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Prediction of horizontal component of earth's magnetic field over Indian sector using neural network model

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ABSTRACT

Present work is the first attempt to predict horizontal component of earth's magnetic field (H) and range in H (ΔH) over Indian sector by considering the stations, namely, Trivandrum, Pondicherry, Visakhapatnam, and Nagpur, using the concept of neural network (NN). Through training procedure, solar flux ($F10.7$), latitude, longitude, day of the year, local time, Ap index, IMF Bz, and ion number density are identified as the optimum choice of input parameters, whereas the inclusion of solar wind pressure and velocity has not significantly improved the performance of the model. Thus an appropriate neural network model, NSSHC has been developed with 12 hidden neurons and 500 iterations to predict H component and range in H (ΔH) during the period 1996–2001, to capture diurnal, seasonal, latitudinal, magnetic and solar activity effects.

1. Introduction

Artificial Neural Networks (ANNs) are well suited to environmental modelling as they are nonlinear, relatively insensitive to data noise, and perform reasonably well when limited data are available. When ANNs are used for the prediction of environmental variables, the modelling philosophy employed is similar to that used in the development of more conventional statistical models. Infact, it has been suggested that ANNs represent variations on common statistical themes. In both cases, the purpose of the model is to capture the relationship between a historical set of model inputs and corresponding outputs. This is achieved by repeatedly presenting examples of the input/output relationship to the model and adjusting the model coefficients (i.e., the connection weights) in an attempt to minimise an error function between the historical outputs and the outputs predicted by the model. An advantage of using neural networks is that they often can be quickly constructed using available data at a very low cost when compared with developing conventional expert systems. The saving in time and cost is achieved by replacing the process of knowledge acquisition and knowledge base construction with the process of training networks. Another, perhaps more significant, advantage is that neural networks can learn from examples and make predictions for new situations. Therefore, neural networks can often be trained to solve a problem once a sufficient amount of representative data becomes available to constitute a good training set, even before the problem is fully understood or before human experts are able to formulate their knowledge in an organized, complete and consistent manner to allow an expert system solution (Bishop, 1996; Hertz, 1993; Koons and Gorney, 1991; Lundstedt, 1992; Gorney et al., 1993; Lundstedt and Wintoft, 1994).

In the framework of space weather an important role is played by geomagnetic storms, which are comprised of processes occurring in near-Earth space. Recently, major efforts have been devoted to obtain global empirical models of the vertical plasma drifts using radar, magnetometer, satellite, and ionosonde observations (e.g., Richmond et al., 1980; Fejer and Scherliess, 1995; Batista et al., 1996; Scherliess and Fejer, 1999; Sobral et al., 2003). The ionospheric effects of prompt penetration electric fields (PPEFs) for a variety of interplanetary magnetic field directions were presented by Tsurutani et al. (2004). The dayside ionospheric storms due to PPEFs are characterized by transport of near-equatorial plasma to higher altitudes and latitudes, forming a giant plasma fountain (super-fountain).

During geomagnetic storms, very intense fluctuations of the horizontal component of the ground magnetic field are observed (Gonzalez et al., 1994; Tsurutani et al., 1995) due to variations in the equatorial ring current. An energy source of the geomagnetic phenomena is the Sun which transfers energy to the Earth's

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magnetosphere by means of streams of the solar wind (SW). The magnetosphere is usually closed for SW, and energy from SW put in magnetosphere only in a case when interplanetary magnetic field (IMF) has a significant component parallel to the terrestrial magnetic dipole, i.e. approximately negative (southward) IMF Bz component (Gonzalez et al., 1994; Petrukovich et al., 2001 and references therein). In a case when rate of energy input is higher than rate of its quasi-stationary dissipation, energy collects in the magnetosphere. When its amount reaches and exceeds some certain level, any small disturbance outside or inside magnetosphere can result in release of this energy (so-called "trigger" mechanism) as reconnection of magnetic field, global reorganization of current systems of magnetosphere and heating/acceleration of plasma, i.e. generate magnetospheric disturbance.

Artificial intelligence (AI) has been increasingly recognized as a powerful analysis tool in various areas, especially in solar–terrestrial physics. Neural networks (NNs) are a branch of AI methods which are proving particularly successful in solar–terrestrial time series prediction and pattern recognition; they appear to be especially effective in modelling the time development of irregular processes (Koons and Gorney, 1991; Lundstedt, 1992; Gorney et al., 1993; Lundstedt and Wintoft, 1994; Williscroft and Poole, 1996; Wu and Lundstedt, 1996).

Recently, Unnikrishnan et al. (2006) analysed the deterministic chaotic behaviour of GPS TEC fluctuations at mid-latitude, and equatorial/low latitude regions of Indian subcontinent (Unnikrishnan and Ravindran, 2010) by employing the nonlinear aspects like mutual information, fraction of false nearest neighbours, phase space reconstructions, and chaotic quantifiers. Also they compared the possible chaotic behaviour of ionosphere during geomagnetic storms and quiet times, under different seasons, local times, and latitudes using dynamical and topological invariants. Their study emphasis that the influence of an external stochastic driver (solar wind) could alter the inherent dynamics of a system (ionosphere) if the coupling is powerful, and hence this could be a possible reason for the deviation of the values of Lyapunov exponent during storms from the respective quiet time values (Unnikrishnan et al., 2006). Nonlinear dynamical models of the magnetosphere derived from observational time series data using phase space reconnection techniques have yielded new advances in the understanding of its dynamics.

The importance of nonlinear dynamical studies to space weather arises from its ability to reconstruct the dynamics from the observational data of a limited number of variables. In the input–output studies the local linear technique has been successful in yielding simple predictive models of the global magnetospheric dynamics by using the main features of the system. In the present work, for the first time, the horizontal component of earth's magnetic field (H) and range in H (ΔH) over Indian sector are predicted using the concept of neural network (NN), by designing NSSHC (Nair Service Society Hindu College) model.

Studies of Pavlos et al. (1999a,b,c) revealed that the random character of the magnetospheric time series could be caused by the chaotic low-dimensional internal dynamics of the magnetospheric system, while this character only appears when the solar wind input takes appropriate values. As the solar wind is continuously changing its state the magnetospheric dynamics can live intermittently on a low-dimensional chaotic attractor. Another study using energetic ions' signal also suggests the existence of two different physical processes related to the magnetospheric dynamics: the first process corresponds to a stochastic external component and the second process corresponds to a low-dimensional chaotic component. Hence, the internal instability of the magnetosphere system may be suppressed/modified and the system may transit more towards stochasticity rather than deterministic chaoticity. The complex behaviour of magnetosphere is mainly due to the solar wind and the critical feature of persistency in the magnetosphere could be the result of a combined effect of solar wind and internal magnetospheric activity.

2. Data and methodology

As a requirement for training a NN, input parameters representing the variables that the output responds to are required. Day number (DN), $1 \leq \mathrm{DN} \leq 365$, represents the seasonal variation and hour (HR), $0 \leq \mathrm{HR} \leq 23$, the diurnal variation. The HR input is in Local Time (LT). As explained in Poole and McKinnell (2000) the DN and HR inputs are split into their cyclic components and presented to the NN as four inputs, two for DN (DNS and DNC) and two for HR (HRS and HRC). These four inputs are calculated as follows:

$$\begin{aligned}
\mathrm{DNS} &= \sin\left(\frac{2\pi \times \mathrm{DN}}{365.25}\right)\\
\mathrm{DNC} &= \cos\left(\frac{2\pi \times \mathrm{DN}}{365.25}\right)\\
\mathrm{HRS} &= \sin\left(\frac{2\pi \times \mathrm{HR}}{24}\right)\\
\mathrm{HRC} &= \cos\left(\frac{2\pi \times \mathrm{HR}}{24}\right)
\end{aligned} \tag{1}$$

As the first step, we predicted H component as a function of diurnal, seasonal, solar and magnetic activity variations, which are assigned as the basic parameters (BP) to be fed as the input of neural network. As the second stage, probable solar wind parameters, IMF Bz, ion number density, solar wind velocity, and solar wind pressure are included one by one and the improvement of the model efficiency is checked in terms of Root Mean Square Error (RMSE) between the predicted and observed values.

The NN has to be trained with a similar time series before it can make any prediction, and the dataset used for training is called training set. Infact the training datasets are selected from different geophysical conditions, representing diurnal, seasonal, latitudinal, solar and magnetic activity variabilities. It is to be noted that, the data sets used for testing are not the part of those used for training. For training the network, we have selected three months namely, February, July, and September, representing three seasons winter, summer, and equinox for low (1996), moderate (1998) and high (2001) solar activity periods observed at various stations, Trivandrum (TVM), Pondicherry (PND), Visakhapatnam (VSK), and Nagpur (NGP) over the Indian equatorial sector (Table 1). As the next step, by feeding the hourly values of optimum choice of input parameters, H component of earth's magnetic field is predicted at different locations, local times, seasons, solar and magnetic activities, and thus the efficiency of NN designed is validated (see Tables 3–6). Fig. 1 presents the location of stations considered in the present study.

By performing similar procedures, range in H (ΔH) is also predicted as a function of diurnal, seasonal, solar and magnetic activity variations.

Table 1
List of stations considered.

Station name	GG LAT (°N)	GG LONG (°E)	GM LAT (°N)
Trivandrum	8.480	76.950	−0.52
Pondicherry	11.917	79.917	2.62
Visakhapatnam	17.683	83.317	8.06
Nagpur	21.150	79.083	11.83