ANNALS OF GEOPHYSICS, VOL. 45, N. 1, February 2002

Long-term trends in f_0F_2 over Grahamstown using Neural Networks

Allon W.V. Poole and Martin Poole
Department of Physics and Electronics, Rhodes University, Grahamstown, Republic of South Africa

Abstract
Many authors have claimed to have found long-term trends in f_0F_2, or the lack thereof, for different stations. Such investigations usually involve gross assumptions about the variation of f_0F_2 with solar activity in order to isolate the long-term trend, and the variation with magnetic activity is often ignored completely. This work describes two techniques that make use of Neural Networks to isolate long-term variations from variations due to season, local time, solar and magnetic activity. The techniques are applied to f_0F_2 data from Grahamstown, South Africa (26 E, 33 S). The maximum long-term change is shown to be extremely linear, and negative for most hours and days. The maximum percentage change tends to occur in summer in the afternoon, but is noticeably dependent on solar activity. The effect of magnetic activity on the percentage change is not marked.

Key words *long-term trends – Neural Networks – f_0F_2 – ionosphere*

1. Introduction

The ionospheric quantity f_0F_2 is well known to vary with season (day number, DN); diurnally (hour LT, HR); and with solar activity and magnetic activity. We need now to consider a fifth variation, which we can call Long-Term Trend (LTT). We approached the problem using two techniques.

2. The techniques

Technique 1 – The methods of training a Neural Network (NN) have been described elsewhere (Poole and McKinnell, 2000) and will not be repeated in detail here. Briefly, the NN was trained with all usable hourly f_0F_2 data from 1973-2000 as output or target data, and the four variables DN, HR, F2 and A16 as concomitant input data. F2 is a two month running mean of the solar 10.7 cm flux, used as a measure of solar activity, and A16 is a two day running mean of the 3 hourly magnetic index, a_k, used to measure magnetic activity. After training, the NN produces a value of f_0F_2 for any combination of the input variables.

The choice of two months for F2 and two days for A16 was based on the results of an independent investigation in which NNs were trained with input variables of different lengths, the optimum length being chosen as that length which produced the minimum rms error (Williscroft and Poole, 1996). The NN produces the function F_1 such that $f_0F_2 = F_1$(DN, HR, F2, A16). We will call f_0F_2 evaluated in this way f_0F_2(NN). The function F_1 thus embodies the variation of f_0F_2 for all combinations of the four input variables, so that the residuals R evaluated according to $R = f_0F_2(\text{measured}) - f_0F_2(\text{NN})$ will

Mailing address: Dr. Allon W.V. Poole, Department of Physics and Electronics, Rhodes University, Grahamstown 6140, Republic of South Africa; e-mail: A.Poole@ru.ac.za

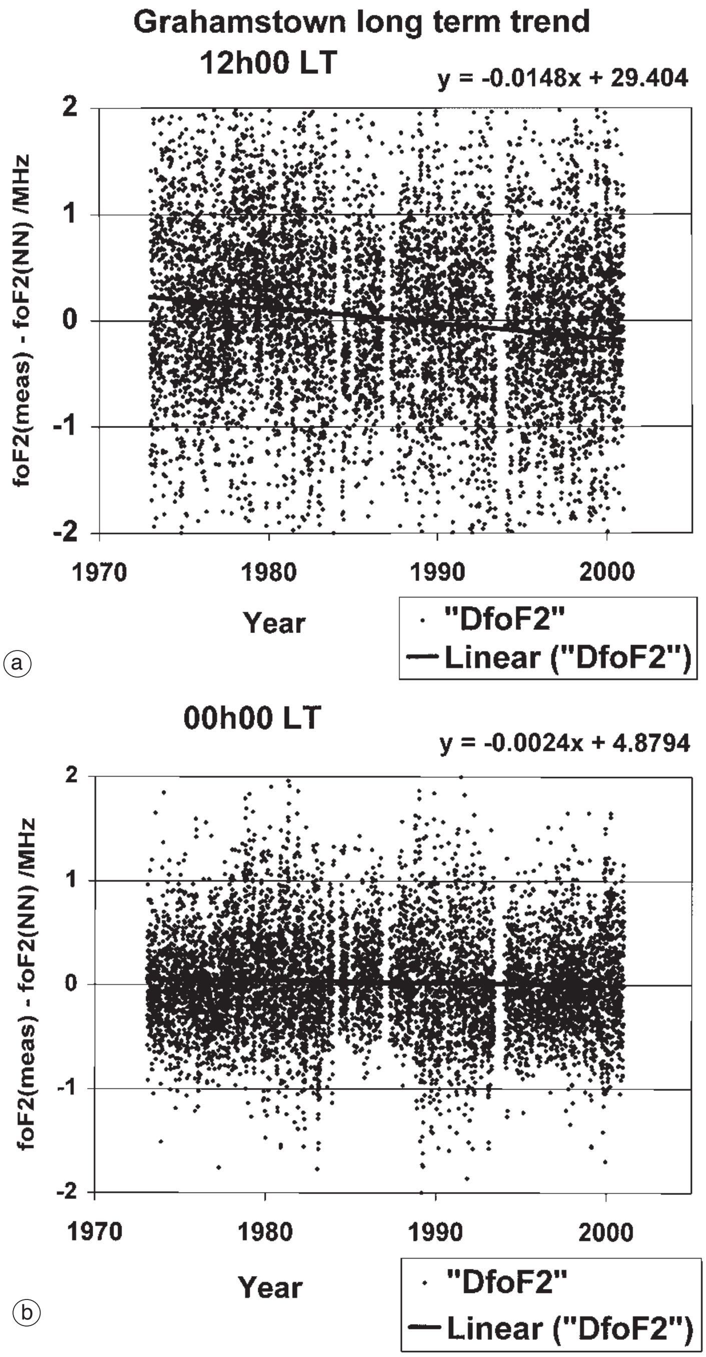

Fig. 1a,b. The residual R plotted as a function of time for HR = a) 12 h 00 and b) 00 h 00, each with a fitted linear regression line.

be independent of DN, HR, F2 and A16.

The residuals are due to short term, seemingly random and chaotic deviations of measured f_0F_2 from the model F_1. However, the residuals will contain information about long-term variation, if it exists, since a variable representing LTT was not included in the input to the NN. Accordingly, we computed the residuals R for each datum used in the training. These R were then grouped by hour and plotted against time. The results are shown in figs. 1a,b for 12 h 00 and 00 h 00 respectively. A trendline has been fitted to both, the slope of which gives the average rate of change of the residuals with time in MHz/year. This method of plotting the residuals *versus* time is similar in principle to that used by Foppiano *et al.* (1999), and Upadhyay and Mahajan (1998). It is also of interest that when the trendline was fitted to the two groups (1973-1986) and (1987-2000) separately, almost identical slopes were obtained, indicating a negligible second derivative with respect to time.

Technique 2 – For this treatment we included the index (1-245448) which measured the chronological position of each hourly datum (1 = 00 h 00, 1 January 1973; 245448 = 23 h 00, 31 December 2000) as an indicator for LTT. We trained a NN with this extra input to create a function F_2 (DN, HR, F2, A16, LTT) and then interrogated this network with appropriate synthetic data to determine long-term trends for a variety of situations. To show the linearity of the general decline in f_0F_2, the NN was interrogated at 5 equally spaced times during the total period, corresponding to LTT = 10 000, 60 000, 110 000, 160 000 and 210 000, for the 16 combinations of DN = 81, 172, 265, 356 and HR = 00 h 00, 06 h 00, 12 h 00 and 18 h 00, for low solar activity and low magnetic index. These are presented in the 16 graphs in fig. 2. The chosen daynumbers DN = 81, 172, 265 and 356 correspond to autumn equinox, winter solstice, spring equinox and summer solstice respectively. In the diagrams of fig. 2 the index LTT along the x-axis has been converted back to years for clarity. The values of f_0F_2 and the error bars are formed by taking the mean, and standard deviation of the mean, of 20 Neural Networks all trained with the same data but with unique, arbitrary and random starting conditions. Because NNs proceed to their final value by an iterative process involving least squares, they do not provide unique solutions, and need to be averaged to minimize this statistical variation. The calculated uncertainty in the evaluation of f_0F_2 from the NNs varies slightly with the input parameters, but is of the order of 0.03 MHz, well below the long-term changes made evident by this investigation. In this context, «low» is the lower quartile value of all the F2 or A16 data in the period 1973-2000. We have diagrams similar to fig. 2 for the three other combinations of (F2, A16) = (low, high), where «high» is similarly the value of the upper quartile. These diagrams are similar to fig. 2 but differ in the magnitudes of the slopes, and are not presented here. Figure 2 is presented to illustrate the extreme linearity of the decreases, where present. Because of this linearity, it is meaningful to express the change as a simple difference between the values given by F_2 for LTT = 10 000 and LTT = 210 000, a separation in time corresponding to 22.83 years. We calculated the quantity

$$\Delta f_0F_2(\mathrm{DN, HR}) =$$
$$F_2(\mathrm{DN, HR, L, L}, 210\,000) -$$
$$- F_2(\mathrm{DN, HR, L, L}, 10\,000)$$

and plotted it in two dimensions against DN (converted to months) and HR in fig. 3a-d.

The fig. 3a shows a general negative change in f_0F_2 with time, with peaks occurring as shown in table I.

There is a small positive change of + 0.07 MHz which peaks at (DN, HR) = (196, 18 h 00).

The values of the other input parameters F2 and A16 for each of the figs. 3a to 3d are given in table II.

In table II, the symbols L and H refer to the lower and upper quartile values of F2 and A16, evaluated over the period 1973-2000, and so represent «low» and «high» values of solar and magnetic activity. Figure 3a is thus the response for low solar and low magnetic activity. Figures 4a to 4d show the same differences, but presented as a percentage change according to $\Delta f_0F_2\% = [f_0F_2(\mathrm{NN, LTT} = 210\,000) - f_0F_2(\mathrm{NN, LTT} = 10\,000)] \times 100 / f_0F_2(\mathrm{NN, LTT} = 10\,000)$.

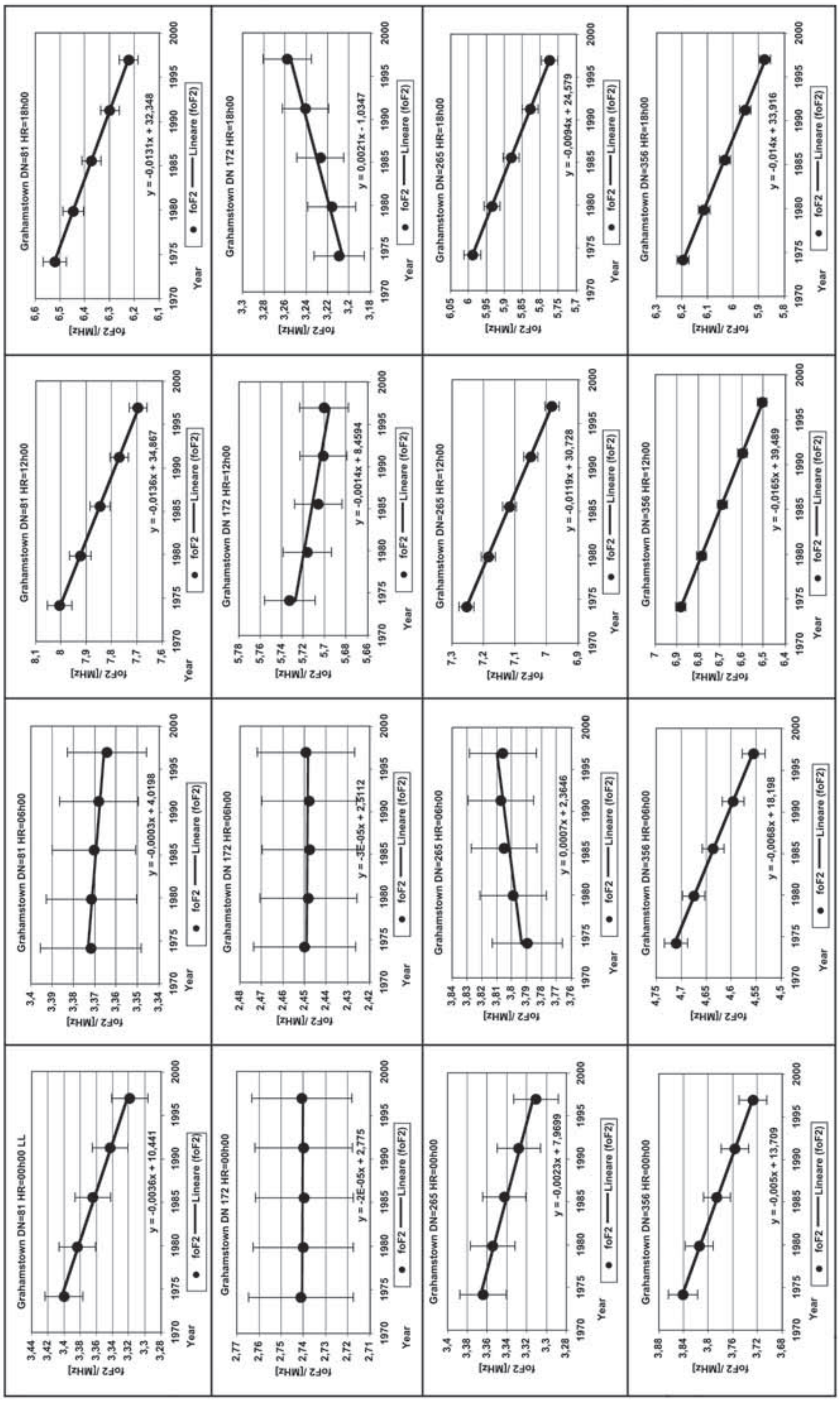

Fig. 2. Evaluations of the Neural Network function F_2(DN, HR, F2, A16, LTT) for various combinations of DN and HR, with F2 = L (low), A16 = L (low). The five points on each graph correspond to five equally spaced values of LTT between 10 000 and 210 000.

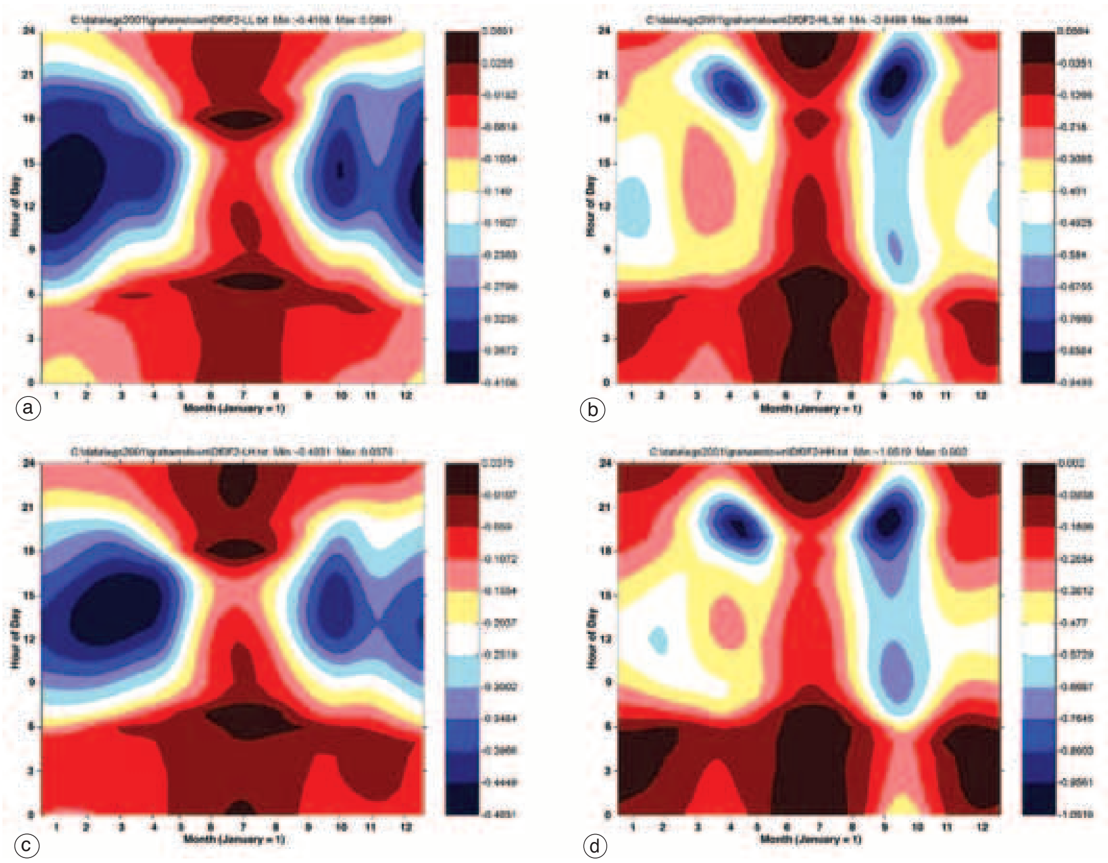

Fig. 3a-d. Contour maps of the function Δf_0F_2 *versus* DN and HR for F2, A16 = a) LL; b) HL; c) LH, and d) HH.

3. Discussion and conclusions

The slope of the regression line through the 12 h 00 residuals shown in fig. 1a was found to be – 0.01479 ± .00012 MHz/year, calculated using standard techniques. The small value of the uncertainty in the slope attests to the statistical reliability of the result, and is a consequence of the large number (8083) of points in the regression. Note that these residuals include every combination of DN, F2 and A16 that was present in the data, and so represent a decrease averaged over all these variables. This is an important point because, as will be shown, the decrease is dependent on all these variables to a greater or lesser extent. The second technique, indeed, gives results that are specific for parti-

Table I. Peak values of negative change.

DN	HR	Δf_0F_2/[MHz]	MHz/year
23	13h00	–0.41	–0.018
286	15h00	–0.37	–0.016

Table II. Upper and lower quartile value of F2 and A16

Figure	F2	A16
3(a)	L	L
3(b)	H	L
3(c)	L	H
3(d)	H	H

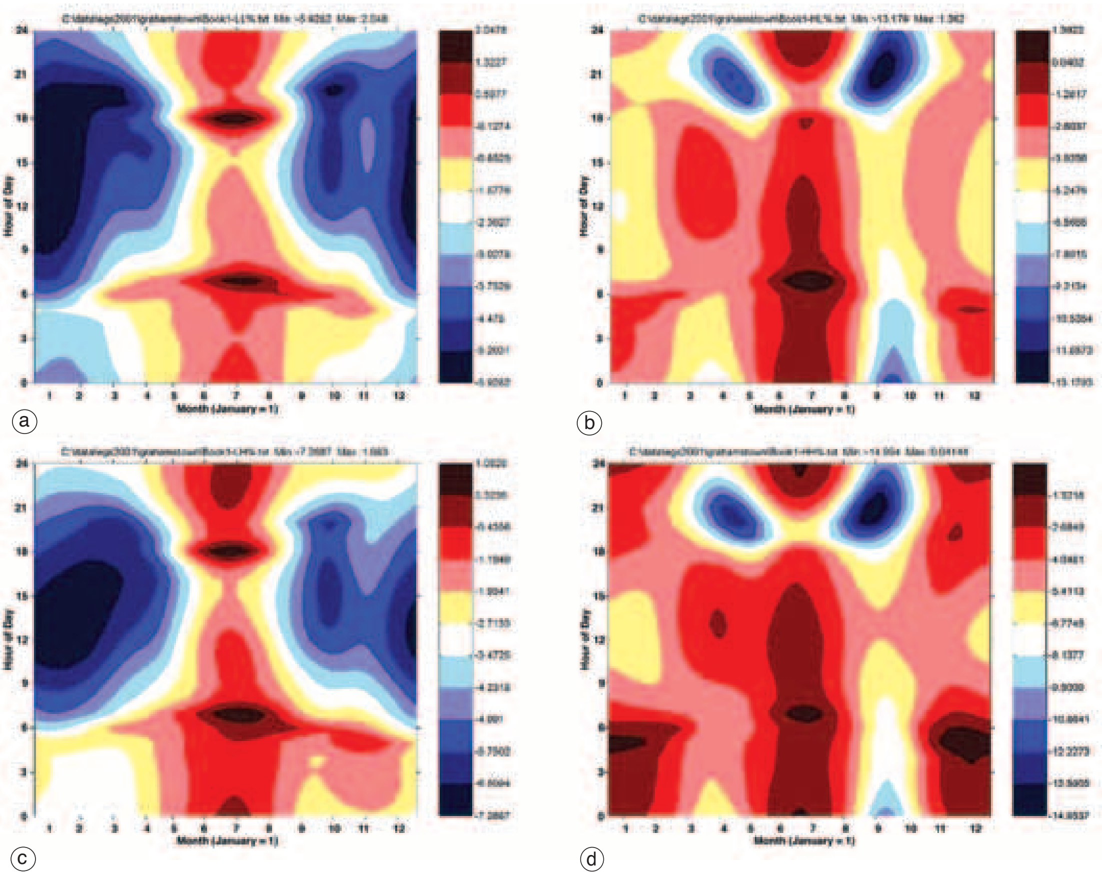

Fig. 4a-d. Contour maps of the function Δf_0F_2 *versus* DN and HR for F2, A16 = a) LL; b) HL; c) LH, and d) HH.

cular values of DN, HR, F2 and A16, and can be regarded as an average long-term behaviour for any chosen set of the four input variables. A comparison of the two techniques is possible by choosing an hour (HR = 12 h 00) and averaging Δf_0F_2(12 h 00) over DN = 1 – 365 for each of the four combinations of F2, A16 = H,L and dividing by the 22.83 year separation. This can be compared with the figure quoted above, and is found to be – 0.015 MHz/year, which shows consistency in the two techniques. The equivalent results for 00 h 00 are – 0.00244 ± .00067 MHz/year (technique 1) and – 0.00557 MHz/year (technique 2) which agree at least in their order of magnitude.

A general result is that, at low solar activity, the largest negative percentage change occurs between 09 h 00 and 20 h 00 during late summer (figs. 4a,c). At high solar activity, there are very pronounced negative peaks at around 21 h 00 near the equinoxes. The effect of increased magnetic activity is not marked (compare figs. 4a with 4c, 4b with 4d). Note that the contention by, for instance, Danilov (2000), that longterm trends in f_0F_2 could be explained by changes in the spatial and temporal morphology of magnetic storms would not be revealed by these techniques since the influence of such storms is specifically removed from the residuals in technique 1, and specifically catered for in technique 2.

We have not, in this publication, attempted an explanation for these quite large negative trends in f_0F_2 over Grahamstown. They appear to be amongst the largest reported in the literature (Foppiano *et al.,* 1999; Upadhyay and Mahajan, 1998; Chandra *et al.*, 1997). We intend to analyse data from other stations before venturing an explanation. However, the methods we have used, involving Neural Networks to remove the known dependencies, appear to be reliable, and stress the fact that long-term trends are very dependent on season, local time, solar activity and to a lesser extent, magnetic activity. It is thus not possible to make quantitative statements about long-term trends unless one is specific about geophysical circumstances (DN, HR, F2, A16) under which the comparisons are made. These dependencies should provide valuable clues to the reasons for the changes, when applied to other ionospheric stations.

REFERENCES

CHANDRA, H., G.D. VYAS and S. SHARMA (1997): Long-term changes in ionospheric parameters over Ahmedabad, *Adv. Space Res.*, **20**, 2161-2164.

DANILOV, A.D. (2000): F_2-region response to geomagnetic disturbances, *J. Atmos. Sol.-Terr. Phys.,* **63**, 441-449.

FOPPIANO, A.J., L. CID and V. JARA (1999): Ionospheric long-term trends for South American mid-latitudes, *J. Atmos Sol.-Terr. Phys.,* **61**, 717-723.

POOLE, A.W.V and L.A. MCKINNELL (2000): On the predictability of f_0F_2 using Neural Networks, *Radio Sci.,* **35**, 225-234.

UPHADYAY, H.O. and K.K. MAHAJAN (1998): Atmospheric greenhouse effect and ionospheric trends, *Geophys. Res Lett.*, **5**, 3375-3378.

WILLISCROFT, L.A. and A.W.V. POOLE (1996): Neural Networks, f_0F_2, sunspot number and magnetic activity, *Geophys. Res. Lett.,* **23**, 3659-3662.