A Neural Network Model for the Critical Frequency of the F2 Ionospheric Layer over Cyprus

Haris Haralambous and Harris Papadopoulos

Computer Science and Engineering Department, Frederick University,
7 Y. Frederickou St., Palouriotisa, Nicosia 1036, Cyprus
{H.Haralambous,H.Papadopoulos}@frederick.ac.cy

Abstract. This paper presents the application of Neural Networks for the prediction of the critical frequency *foF2* of the ionospheric F2 layer over Cyprus. This ionospheric characteristic (*foF2*) constitutes the most important parameter in HF (High Frequency) communications since it is used to derive the optimum operating frequency in HF links. The model is based on ionosonde measurements obtained over a period of 10 years. The developed model successfully captures the variability of the *foF2* parameter.

Keywords: Ionosphere, HF communications, F2 layer critical frequency.

1 Introduction

Skywave HF communiations utilize the ability of the ionosphere to reflect waves up to 30 MHz to achieve medium to long-distance communication links with a minimum of infrastructure (figure 1). The ionosphere is defined as a region of the earth's upper atmosphere where sufficient ionisation can exist to affect the propagation of radio waves in the frequency range 1 to 30 MHz. It ranges in height above the surface of the earth from approximately 50 km to 600 km. The influence of this region on radio waves is accredited to the presence of free electrons.

The uppermost layer of the ionosphere is the F2 layer which is the principal reflecting region for long distance HF communications [1,2,3]. The maximum frequency that can be reflected at vertical incidence by this layer is termed the F2 layer critical frequency (*foF2*) and is directly related to the maximum electron density of the layer. The F2 layer critical frequency is the most important parameter in HF communication links since when multiplied by a factor which is a function of the link distance, it defines the optimum usable frequency of operation. The maximum electron density of free electrons within the F2 layer and therefore *foF2* depend upon the strength of the solar ionising radiation which is a function of time of day, season, geographical location and solar activity [1,2,3]. This paper describes the development of a neural network model to predict *foF2* above Cyprus. The model development is based on around 33000 hourly *foF2* measurements recorded above Cyprus from 1987 to 1997. The practical application of this model lies in the fact that in the absence of any real-time or near real-time information on *foF2* above Cyprus this model can provide an alternative method to predict its value under certain solar activity conditions.

D. Palmer-Brown et al. (Eds.): EANN 2009, CCIS 43, pp. 371–377, 2009.

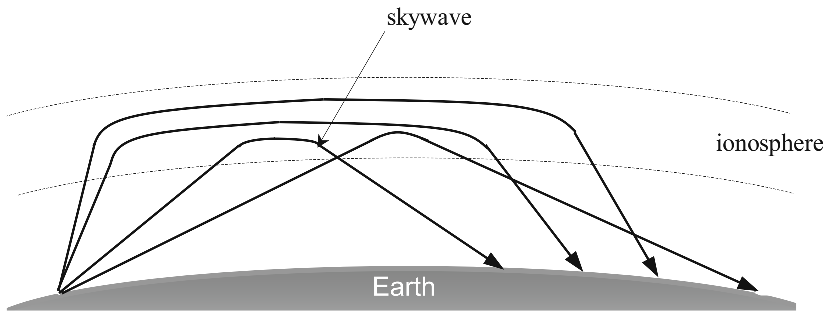


Fig. 1. Skywave communication modes via the ionosphere

2 Characteristics of the F2 Layer Critical Frequency

Measurements of *foF2* are conducted by ionosondes which are special types of radar used for monitoring the electron density at various heights in the ionosphere. Their operation is based on a transmitter sweeping through the HF frequency range transmitting short pulses. These pulses are reflected at various layers of the ionosphere, and their echoes are received by the receiver and analyzed to infer the ionospheric plasma frequency at each height. The maximum frequency at which an echo is received is called the critical frequency of the corresponding layer. Since the F2 layer is the most highly ionized ionosperic layer its critical frequency *foF2* is the highest frequency that can be reflected by the ionosphere. This implies that by operating close to that frequency when establishing oblique communication links will provide maximum range and at the same time favourable propagation conditions.

Solar activity has an impact on ionospheric dynamics which in turn influence the electron density of the ionosphere. The electron density of the F2 layer exhibits variability on daily, seasonal and long-term time scales in response to the effect of solar radiation. It is also subject to abrupt variations due to enhancements of geomagnetic activity following extreme manifestations of solar activity disturbing the ionosphere from minutes to days on a local or global scale.

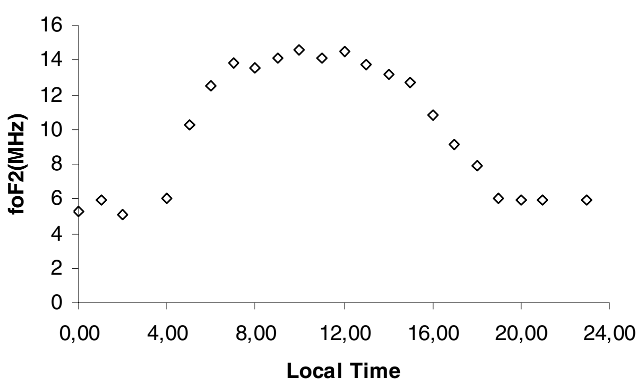
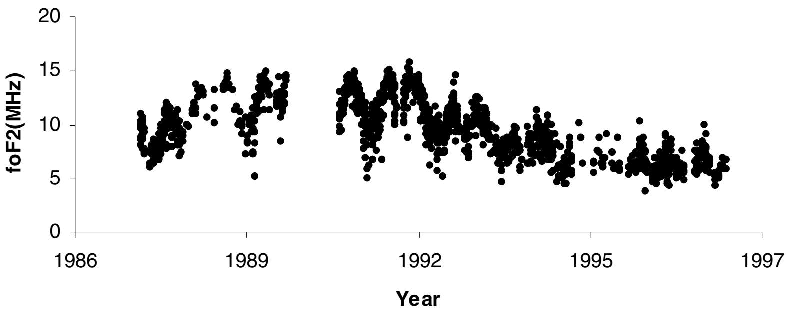


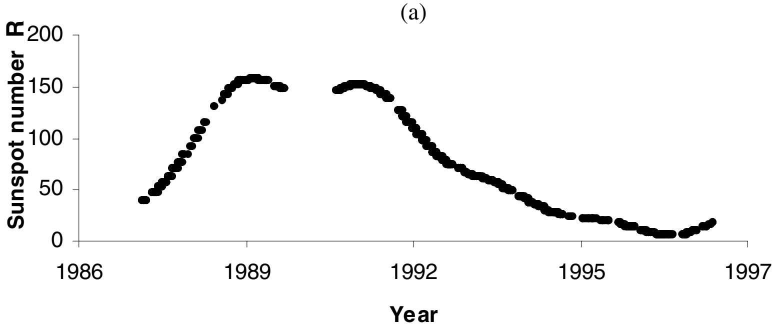
Fig. 2. Diurnal variation of *foF2*

The most profound solar effect on *foF2* is reflected on its daily variation as shown in figure 2. As it is clearly depicted, there is a strong dependency of *foF2* on local time which follows a sharp increase of *foF2* around sunrise and gradual decrease around sunset. This is attributed to the rapid increase in the production of electrons due to the photo-ionization process during the day and a more gradual decrease due to the recombination of ions and electrons during the night.

The long–term effect of solar activity on *foF2* follows an eleven-year cycle and is clearly shown in figure 3(a) where all the values of *foF2* are plotted against time as well as a modeled monthly mean sunspot number *R* which is a well established index of solar activity (figure 3(b)). We can observe a marked correlation of the mean level of *foF2* and modeled sunspot number.



(a)



(b)

Fig. 3. Long-term *foF2* and solar activity variation with time

There is also a seasonal component in the variability of *foF2* which can be attributed to the seasonal change in extreme ultraviolet (EUV) radiation from the Sun. This can be clearly identified in figure 4 for noon values of *foF2* for year 1991 according to which in winter *foF2* tends to be higher than during the summer. In fact this variation reverses for night-time *foF2* values. This particular phenomenon is termed the winter anomaly. In addition to the effects of solar activity on *foF2* mentioned above we can also identify a strong effect on the diurnal variability as solar activity gradually increases through its 11-year cycle. This is demonstrated if figure 5 where the diurnal variation of *foF2* is plotted for three different days corresponding to low (1995), medium (1993) and high (1991) sunspot number periods. It is evident from this figure that the night to day variability in *foF2* increases as sunspot number increases.

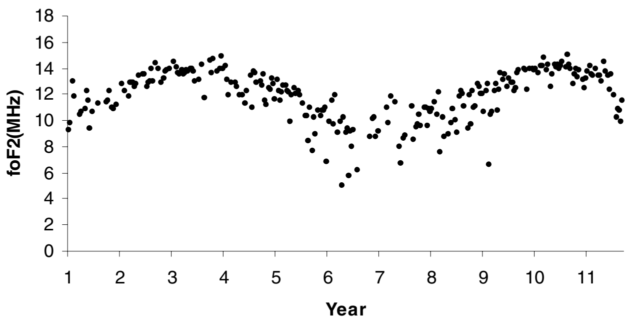


Fig. 4. Seasonal variation of *foF2* at 12:00

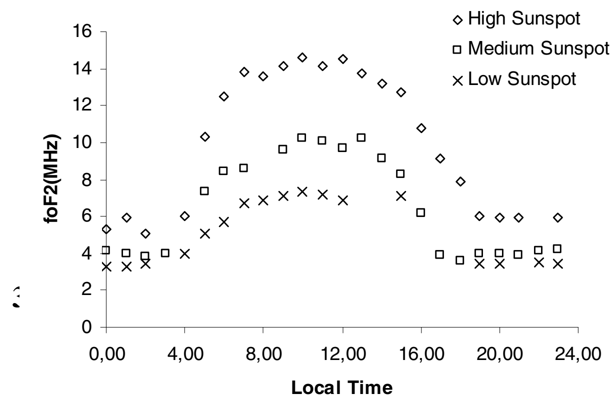


Fig. 5. Diurnal variability of *foF2* for low, medium and high solar activity

3 Model Parameters

The diurnal variation of *foF2* is clearly evident by observing figure 2 and figure 5. We therefore include hour number as an input to the model. The hour number, *hour*, is an integer in the range $0 \leq hour \leq 23$. In order to avoid unrealistic discontinuity at the midnight boundary, *hour* is converted into its quadrature components according to:

$$sinhour = \sin\left(2\pi \frac{hour}{24}\right) \tag{1}$$

and

$$coshour = \cos\left(2\pi \frac{hour}{24}\right) \tag{2}$$

A seasonal variation is also an underlying characteristic of *foF2* as shown in figure 4 and is described by day number *daynum* in the range $1 \leq daynum \leq 365$. Again to avoid unrealistic discontinuity between December 31st and January 1st *daynum* is converted into its quadrature components according to:

$$sinday = \sin\left(2\pi \frac{daynum}{365}\right) \tag{3}$$

and

$$cosday = \cos\left(2\pi \frac{daynum}{365}\right) \tag{4}$$

Long-term solar activity has a prominent effect on *foF2*. To include this effect in the model specification we need to incorporate an index, which represents a good indicator of solar activity. In ionospheric work the 12-month smoothed sunspot number is usually used, yet this has the disadvantage that the most recent value available corresponds to *foF2* measurements made six months ago. To enable *foF2* data to be modelled as soon as they are measured, and for future predictions of *foF2* to be made, the monthly mean sunspot number values were modeled using a smooth curve defined by a summation of sinusoids (figure 3(b)).

4 Experiments and Results

A Neural Network (NN) was trained to predict the *foF2* value based on *sinhour, coshour, sinday, cosday* and *R* (modeled sunspot number) model parameters. The 33149 values of the dataset recorded between 1987 and 1997 were used for training the NN, while the 3249 values of the more recent dataset recorded from 18.09.08 until 16.04.09 were used for testing the performance of the trained NN. The training set was sparse to a certain degree in the sense that many days had missing *foF2* hourly values and this did not allow the dataset to be approached as a time-series.

The network used was a fully connected two-layer neural network, with 5 input, 37 hidden and 1 output neuron. Both its hidden and output neurons had tan-sigmoid activation functions. The number of hidden neurons was determined by trial and error. The training algorithm used was the Levenberg-Marquardt backpropagation algorithm with early stopping based on a validation set created from the last 3000 training examples. In an effort to avoid local minima ten NNs were trained with different random initialisations and the one that performed best on the validation set was selected for application to the test examples. The inputs and target outputs of the network were normalized setting their minimum value to -1 and their maximum value to 1. The results reported here were obtained by mapping the outputs of the network for the test examples back to their original scale.

The RMSE of the trained NN on the test set was 0.688 MHz, which is considered acceptable for a prediction model [4,5,6]. To further evaluate the performance of the developed network, a linear NN was applied to the same data and the performance of the two was compared. The RMSE of the linear NN on the test set was 1.276 MHz, which is almost double that of the multilayer NN. Some examples of measured and predicted *foF2* values are given in figure 6. These demonstrate both the good performance of the developed NN and its superiority over the linear model.

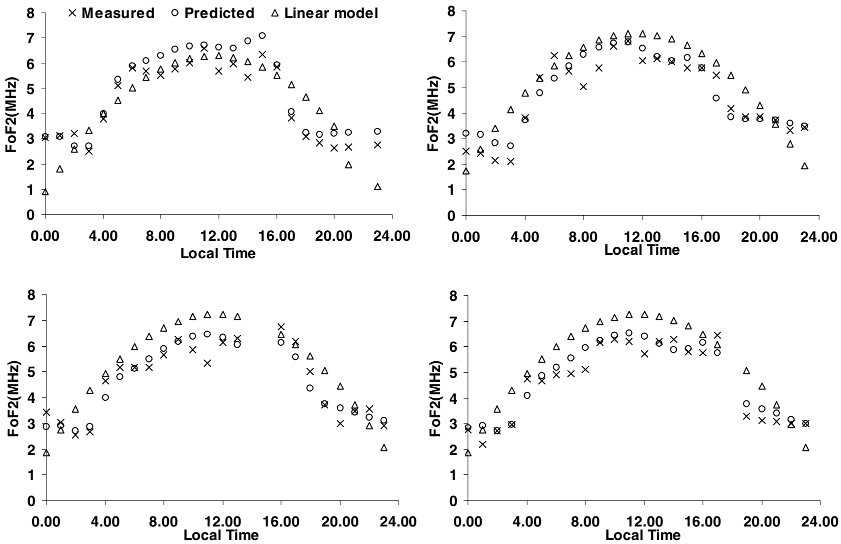


Fig. 6. Examples of measured and predicted *foF2* values

Despite the good agreement of measured and predicted values under benign geomagnetic conditions we have noticed several occasions where the discrepancy between them increases significantly. This is the case particularly during geomagnetic storms due to the impact of the disturbed magnetic field on the structure of the ionosphere causing rapid enhancements or depletions in its electron density. An example of such an occasion is given in figure 7. It is evident that around 15:00 the intense geomagnetic activity causes an increase in the error in the model due to excursions of *foF2* from its undisturbed behaviour.

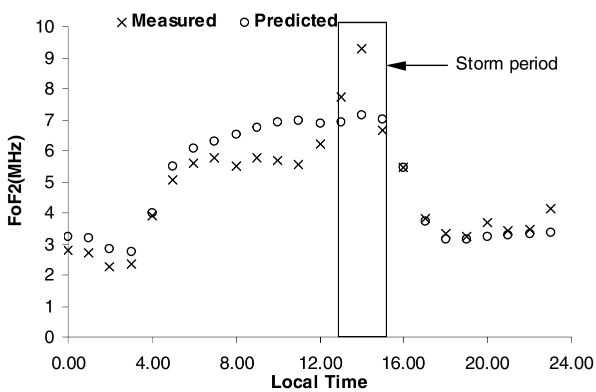


Fig. 7. Increase of model error under geomagnetically disturbed conditions

An alternative option would be to attempt a short-term forecasting model by using recent values of the modeled parameter as inputs to the model. However this would necessitate the operation of an ionosonde and the availability of near real-time data to the model user which is not very practical especially in the absence of an internet connection.

5 Conclusions and Future Work

In this paper we have presented the development of a neural network model for the long-term prediction of critical frequency of the F2 ionospheric layer (*foF2*) above Cyprus. The model has been developed based on a data set obtained during a period of ten years and tested on a dataset of seven months that was recently obtained. The model has produced a good approximation of the different time-scales in the variability of the modeled parameter. The next step will be to investigate the possibility to incorporate a geomagnetic index as an input parameter in order to represent better the geomagnetic variability of the electron density of the ionosphere. In addition the model will be further updated as we collect more *foF2* measurements in the next few years.

References

1. Goodman, J.: HF Communications, Science and Technology. Nostrand Reinhold (1992)
2. Maslin, N.: The HF Communications, a Systems Approach, San Francisco (1987)
3. McNamara, L.F.: Grid The Ionosphere: Communications, Surveillance, and Direction Finding. Krieger Publishing Company, Malabar (1991)
4. Altinay, O., Tulunay, E., Tulunay, Y.: Forecasting of ionospheric critical frequency using neural networks. Geophys. Res. Lett. 24, 1467–1470 (1997)
5. Cander, L.R., Lamming, X.: Forecasting Neural networks in ionospheric prediction and short-term forecasting. In: 10th International Conference Conferenceon Antennas and Propagation, Edinburgh, April 14-17, vol. 436, pp. 2.27-2.30. IEE Conference Publication (1997)
6. Wintoft, P., Cander, L.R.: Short term prediction of foF2 using time delay neural networks. Phys. Chem. Earth (C) 24, 343–347 (1999)