

The length of the time-delay line is determined by the order of the system being modelled and the noise level in the data. If e.g. the unknown function that the network should model is a sine curve we have to solve the second order difference equation $x(t+1) = f(x(t), x(t-1))$ (Swingler, 1996). Thus to solve this problem the network inputs should be $x(t)$ and $x(t-1)$. If the data is noisy then the time-delay line should be extended so that the network can average out the noise.

Once the network has been trained the importance of the different weights can be estimated with a method called optimal brain damage (OBD) (LeCun et al., 1990). Through the learning process we calculated the first derivatives of the error E with respect to the weights. Then by calculating the second derivatives we can estimate how much the error would increase if we removed a specific weight, and thus determine the importance of the weight. Low-importance weights are removed and the network is retrained. This method also allows us to estimate which inputs are the most important.

4 One hour ahead predictions

Our goal here is to use different neural networks to make 1-hour-ahead predictions of the critical plasma frequency foF2 in the F2 layer. The two authors made two different approaches with respect to the network architectures and the selection of training and testing data sets. Before discussing the specific neural networks used to make 1- hour-ahead predictions we will make a comparison with two simple models: persistence and linear filters.

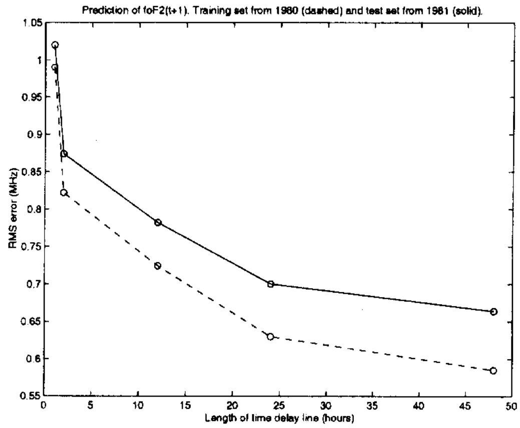

Fig. 1. The figure shows how both the training error (dashed line) and the test error (solid line) decreases when the length of the time-delay line is increased. The computations are made for time delay lines of length 1, 2, 12, 24, and 48 hours.

4.1 Comparison with persistence

The simplest approach to time-series modelling is the use of persistence, i.e.

$$y(t+1) = y(t). \tag{4}$$

If the signal is varying slowly the calculated RMS error and correlation will be good although the predictions are always lagging with one time step.

Starting with a neural network with only one input unit and then successively increasing the number of input units (i.e. the length of the time-delay line) and retraining the neural network the RMS error on the test set decreases as in Fig. 1.

In Fig. 2 we show an example of a prediction using only one input unit, which is similar to what we expect from persistence. From Fig. 1 we also see that there is a comparably large decrease in the error going from 1 input unit to 2 input units. This is due to the fact that when the input signal is $(x(t-1), x(t))$ both the signal itself and the first derivative of the signal is available to the neural network, and thus the network can use both the current value and the slope to predict the next value $x(t+1)$. Increasing the length of the time-delay line has two effects: higher order derivatives of the signal will be available, and any random fluctuations of the signal will be smoothed out.

4.2 Comparison with linear filters

We can also study the prediction accuracy by varying the number of hidden units. The RMS error decreases

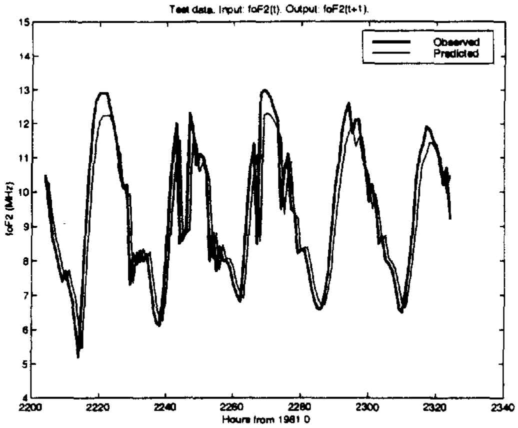

Fig. 2. Observed (thick line) and predicted (thin line) foF2 for 5 days in 1981. The prediction is made with only the current value of foF2 as input, i.e. one input unit.

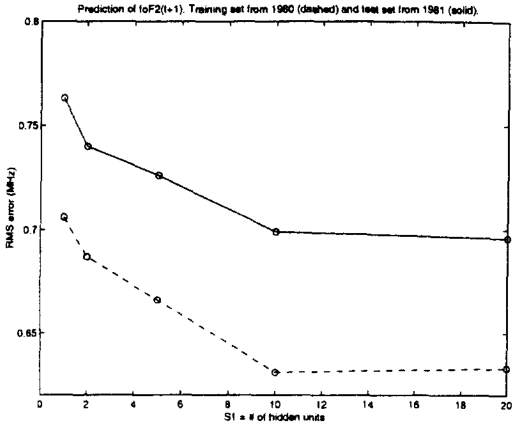

Fig. 3. The figure shows how the training error (dashed line) and the test error (solid line) decreases when more hidden units are used.

when the number of hidden units is increased to 10, and then levels out when more units are added (Fig. 3). The input time-delay line is 24 hours long. With only one hidden unit Eq.(2) becomes

$$y^{\mu} = vg\left(\sum_j w_j x_j^{\mu}\right), \tag{5}$$

which is equivalent to a linear filter.

4.3 Neural network pruning

Using a time delay line of the 50 previous hours of foF2 and applying the OBD method reveals that many input units and hidden units can be removed without affecting the prediction accuracy. Figure 4 shows the importance of each input unit estimated from the training set. It is clear that the measured foF2 values at hour t and $t-1$ have the greatest influence on the prediction of foF2($t+1$). We also see that foF2 around hours $t-23$ and $t-47$ are of importance due to the cyclic variation of foF2.

This is in agreement with the results from (Cander et al., 1998) who used the hybrid time-delay multilayer perceptron neural network in one hour ahead forecasting of foF2 values at different European ionospheric stations. However, in their approach a background ionosphere has been involved and appropriate deviations were used as input parameters at times t, $t-1$, $t-23$ and $t-47$. Similar results are also obtained by calculating the autocorrelation function to predict foF2 (Muhtarov and Kutiev, 1997). After pruning the network and continued training leaves us with a network with 3 hidden units and 17 input units that performs as well as the original network which had 10 hidden units and 50 input units. The total number of weights has decreased from 521 to 58.

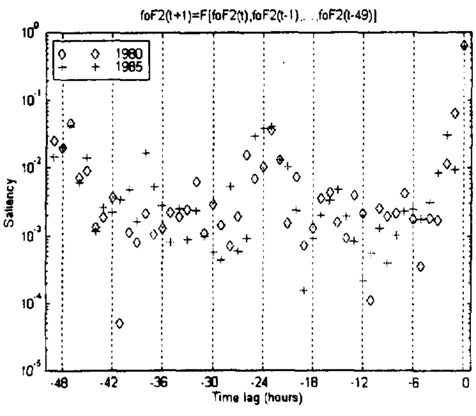

Fig. 4. The relative importance of the input units calculated on the training set for the two networks trained on data from 1980 and 1985, respectively.

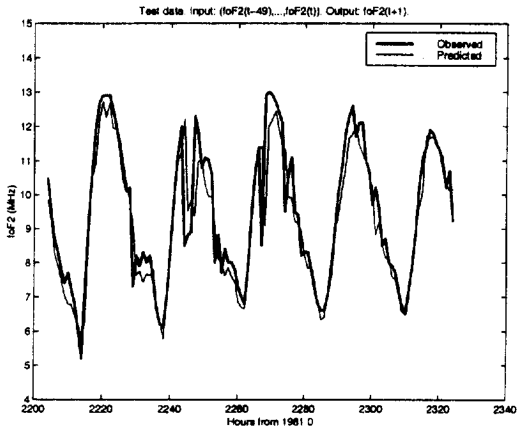

Fig. 5. The observed (thick line) and the predicted (thin line) foF2 during solar maximum.

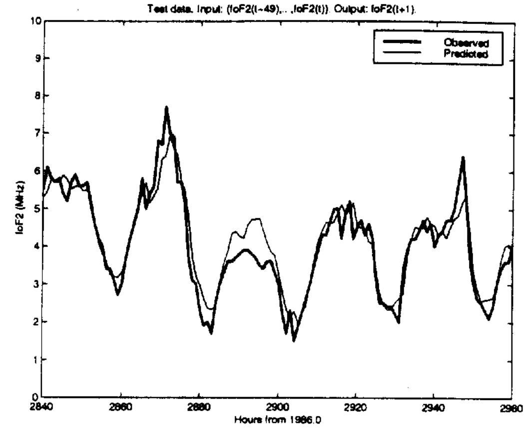

Fig. 6. The observed (thick line) and the predicted (thin line) foF2 during solar minimum.

5 Results and discussion

The models presented here have been applied to the ionospheric station at Slough. Figure 5 shows a comparison of the observed foF2 diurnal variations with one-hour-ahead prediction by the neural network during a five-day period in 1981. At the beginning of the interval the agreement between observed and predicted foF2 values was not very good because of highly disturbed ionosphere. Later on the agreement improves. The overall RMS error on the training set in 1980 was 0.581 MHz with a correlation of 0.976 and 0.661 MHz with correlation of 0.97 on test set in 1981.

As can be seen in Fig. 6, the agreement between observed and predicted foF2 during the five days in 1986 was very good even during disturbed conditions. The overall RMS error on the training set in 1985 was 0.362 MHz with a correlation of 0.958 and 0.365 MHz with a correlation of 0.956 on test set in 1986. Lower overall RMS values reflect less perturbed ionosphere over the years of low solar activity.

Similar results has been obtained by the hybrid time-delay multilayer perceptron neural network trained with Slough foF2 data from January to August and October to December 1995 and tested on September 1995 set. Figure 7 shows an example of the comparison between neural network and observed foF2 values during two days of disturbed ionosphere surrounding by a relatively quiet periods.

Again predicted foF2 is in very good agreement with the observations during the relatively quiet ionosphere but less so during the disturbed period on 27 and 28 September. However, this agreement is still much better than in case of monthly median values shown in Fig. 7 to demonstrate the complexity of the ionospheric day-to day variability. The overall RMS error for September 1995 was 0.45 MHz.

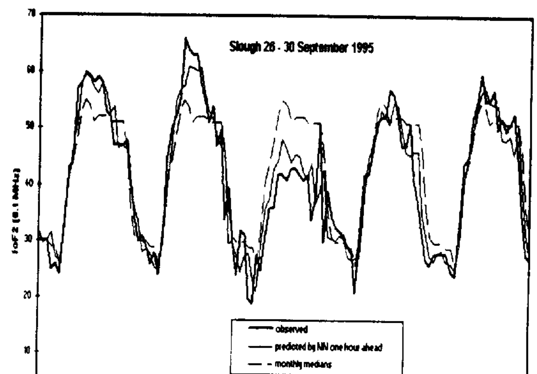

Fig. 7. Observed, predicted and monthly median foF2 values for 26-30 September 1995.

6 Conclusions

We have used time series prediction capabilities of artificial neural networks to develop a technique for 1-hour-ahead prediction of the key ionospheric parameter: the critical frequency of F2 layer. It is shown that the 1- hour-ahead predictions of foF2 can be made with a high accuracy with different neural networks. In addition, it is demonstrated that the most important input is a time-series of foF2 itself, which is able to describe most of the variance in the 1-hour-ahead predicted foF2 values. However, this is certainly not the case at ionospheric storm onset when the network degrades to persistence and thus fails to make accurate predictions. To further improve the predictions the onset of ionospheric storms has to be modelled. As geomagnetic storms can cause ionospheric storms through composition changes and travelling atmospheric disturbances (Prölls, 1995) it should be possible to predict the onset of the ionospheric storm from different hourly average geomagnetic indices, such as Dst and AE. Although these indices may not be available in real time they can be predicted to a high accuracy when real-time solar wind data is available (Lundstedt and Wintoft, 1994; Gleisner et al., 1996). Such a study is in progress showing further advantages in using neural network as it allows a parameter study in which the various parameters represents different physical properties.

Acknowledgements. P. Wintoft would like to thank the Royal Society and the Royal Swedish Academy of Sciences for a two-month study visit award at the Radio Communications Research Unit, CLRC Rutherford Appleton Laboratory. This work has been funded by the Radio Communications Agency of the DTI as part of the National Radio Propagation Program at Rutherford Appleton Laboratory.

References

Altinay, O., E. Tulunay, and Y. Tulunay, Forecasting of ionospheric critical frequency using neural network, *Geophys. Res. Lett.*, *24*, 1467–1470, 1997.

Cander, Lj.R. and X. Lamming, Neural networks in ionospheric prediction and short-term forecasting, *10th International Conference on Antennas and Propagation, 14-17 April 1997, Edinburgh, IEE Conference Publication*, *436*, 2.27–2.30, 1997.

Cander, Lj.R., S. Stankovic, and M. Milosavljevic, Dynamic ionospheric prediction by neural networks, *Proc. of the Second International Workshop on Artificial Intelligence Applications in Solar-terrestrial Physics*, ESA WPP-148 Proceedings, Eds. I. Sandahl and E. Jonsson, European Space Agency, Paris, 225–228, 1998.

Gleisner, H., H. Lundstedt, and P. Wintoft, Predicting geomagnetic storms from solar-wind data using time- delay neural networks, *Ann. Geophys*, *14*, 679–686, 1996.

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

LeCun, Y., J.S. Denker, and S.A. Solla, Optimal brain damage, *Advances in Neural Information Processing Systems II*, Ed. D.S. Touretzky, Morgan Kaufmann, San Mateo, 1990.

Lundstedt H., and P. Wintoft, Predictions of geomagnetic storms from solar wind data with the use of a neural network, *Ann. Geophys*, *12*, 19–24, 1994.

Muhtarov, P., and I. Kutiev, Autocorrelation method for temporal interpolation and short-term prediction of ionospheric data, *Bulgarian Geophys. J.*, *23*, 2-4, 1997.

Poole, A.W.V. and L.A. McKinnell, Short term prediction of foF2 using neural networks, *Proc. Of Session G5 at the XXVth General Assembly of URSI, WDC Report UAG-105, Lille, 28 August - 5 September 1996, France*, 109–111, 1998.

Prölls, G.W., Ionospheric F-Region Storms, *Handbook of atmospheric electrodynamics*, Ed. H. Volland, CRC Press, Inc., 195–248, 1995.

Swingler, K., *Applying neural networks, a practical guide*, Academic Press Limited, London, 1996.