Artificial neural network applications in ionospheric studies

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Abstract
The ionosphere of Earth exhibits considerable spatial changes and has large temporal variability of various time scales related to the mechanisms of creation, decay and transport of space ionospheric plasma. Many techniques for modelling electron density profiles through entire ionosphere have been developed in order to solve the «age-old problem» of ionospheric physics which has not yet been fully solved. A new way to address this problem is by applying artificial intelligence methodologies to current large amounts of solar-terrestrial and ionospheric data. It is the aim of this paper to show by the most recent examples that modern development of numerical models for ionospheric monthly median long-term prediction and daily hourly short-term forecasting may proceed successfully applying the artificial neural networks. The performance of these techniques is illustrated with different artificial neural networks developed to model and predict the temporal and spatial variations of ionospheric critical frequency, f_0F_2 and Total Electron Content (TEC). Comparisons between results obtained by the proposed approaches and measured f_0F_2 and TEC data provide prospects for future applications of the artificial neural networks in ionospheric studies.

Key words *electromagnetic waves – ionospheric modelling – prediction – forecasting – artificial neural networks – time series analysis*

1. Introduction

The history of ionospheric research, starting with the pioneering experiments by Appleton and Barnett (1925) and Breit and Tuve (1926), is long and rich in physics and chemistry (*e.g.*, Rishbeth *et al.*, 1996 and references therein). The Earth's ionosphere is composed of space cold plasma produced by a neutral atmosphere absorption of solar extreme ultra-violet and *X*-ray radiations. Since the real ionosphere is a dynamic system that is primarily coupled to the magnetosphere above and neutral atmosphere below and strongly affected by such highly dynamic features as neutral winds, atmospheric tides, motion due to electric and magnetic fields, and auroral particles at higher latitudes, it is only in principle possible to model the very complex physical processes taking place in the ionosphere. A number of studies have addressed the well-documented problem of development a completely physical ionospheric model (Schunk and Sojka, 1996a and references therein). As all physical ionospheric models depend on magnetospheric inputs such as energy, momentum and ionisation sources associated with substorm and storm dynamics, it seems that no major breakthroughs are probable in theoretically solving the coupled magnetospheric – solar wind – ionosphere problems. Therefore, it is widely thought that theoretical model results in real time specification of the ionospheric structure and dynamics provide significant but still limited success (Anderson *et al.*, 1998).

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In most studies, the important ionospheric parameters such as the electron density, neutral and ion compositions and temperatures are given empirically or semi-empirically based on observations by world-wide ionosonde, rocket and satellite experiments and radar (Cander *et al.*, 1996 and references therein). Models calculate these parameters when the location (latitude, longitude and altitude), time (month, local or universal time) and solar-terrestrial activity (sunspot number, solar flax $F_{10.7}$, geomagnetic indexes) are given as inputs. There are a variety of empirical and hybrid techniques for using the past history of a physical system to predict its future response to changing conditions. However, the quality of these techniques depends very much on measurements and having an adequate latitude-longitude distribution of observations. Furthermore, a common problem encountered in both the empirical and physical ionospheric modelling was the dependence upon solar-terrestrial indexes. Although various techniques have different strengths and weaknesses, it seems that the best technique is to use the data to obtain understanding of the system and then derive somehow a model that predicts the outcome of specific inputs.

Recently it has become clear that the techniques derived from artificial intelligence research and modern computer science provide a number of system aids that can be used to analyse and predict the behaviour of complex solar-terrestrial dynamic systems (*e.g.*, Joselyn *et al.*, 1993; Lundstedt and Wintoft, 1994; Hill and Koschmieder, 1995; Galkin *et al.*, 1996; Sutcliffe, 1997; Wintoft and Lundstedt, 1997; Conway *et al.*, 1998). Methods of artificial intelligence have provided tools which potentially make the task of ionospheric modelling and forecasting possible. They can therefore be used to assist ionospheric forecasters in making highly accurate long-term predictions and short-term forecasting. One of them, the artificial neural network, in essence a non-linear prediction filter, provides means of encapsulating empirical knowledge about relations in data. It allows experimentation with different architectures and paradigms to prototype solutions to real scientific problems. Methods of data analysis for testing the usefulness of non-linear techniques in space plasma physics have recently been examined by Wernik (1996 and references therein). It is shown that non-linear processes play an important role in irregular behaviour of the measured ionospheric parameters (*e.g.*, Wernik and Yeh, 1996; Dominici *et al.*, 1997 and references therein). One can argue that artificial neural network models lack the physical interpretation that is provided by physical or hybrid ionospheric models. This difficulty can be easily removed in the light of more recent studies which focus on extracting information on physical processes by suitable data analysis.

This paper presents the first review of the results received by different groups in the artificial neural network applications in ionospheric prediction and forecasting studies. In the next section, structure determination of a neural network is discussed. Real examples are employed to demonstrate the application of the proposed methods. Section 3 deals with prediction of the monthly median and forecasting of daily hourly f_0F_2 values while section 4 is concerned with the role of neural networks in one hour in advance TEC prediction. In the concluding section the main results of this paper are discussed and summarised while relevance to ionospheric modelling is briefly outlined.

2. Artificial neural network

A simple way to introduce a basic idea about artificial neural network in ionospheric studies is to use a schematic description as in fig. 1. A neural network is composed of several layers of neurons: an input layer, one or more hidden layers and an output layer. Each layer of

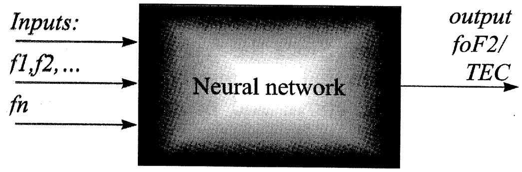

Fig. 1. A schematic diagram of an artificial neural network.

neurons receives its input from the previous layer or from the network input. The output of each neuron feeds the next layer or the output of the network. The first layer is always an input layer that distributes the inputs to the hidden layer. The unknown parameters of any neural network are the weights which can be found through training with different algorithms on the known input-output patterns. Therefore, training a neural network involves a data base of examples which are values for the input and output. The neural networks would learn by adjusting the weights connecting neurons in different layers to minimise the error of outputs. These algorithms try to minimise the error between the desired output and the network output by adjusting the weights according to gradient descent. The functionality of different neural networks is described in detail by Haykin (1994) and Swingler (1996 and references therein).

3. f_0F_2 modelling

A long time series of scaled data sets from routine ionospheric sounding records has become an excellent example of time series data with which to test the abilities of neural networks in ionospheric studies (Williscroft and Poole, 1996; Altinay *et al.*, 1997; Cander and Lamming, 1997; Poole and McKinnell, 1998; Cander *et al.*, 1998a). This study is focused on one ionospheric characteristic, f_0F_2 (in MHz), the F_2 layer ordinary critical frequency which is directly related to the maximum F_2 layer electron density NmF_2 (in electrons/m^3) by the well known relation

$$NmF_2 = 1.24\times10^{10}[f_0 F_2]^2 .$$

The f_0F_2 parameter is measured unambiguously at ground ionospheric sounding stations distributed globally and has an important role in both ionospheric physics and high-frequency com-

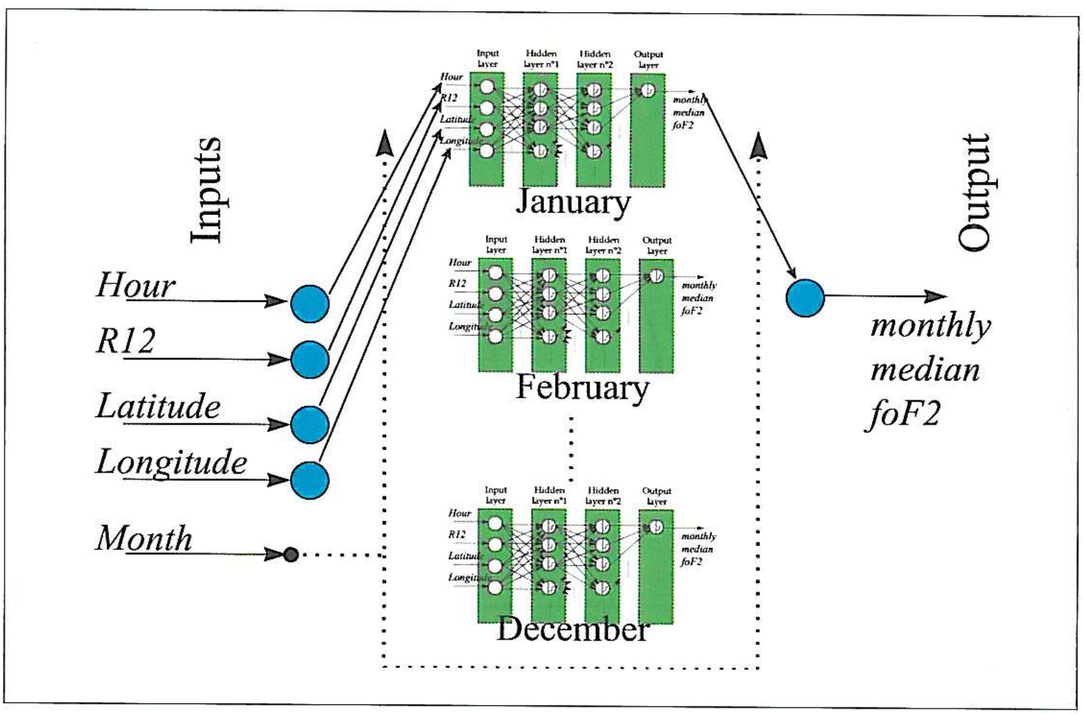

Fig. 2. The modular neural network (from Lamming and Cander, 1998a).

munication. However, the proposed approaches can be applied to any other E and F regions standard ionospheric characteristics.

3.1. *Prediction of the monthly median f_0F_2*

For monthly median f_0F_2 prediction a modular architecture of the neural network has been introduced by Lamming and Cander (1998a,b). This architecture is composed of 12 networks, one for each month of the year which solves the problem independently. Figure 2 illustrates the general idea of implementing a modular architecture in two different applications: i) single station modelling with three inputs: hour, month and solar activity index, and ii) 2D modelling over Europe with two additional inputs: geographical latitude and longitude.

The result of the single station application is given in fig. 3 for a typical mid-latitude European ionospheric station Poitiers (46°N, 00°E). The comparison between predicted and observed f_0F_2 values is in good agreement throughout most of the months at high levels of solar activity in 1990. The only discrepancy between predicted and observed f_0F_2 occurs in some cases at night hours, as expected since solar activity index R_{12} is used as an input parameter. In the 2D application it is found that the neural network model can very well interpolate spatially f_0F_2 values between the ionospheric stations in a restricted area and generates the f_0F_2 maps. An example map is shown in fig. 4. It is clear from the data and the simulation that the neural network 2D regional model gives a very realistic f_0F_2 representation over the geographical area considered. The success of the proposed neural network technique has also been tested by using results from the classical ITU-R and PRIME models (see Lamming and Cander, 1998b).

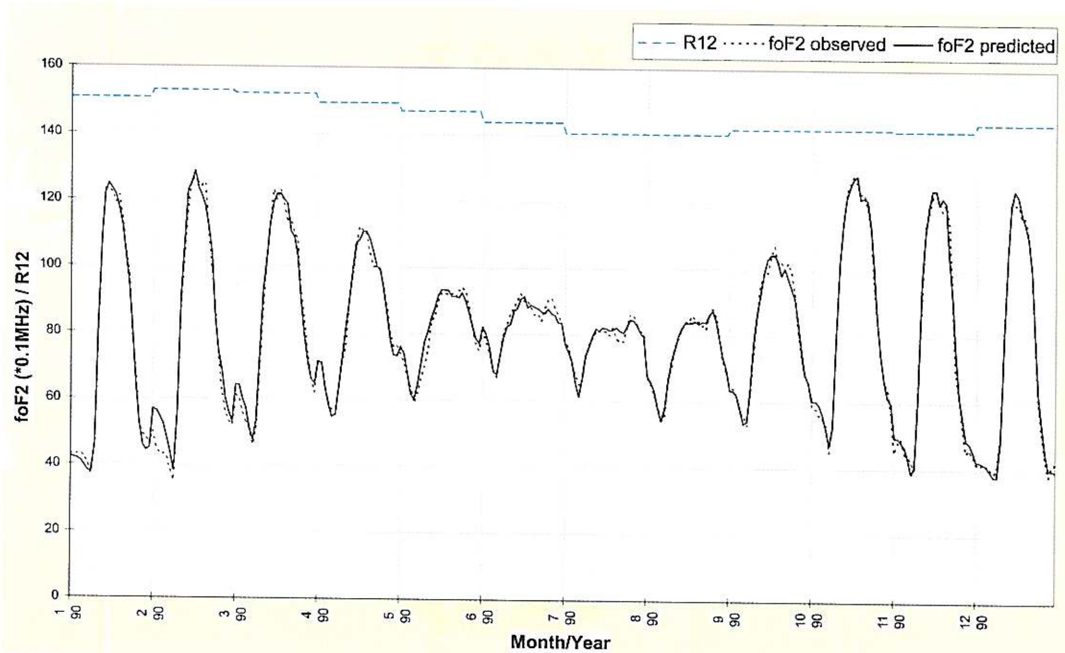

Fig. 3. A comparison of f_0F_2 predicted by neural network with the observations at Poitiers during all months of 1990. Solar activity index R_{12} variations are also shown (from Lamming and Cander, 1998a).

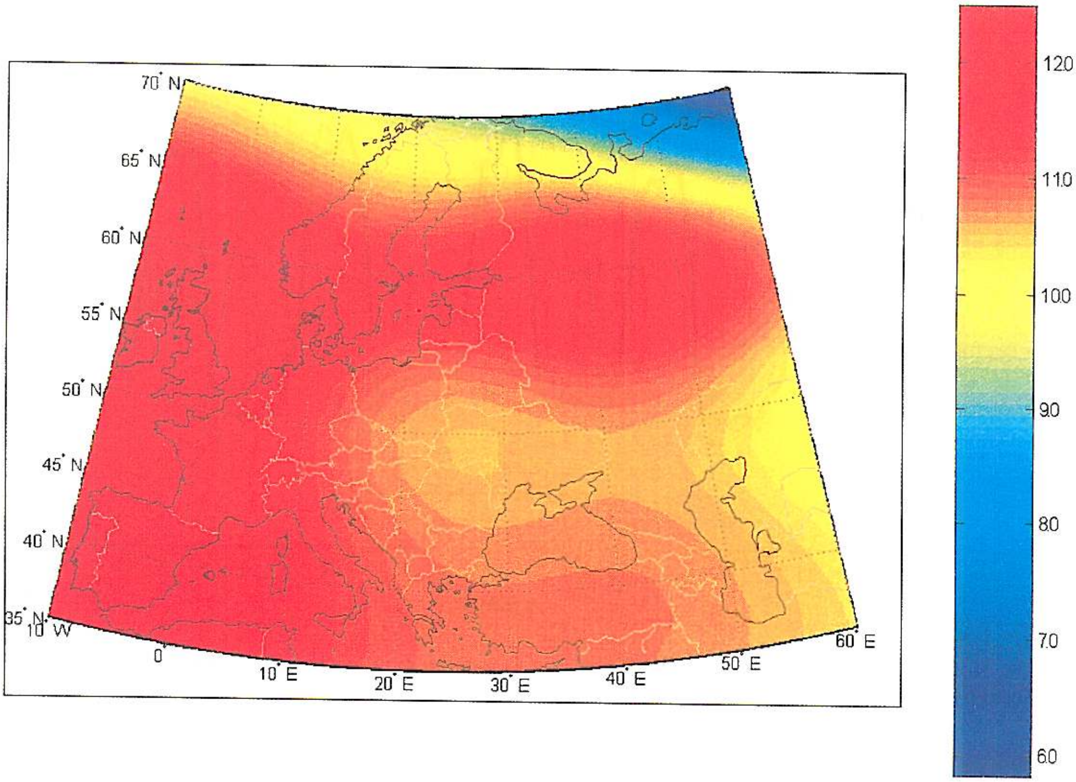

Fig. 4. Monthly median f_0F_2 (MHz) over Europe at 1200 UT in January when R_{12} = 150 (from Lamming and Cander, 1998b).

3.2. *Forecasting of the daily hourly f_0F_2*

During fast changes in ionospheric conditions, monthly median prediction is not sufficient and daily hourly f_0F_2 forecasting is required. Successful attempts to build different artificial neural network models for one hour ahead prediction were made by a few authors (Altinay *et al.*, 1997; Poole and McKinnell, 1998; Cander *et al.*, 1998b; Wintoft and Cander, 1998). One approach that uses the hybrid time-delay multi-layer percepton neural network with twelve input parameters including among others f_0F_2 values at particularly selected hours (t, t-1, t-23, t-47), daily sunspot number R_i and geomagnetic ring current index D_{st} to produce one output f_0F_2 value at hour $t+1$ has been illustrated here by examples in figs. 5 and 6. A detailed description of this type of neural network as far as its architecture, first and second hidden layers, learning and test data sets are concerned can be found in Cander *et al.* (1998b). Close examination of fig. 5 shows that there is an excellent agreement between measured f_0F_2 values at Rome ionospheric station (41.9°N, 12.5°E) during high solar activity period of five days on 1-5 December 1990 and one hour ahead predicted f_0F_2 values. It should be emphasised that this comparison is given for an easy case of mid-latitude station during quiet geomagnetic activity.

This agreement is not so good at fig. 6 where disturbed ionospheric conditions at low level of solar activity were in progress during six days on 4-9 December 1995. In comparing the neural network results shown in fig. 6 with

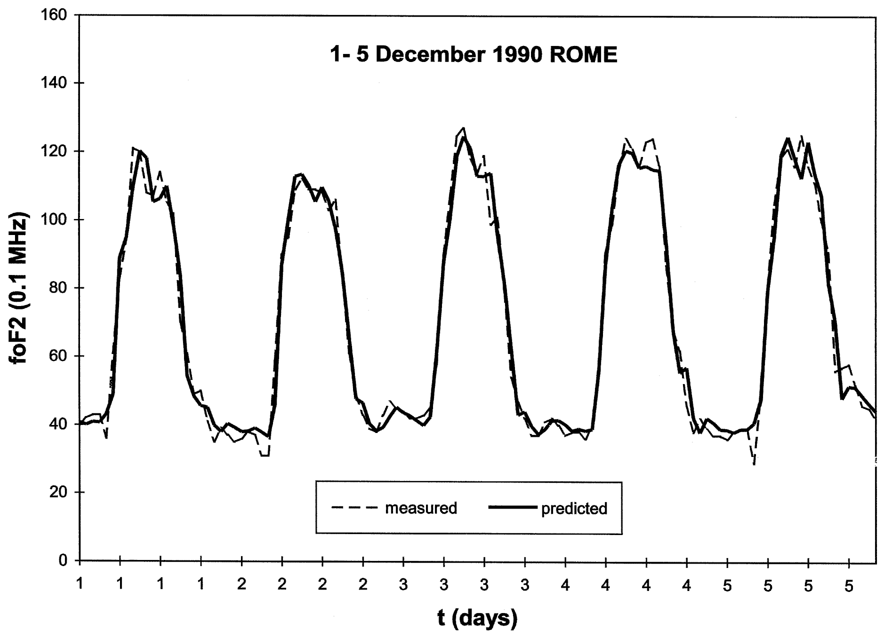

Fig. 5. Hourly f_0F_2 values at Rome ionospheric station as measured on 1-5 December 1990 (dashed line) and predicted by neural network one hour ahead (solid line).

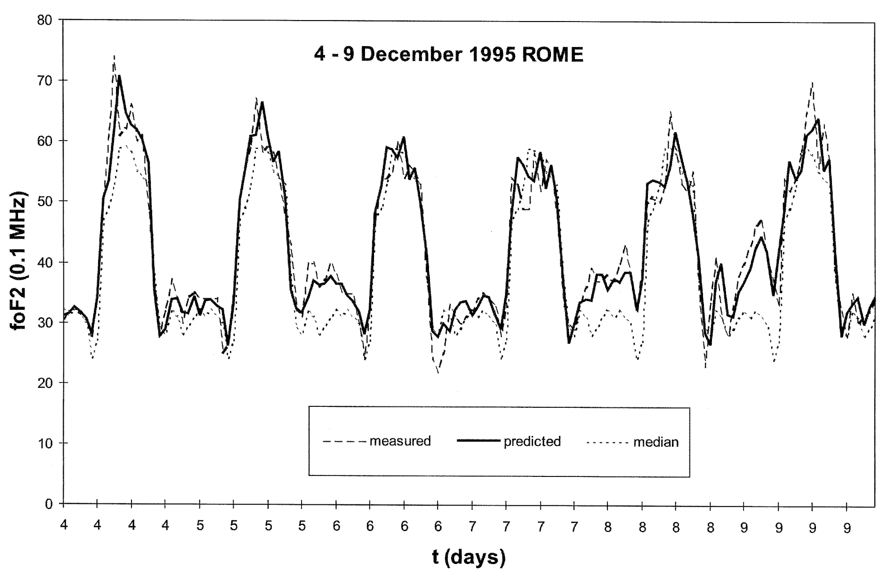

Fig. 6. Hourly f_0F_2 values at Rome ionospheric station as measured on 4-9 December 1995 (dashed line) and predicted by neural network one hour ahead (solid line). Monthly median f_0F_2 variation is given by dotted line.

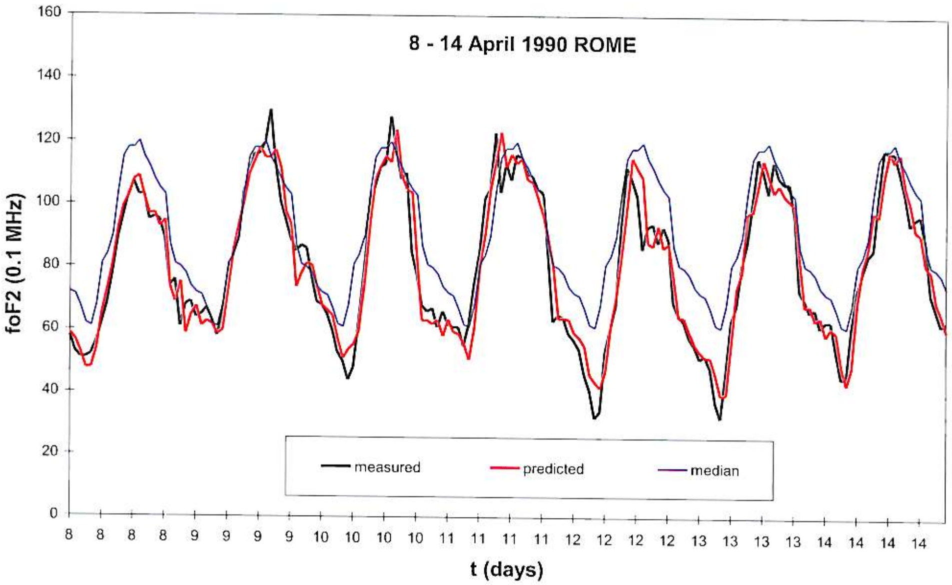

Fig. 7. Hourly f_0F_2 values at Rome ionospheric station as measured on 8-14 April 1990 (black line) and predicted by neural network one hour ahead (red line). Monthly median f_0F_2 variation is given by the blue line.

observations, attention must be paid to the fact that there were a number of phenomena which cannot be related to any typical day-to day ionospheric variability. The differences between daily hourly f_0F_2 values and their corresponding monthly median values are especially pronounced at night. However, the predicted f_0F_2 values still follow the measured f_0F_2 values at Rome much more closer than monthly median values.

3.3. *Forecasting the daily hourly f_0F_2 during ionospheric storms*

To study the forecasting capabilities of the neural network method during ionospheric storms an experiment was done resulting in fig. 7. The test was based on April 1990 (mean monthly sunspot number R_i = 140.3) data for Rome station. Figure 7 gives results for one hour ahead f_0F_2 forecasting over a seven day period, 8-14 April 1990. A great geomagnetic storm occurred on 10 April when A_p reached the value of 124. During this period, observations at Rome exhibit a lasting and smoothly varying negative storm effect when the f_0F_2 values were depressed significantly below the monthly median values which represent here the quiet ionospheric conditions. Again, the agreement between predictions and observations is very good. These results clearly imply that artificial neural network techniques are particularly robust during ionospheric storms when reliable quantitative forecasting one hour ahead can easily be obtained.

4. Forecasting TEC

In this section, experimental TEC data are compared with one hour ahead TEC predicted by the neural network. Ionospheric TEC is the total electron content (in electrons/m^2) of a vertical column of 1 m^2 cross section. The TEC data were determined from Faraday rotation observations at Florence (43.8°N, 11.2°E) using the signal of the OTS-2 satellite (Ciraolo and

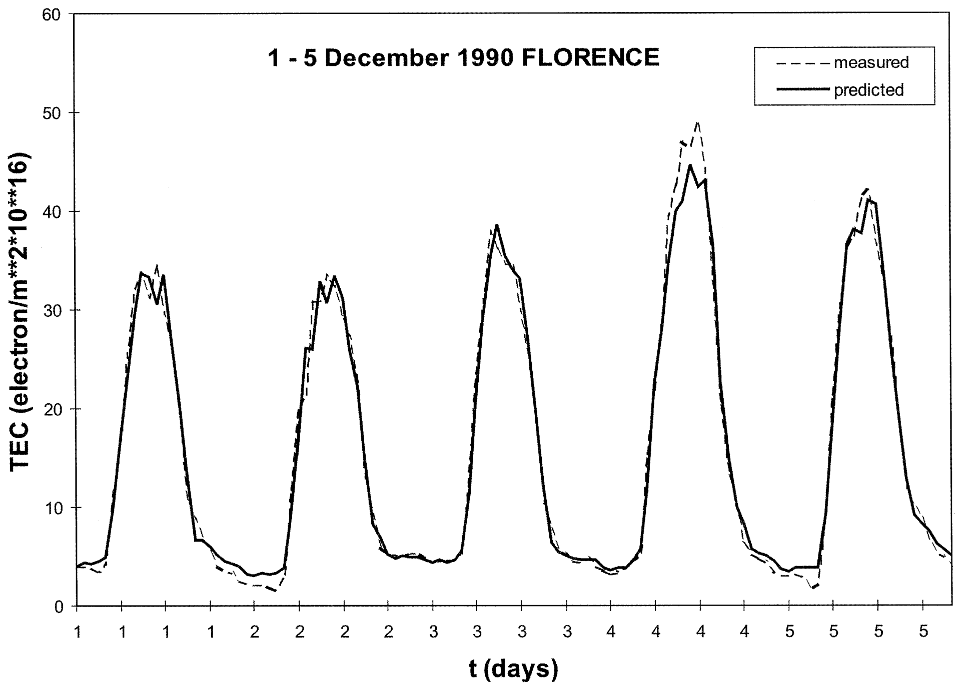

Fig. 8. The diurnal variation of the observed (dashed line) and one hour ahead predicted (solid line) values of TEC (Total Electron Content) for Florence on 1-5 December 1990.

Spalla, 1994). The f_0F_2 neural network forecasting model was modified to introduce the TEC prediction one hour ahead. Extensive comparisons were made between observed values of TEC and those calculated using neural networks. Figure 8 illustrates a very small subset of the comparisons which could be made using the available TEC database. As in the case of f_0F_2 prediction at Rome ionospheric station for the same five day period (fig. 5), the agreement between model and observations generally ranges from good to very good. Some discrepancies occur only during the early morning hours and at the peak daily values on 4 December.

5. Discussion and summary

In reviewing the artificial neural network applications in ionospheric studies, the first concern that one may have is the advantages of these new approaches. Real time ionospheric specification and forecasting has important implications for ionospheric weather and time delay corrections of the Global Position System. If ionospheric modelling is to progress from the climatology level to the weather level (Schunk and Sojka, 1996b) then: i) key observation data must be moved into the forecast environment in real time; ii) multi-site data taken in real time are needed. Results in previous sections described how the artificial neural networks can improve the ionospheric long term prediction and short-term forecasting at the single ionospheric stations as well as at restricted area of Europe.

In all examples given, different neural networks have been trained to model and predict the f_0F_2 and TEC, measured at mid-latitude ionosphere during different solar and geomagnetic conditions. Comparisons with the local monthly median and daily hourly f_0F_2 and TEC values enable an optimum set of data and prediction efficiency for different neural network architecture to be determined. Numerical experiments extensively conducted also confirm that applying the different methods many input units and hidden units can be removed without affecting the prediction accuracy, making the whole computing procedure much simpler (Wintoft and Cander, 1998). It is apparent from the representative examples in figs. 3, 4, 5, 6, 7 and 8 that the neural networks yield results that are generally just as good as those observed. More importantly, however, is the fact that the most significant input in any of those neural network architectures is a time-series of f_0F_2 or TEC itself which is able to describe most of the solar cycle, seasonal, daily and hourly variations of relevant parameters. This is certainly not the case during the ionospheric storm periods although the new methods yield values of f_0F_2 and TEC that are much closer to observations than any other known traditional techniques (Cander, 1998).

Indeed, it seems that the neural network approach can be an alternative to classical methods of ionospheric prediction and forecasting because the artificial neural networks are: i) empirical models that can describe ionospheric non-linear phenomena; ii) learned on measured f_0F_2, TEC or any other standard ionospheric characteristic from which they extract the underlying functional relationships, and iii) fast enough, if the architecture is properly designed, to be used in many different applications including real-time ionospheric specification and prediction. It is expected that future progress will be soon accomplished in neural network applications in ionospheric studies by recent research projects which are already underway: among others, the COST 251 project on «Improved quality of ionospheric telecommunication systems planning and operation». Progress can be expected in short-term forecasting of daily f_0F_2 and TEC variations 24-h ahead, a few hours ahead during ionospheric storms and developing regional models of long-term ionospheric changes.

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