Artificial neural network (ANN) for modelling earth’s magnetic field belonging to solar minimum observed at a low latitude station Alibag

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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. By using solar flux (F10.7), day of the year, local time, and Ap as input, an appropriate ANN has been developed to model north-south component (X component) of earth’s magnetic field belonging to solar minimum period for Alibag (18.6°N, 72.87°E, geomagnetic latitude 10.37°N), a low latitude station of Indian sub-continent. For training the network three months, namely February, June, and September, were selected which represent three seasons winter, summer, and equinox, respectively of 2007 and 2008. Based on this analysis, it is observed that ANN model with 10 hidden neurons has good performance for 500 iterations. For testing the efficiency of ANN, hourly values of input and north-south component (X component) of earth’s magnetic field observed during January, October 2007 and May 2008 were used. To confirm the functional aspects of this model, similar investigations were carried out for other periods, January, October 2008, and May 2007. In this study, for the first time, artificial neural networks (ANNs) are utilised to develop a geomagnetic daily variation model for an Indian sub-continent station, Alibag.

Keywords: Artificial neural network, Earth’s magnetic field, Solar minimum, Geomagnetic daily variation model

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1 Introduction

Artificial neural network (ANN) is a mathematical model which has some kind of distributed architecture, that is, consists of processing nodes (analogous to neurons) with multiple connections (analogous to dendrites and axons). These connections generally have adaptable parameters which modify the signals that pass along them. There are numerous types of artificial neural networks for addressing different types of problems such as modelling memory, performing pattern recognition, and predicting the evolution of dynamical systems. Most networks, therefore, perform some kind of data modelling and they may be split into two broad classes: supervised and unsupervised. The former refers to networks which attempt to learn the relationship between data and parameter domain while the latter refers to networks used to find natural groupings with a data set independently of external constraints.

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 conventional statistical models. In fact, 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 minimize 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 is 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.

It has been known for decades that solar activity influences the near-Earth environment through the solar wind variable flow and energetic particles emissions. The description of such influences and the development of tools for their nowcasting and forecasting is the subject of space weather. It is now widely accepted that space weather effects may damage critical equipment, such as communication satellites or power lines and pipelines on the ground, and disrupt HF communications and GPS links, etc. As such, the prediction of space weather effects has both scientific and economical reasons.

In the framework of space weather, an important role is played by geomagnetic storms, which are comprised of processes occurring in near-Earth space. During geomagnetic storms, very intense fluctuations of the horizontal component of the ground magnetic field are observed due to variations in the equatorial ring current.

In this study, for the first time, the concept of artificial neural networks (ANNs) is utilised to develop a geomagnetic daily variation model for an Indian sub-continent station, Alibag, to generate north-south component (X component) of earth’s magnetic field. By using this procedure, parameters have been identified, which may be given as input to the network output. The identified parameters are, namely solar flux (solar radio flux F10.7), day of the year, local time, and Ap.

2 Data, Methodology and Analysis

For an input data vector, \( \{ I_k^i, k=1,2,\ldots,m \} \), with m components, the network output is given by Eq. (1)

\[
O^\mu = g_o \left( \sum_j W_j g_H(x) \left( \sum_k w_{jk} I_k^i + \theta_j \right) + \theta \right)
\]  

where, \( g_H(x) \) and \( g_o(x) \) are the activation functions of input and output neurons, respectively. Functional aspect indicates the activation function of the input or output layer. In the present study, activation function used for both input and output layers is logistic. Each input-output sample \( \{ I_k^i, O^\mu \} \) is labeled by superscript \( \mu \). Index \( j \) refers to a hidden layer node, index \( k \) refers to an input layer node, and in the output layer there is only a single node. The weight \( W_j \), thus, connects a hidden layer node with an output layer node, while \( w_{jk} \) connects input and hidden layer nodes.

The terms \( \theta \) and \( \theta \) are the weights associated with the bias input \( I_0 \). Back propagation algorithm is used here, and as the name implies, the errors propagate backwards from the output nodes to the inner nodes by calculating the gradient of the error of the network regarding the network’s modifiable weights. This gradient is used in a gradient descent algorithm to find weights that minimize the error. In this way ANN using back propagation algorithm allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

Inputs are fed to the neurons present at input layer (input layer neurons), and the output of the network is given by the neurons on an output layer. The hidden layers consisting of optimum number of neurons (hidden layer neurons) function as intermediate layers between input and output layers. Each input to the neural network is fed as input into a different input neuron. The input neurons are connected to hidden neurons which perform transformations on the input. The output of these neurons is defined to be the output of the entire network.

The choice of input variables is generally based on a prior knowledge of causal variables. Initially, sufficient models were developed, each using only one of the available input variables. The model that performed best was retained and the effect of the addition of a second variable on model performance is investigated. This procedure was repeated using models with three input variables, four input variables, etc. until the addition of any extra variables did not improve model performance. However, out of the four input parameters considered here, the importance of each input parameter is different. For example, if the first two input parameters are most important, by the inclusion of these two input parameters alone can produce a fairly accurate output. In such cases ANN is able to reproduce the X component fairly accurately although the input parameters are not exhaustive. And the inclusion of the third and fourth input parameters (which are less important) can slightly improve the performance. On
the other hand, if ANN is designed with third and fourth input parameters (which are less important) alone, model output will show more deviation from the observed values. However, if the more important input parameters are added, then again fairly accurate model values are observed. This is the way in which ANN exhibits sensitivity towards input signals, while behaving insensitive to data noise.

For training the network, three months have been selected during 2007 and 2008 namely, February, June, and September, which represent three seasons i.e. winter, summer, and equinox, respectively. For testing the efficiency of ANN, hourly values of input and north-south component (X component) of earth’s magnetic field observed during January, October 2007 and May 2008 were used. To confirm the functional aspects of this model, similar investigations were carried out for other periods, January, October 2008, and May 2007.

Hourly values of data used in the present study were obtained from Coordinated Data Analysis Web (CDAWeb, http://cdaweb.gsfc.nasa.gov/istp_public/) and World Data Center, Kyoto, Japan (http://wdc.kugi.kyoto-u.ac.jp).

3 Results

3.1 Choice of network geometry

Network geometry is generally defined by the number of hidden layer nodes and the number of nodes in each of these layers. The optimum number of hidden layer nodes, generally has to be found using a trial and error approach. However, there are some general guidelines which may be followed. Hecht-Nielsen suggested the following upper limit for the number of hidden layer nodes in order to ensure that ANNs are able to approximate any continuous function:

\[ N^H \leq (2N^I+1) \]  … (2)

where, \( N^H \), is the number of hidden layer nodes and \( N^I \) is the number of input nodes (= number of inputs).

Figure 1(a-f) represent modelled values and observed values of north-south component (X component) of earth’s magnetic field, obtained by changing the hidden layer nodes from 2 to 12. Figure 1(a) shows that modelled values did not match with observed values of north-south component (X component) of earth’s magnetic field, when the number of hidden neurons is 2. But the deviation of modelled values from observed values decreased as the number of hidden neurons increased from 4 to 10 [Fig. 1(b-e)], and thereafter, it begins to increase when the number of hidden neurons is 12 [Fig. 1(f)]. It is clear that better agreement between model and observations is observed when the number of hidden neurons is 10 [Fig. 1(e)].

The ANN model output and therefore, the performance are really sensitive on the choice of number of hidden neurons. There are two proxies to represent the efficiency of the model, which are absolute error and correlation. Absolute error of the model is calculated by subtracting the current output values from the target output values of ANN, which is an indicator of efficiency of model. Efficiency of the model will be higher if the absolute error is smaller. In the present study, the absolute error is estimated by giving different choice of hidden neurons. Based on this analysis, it is observed that ANN model with 10 hidden neurons has smaller absolute error and therefore good performance if the iterations are 500 [Fig. 2(a)]. Another proxy of efficiency of the model is the correlation existing between modelled values and observed values of north-south component (X component) of earth’s magnetic field under various choice of hidden neurons starting from 2 to 12 [Fig. 2(b)]. It shows that value of correlation and the efficiency of the model are higher when hidden neuron=10 (Fig. 2b) and iteration =500.

Figures 3(a-c) exhibit the temporal variations of model values and observed values of north-south component (X component) of earth’s magnetic field during January 2007, May 2008, and October 2007, respectively. To confirm the functional aspects of this model, similar investigation was carried out for other periods, i.e. January, October 2008, and May 2007 [Figs 4(a, b, c, respectively)].

4 Discussion

ANN-based techniques have been particularly successful in predicting a variety of irregular magnetospheric processes such as magnetic storms and disturbance indices. The motivation for the inclusion of the degree of geomagnetic activity as a parameter in the ANN-based geomagnetic daily variation model was that it may partially account for the day-to-day variability of the daily variation. An ANN-based model is simpler since it uses only one set of data, which are functions of all the input parameters, resulting in one set of coefficients (weights). In contrast, the addition of more
geophysical parameters to an ANN-based model has negligible effect on the complexity of the computational process, the only cost is the increased computing time to train the network. Besides season (day of the year) and local time, geophysical parameters which are considered in our new ANN-based regional model are solar flux and degree of magnetic activity. The dependence on geomagnetic
Fig. 2(a) — Variation of absolute error of the output generated by ANN model by giving different choice of hidden neurons and iterations (based on this analysis, it is observed that ANN model with 10 hidden neurons and 500 iterations has good performance).

Fig. 2(b) — Variation of values of correlation between modelled and observed values of north-south component (X component) of earth’s magnetic field by changing the number of hidden neurons and iterations (ANN model with 10 hidden neurons and 500 iterations exhibit highest correlation between observed and modeled values).

Fig. 3 — Actual and model values of north-south component (X component) of earth’s magnetic field observed during: (a) January 2007; (b) May 2008; and (c) 2007 October 2007.
activity is weaker, but was included primarily in an attempt to partially take account of day-to-day variability in the daily variation.

Limitations of ANN include its ‘black box’ nature (i.e. rules of operation are completely unknown), greater computational burden, and the empirical nature of model development. Time and memory required for the present model for 500 iterations are approximately 10 s and 2-3 MB, respectively.

There is an increasing need amongst users of geomagnetic field models for models with greater accuracy and in particular, to have the ability to correct for short term temporal variations. Geomagnetic disturbances are likely to be one of the largest sources of deviation between observed and modelled geomagnetic field values. In recent years, methods of predicting geomagnetic storms and substorms in near real-time from solar wind data using non-linear filters and neural networks have been developed. However, such predictions are limited to hours, or at best days, into the future and require observed solar wind data. Unfortunately, accurate long term prediction or modelling of geomagnetic disturbances is not feasible at present, consequently, it is difficult to correct for deviations as a result of their occurrence. However, large geomagnetic disturbances occur relatively infrequently. The geomagnetic daily variation, although generally smaller in magnitude than most geomagnetic disturbances, occurs on a regular daily basis. Consequently, it will be a more frequent source of deviation in any system utilising a geomagnetic field model. Furthermore, the ANN can be used to make estimates of the daily variation of north-south component (X component) for any date in the past or future if the required input parameters are available. Thus, for example, a
geomagnetic daily variation model will find application in magnetic navigation and geophysical exploration where high degrees of accuracy are required. A geomagnetic daily variation model might also find application in reducing the daily variation effects from satellite data for main field and geomagnetic anomaly modelling. It has been planned to extend this work to develop a more general neural network as the next step, which can also be used for other stations of Indian sub-continent.

5 Conclusions
In this study, for the first time, artificial neural networks (ANNs) are utilised to develop a geomagnetic daily variation model for an Indian low latitude station, Alibag. By using solar flux, day of the year, local time, and Ap as input parameters, an appropriate ANN has been developed to model north-south component (X component) of earth’s magnetic field belonging to solar minimum.

For training the network, three months during 2007 and 2008, namely, February, June, and September, which represent three seasons i.e. winter, summer, and equinox, respectively have been selected. For testing the efficiency of ANN, hourly values of input and north-south component (X component) of earth’s magnetic field observed during January 2007, May 2008 and October 2007 were used. To confirm the functional aspects of this model, similar investigations were carried out for other periods January 2008, October 2008, and May 2007.

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There is an increasing need amongst users of geomagnetic field models for models with greater accuracy and in particular, to have the ability to correct for short term temporal variations. ANN-based techniques have been particularly successful in predicting a variety of irregular magnetospheric processes such as magnetic storms and disturbance indices.

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