Forecasting Geomagnetic Time Series Using Artificial Neural Networks

التنبؤ بتغيرات المغناطيسية الأرضية باستخدام الشبكات العصبونية الصناعية

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الخلاصة: يقدم هذا البحث مدخلا للتنبؤ بالمتواليات الزمنية للمغناطيسية الأرضية باستخدام الشبكات العصبونية الصناعية. وقد استخدمت الشبكة العصبونية لتعلم العلاقة بين قيم البيانات في الماضي والحاضر والمستقبل. ولقد حصلنا على نتائج متوافقة تماما خلال مرحلة التدريب. وكان متوسط نسبة الخطأ للتنبؤ بفترة ٢٤-ساعة مقدما في الأختبار الذى أجرى على البيانات الحقيقية يقل عن ٣٪. وقد أظهرت نتائج التنبؤ بيانات شهر مقدما تقديرات دقيقة للتنبؤ على المدى الطويل.

ABSTRACT-: This paper presents an artificial neural network (ANN) approach to geomagnetic time-series forecasting. The ANN is used to learn the relationship among past, current, and future hourly data records. We obtained a very close fit during the training phase. The average error of 24-hour ahead forecasts in our test on actual data are shown to be less than 3%. The results for forecasting data of one month ahead show that the ANN gives accurate estimates for short-term as well as long-term forecasting.

I. INTRODUCTION

The continuos geomagnetic records of any observatory are highly variable, on some days all the three elements of the geomagnetic field undergo smooth and regular variations while on other days their changes are more or less irregular [1, 2]. The geomagnetic variations may be resolved into secular changes, solar-diurnal and lunar-diurnal changes and abrupt changes resulting from magnetic storms. Recently, the present authors, have initiated research work that provided some rational basis for characterizing and identifying the underlying features of the geomagnetic variations. The project is being carried out at National Research Institute of Astronomy and Geophysics and Mansoura University. It aims at the development of an automated system that records, processes, analyses, and forecasts the geomagnetic activity at Missallate [3].

The present work is an extension of the previous research. It presents a method to make predictions about geomagnetic time series. The basic methods by which such forecasting is made may be classified into two categories in accordance with techniques they employ. One approach treats the data pattern as a time series signal and predicts the function values by using various time series analysis techniques [4-6]. The second approach assumes that there is sufficient *a priori* information that a first-principles derivation may be made to construct an accurate model of the mechanism which is generating the observed process. A new approach based on adaptive networks has been introduced recently [7-9] and used with some success to predict the behavior of chaotic time series- deterministic sequences whose second order statistics seem to indicate that they are random.

In the present paper, we present an algorithm for forecasting the hourly geomagnetic time series. The algorithm utilizes the adaptive networks: a layered perceptron artificial neural network (ANN). As is the case with time series approach, the ANN is used to learn the relationship among past, current and future daily geomagnetic data patterns. It traces previous daily patterns and predicts (i.e. extrapolates) a future pattern. The ANN is able to perform nonlinear modeling and adaptation. We adapted the ANN by exposing it to new data.

The particular data used in this work to train and test the predictive power of the ANN are: an ensemble of hourly records of the three geomagnetic elements H, Z, and D for the period of 1984-1993 at Missalate, Helwan, and ensemble of simulated records [10].

The organization of the paper is as follows: the second section presents a detailed description of the pattern structure of the geomagnetic records. The ANN model and the algorithm used to train the ANN is described in Section III. In the fourth section, we define the forecasting problems, show the topologies of the ANN used in our simulations and analyze the performance in terms of errors (the difference between actual and forecasted data). A discussion of the results and conclusions are presented in Section V.

II. THE PATTERN STRUCTURE OF GEOMAGNETIC RECORDS

For the present study, geomagnetic data for the period of 1984-1993 were obtained from the National Research Institute of Astronomy and Geophysics at Helwan. Measurements were made at the magnetic observatory at Missalate station using the magnetometer Type La cour. This instrument records the changes in the geomagnetic field on a sensitive paper of size 30 X 40 cm. The magnetometer records the daily variations as three traces which are the Z, H and D geomagnetic-field components. The records were then examined, calibrated and then sampled for further data processing and analysis. The sampling rate used for this study is 1 sample/hour. Fig. 1 illustrates a typical example of the hourly geomagnetic records for a period of one month.

A recent study reported by the present authors [3] has asserted that the hourly geomagnetic records are nonrandom signals and they exhibit three consistent types of systematic patterned components; a slow-rate fluctuation component which reflects the long-term variations in the geomagnetic field (mean period 5 days), a recurrent short-duration transient increases of 24-hour period (diurnal fluctuation component) which are relatively large and constitute a major feature of the records reflecting the variations linked to the sun; and a rapid fluctuation component which shows transient increases of 13 hour period.

The investigation of the transient increases phenomenon in the rapid fluctuation component has shown that the transients are patterns generated by some explicit underlying mechanism that organizes the data into this specific form. Fig.2 illustrates the three isolated patterned components for the Z-element

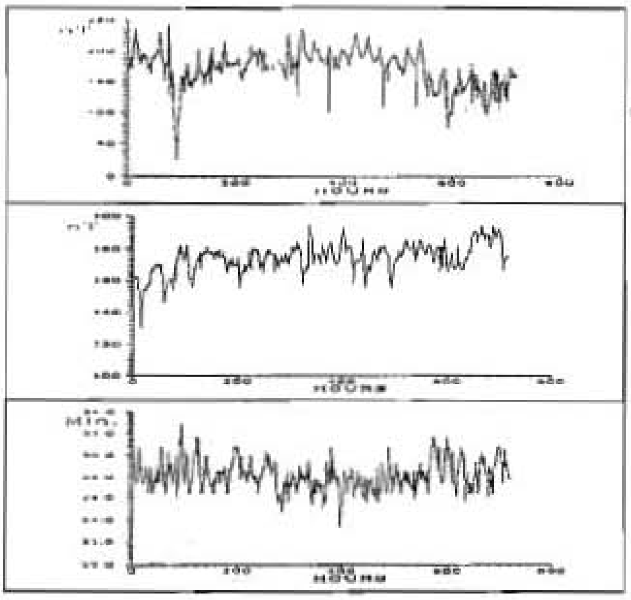

Fig. 1 A typical monthly geomagnetic record (November 1986)
(a) ***H*** element, (b) ***Z*** element, and (c) ***D*** element

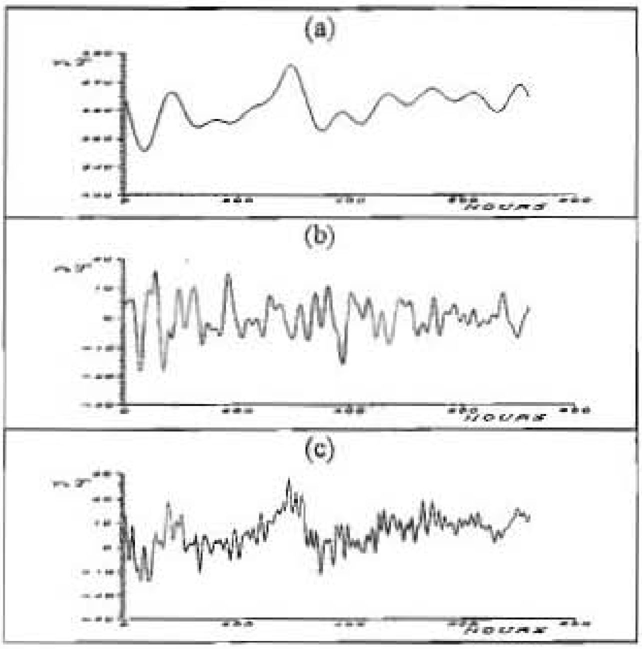

Fig.2 A typical example of the isolated patterned components of the Z-element (November 1986). (a) Slow rate fluctuation component, (b) Diurnal fluctuation component, and (c) Rapid fluctuation component

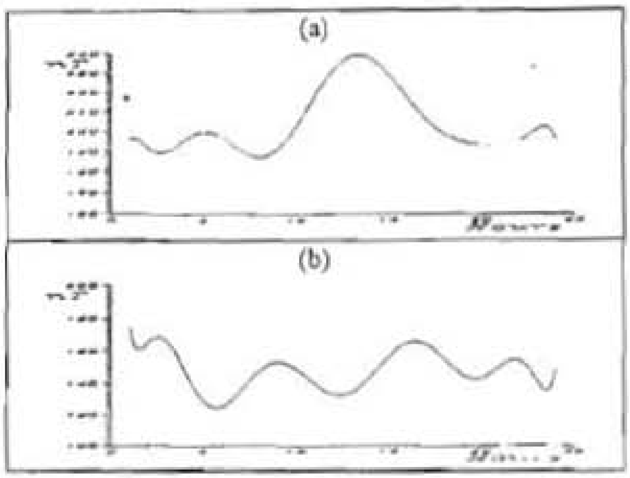

Fig. 3 Hourly pattern of one day: (a) Quiet day, (b) Disturbed day

In addition to the three identified components, geomagnetic data are known to exhibit daily variations. The records normally show two types of diurnal variations [1]: the quiet days and the disturbed days. A quiet day variation is smooth, regular, and low in amplitude, whereas a disturbed day variation is less regular and is associated with magnetic storms. Fig.3 shows examples of quiet and disturbed days. Therefore, the problem of forecasting geomagnetic time-series must take into consideration the pattern structure of these records and one can try to find a single function that gives a future pattern of the time series as its output when some set of past patterns is supplied as its input. This model is implemented by artificial neural networks (ANNs) as will be explained below.

III. NEURAL NETWORKS

III.1 Architecture

An ANN can be defined as a highly connected array of elementary processors called *neurons*. A widely used model called the multi-layered perceptron (MLP) ANN is shown in Figure 4. The MLP type ANN consists of one input layer, one ore more hidden layers and one output layer. Each layer employs several neurons and each neuron in a layer is connected to the neurons in the adjacent layer with different weights. Signals flow into the input layer, pass through the hidden layers, and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer linearly weighted by interconnect values between neurons. The neuron then produces its output signal by passing the summed signal through a sigmoid function [11, 12].

A total of Q sets of training data are assumed to be available. Inputs of $\{i_1, i_2, \ldots, i_Q\}$ are imposed on the top layer. The ANN is trained to respond to the corresponding target outputs, $\{t_1, t_2, \ldots, t_Q\}$, on the bottom layer. The training continues until a certain stop-criterion is satisfied. Typically, training is halted when the average error between the desired and the actual outputs of the neural network over the Q data sets is less than a predetermined threshold. Th: training time required is dictated by various elements including the complexity of t.ie problem, the number of data, the structure of network, and the training parameters used.

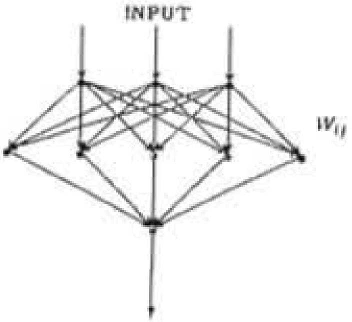

Fig.4 Structure of a three-layered perceptron type ANN

III. 2 Procedure for Training the Network

We use the error back propagation algorithm of Rumelhart et al. [13] to train the network, using mean squared error (MSE), over the training samples as the objective function.. According to the difference between the produced and desired outputs, the network's weights $\{W_{ij}\}$ are adjusted to reduce the output error. The error at the output layer propagates backward to the hidden layer, until it reaches the input layer.

The output from neuron i, O_i, is connected to the input of neuron j through the interconnection weight W_{ij} . Unless neuron k is one of the input neuron, the state of the neuron k is :

$$O_k = f\left(\sum_i W_{ik} O_i \right) \qquad (1)$$

where $f(x) = 1/(1+e^{-x})$, and the sum is over all neurons in the adjacent layer. Let the target state of the output neuron can be defined as :

$$E = \frac{1}{2}(t_k - O_k)^2 \qquad (2)$$

where neuron k is the output neuron.

The gradient descent algorithm adapts the weights according to the gradient error, *i. e.*,

$$\Delta W_{ij} \ \alpha \ -\frac{\partial E}{\partial W_{ij}} = -\frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial W_{ij}} \qquad (3)$$

Specifically, we define the error signal as :

$$\delta_j = -\frac{\partial E}{\partial O_j} \qquad (4)$$

With some manipulation, we can get the following equation :

$$\Delta W_{ij} = \varepsilon \delta_j O_j \tag{5}$$

where ε is an adaptation gain. δ_j is computed based on whether or not neuron j is in the output layer. If neuron j is one of the output neurons,

$$\delta_j = (t - O_j)\, O_j\, (1 - O_j) \tag{6}$$

If neuron j is not in the output layer,

$$\delta_j = O_j\, (1 - O_j) \sum_k \delta_k W_{ik} \tag{7}$$

In order to improve the convergence characteristics, we can introduce a momentum term with again α to Equation 5 .

$$\Delta W_{ij}(n+1) = \varepsilon\, \delta_j O_j + \alpha\, \Delta W_{ij}(n) \tag{8}$$

where n represents the iteration index.

Once the neural network is trained it produces very fast output for given input data. It only requires a few multiplications, additions, and calculations for sigmoid function [8].

IV. RESULTS

The software used for the ANN here is the BrainMaker which is developed by California Scientific Software [14]. A set of actual geomagnetic records is used to train the ANN. In addition, to this training set, an independent set must be available to evaluate the ANN performance. The holdout technique is adopted. The available data records are splitted into two mutually exclusive sets: the training data set and the test set. The data from the first set are used to train the network. The network that results from the training process is then checked against the data from the test data set to determine whether the network is a good representation of the time series and can therefore be expected to make reasonable predictions. This step was accomplished in two ways: (1) to test for short-term prediction accuracy and, (2) to test the network prediction ability for long-term predictions.

The neural network structures used in this paper, including the size of the hidden layer, were chosen from among several structures. The chosen structure is the one that gave the best network performance in terms of accuracy. In most cases, we found that adding one or two hidden neurons did not significantly affect the neural network accuracy.

Table 1 shows five sets used to test the neural network. Each set contains 6 normal days. These test data were not used in the training process of the neural network.

Table 1 Test Data Sets

sets	Test data from
set 1	04/01/86 - 04/06/86
set 2	05/20/86 - 05/25/86
set 3	12/13/89 - 12/18/89
set 4	10/21/91 - 10/26/91
set 5	11/25/86 - 11/30/86

To evaluate the resulting ANN's performance, the following percentage error measure is used throughout this paper :

$$\text{error} = \frac{|\text{actual value} - \text{forecasted value}|}{\text{actual value}} \times 100 \qquad (9)$$

IV.1 Short-Term Forecasting

To test for short-term prediction accuracy, the network is given actual values from the test data set as its input and the resulting output is compared with the next time series data point. This was done for every point in the test data set, and the error statistic was calculated. This error estimates the accuracy of short-term predictions by the network. The ANN was trained to recognize the following cases:

<u>Case 1:</u> Peak value of the day

The peak value at day d is defined as the maximum hour value of the day i.e.

$$\max \{ V(1,d), \ldots, V(24,d) \} \qquad (10)$$

The topology of the ANN for the peak value forecasting is as follows;

Input neurons : V(k-7),V(k-6),V(k-5),V(k-4),V(k-3),V(k-2), and V(k-1)
Hidden neurons : 14 hidden neurons
Output neuron : V(k)

where

k = day of predicted value,
V(k) = *peak value* at day k.

Table 2 shows the percent error of each day in the test sets. The average error for all 5 sets is 1.68 %.

Table 2 Error (%) of Peak Value Forecasting

days	set1	set2	set3	set4	set5
day1	1.23	2.61	1.46	0.60	2.35
day2	0.82	1.11	1.33	1.23	0.32
day3	1.28	2.34	1.90	0.57	2.44
day4	2.05	2.52	2.24	2.04	1.80
day5	2.45	1.50	0.41	2.89	2.40
day6	0.08	1.95	1.35	1.76	2.70
Avg.	1.57	2.02	1.47	1.47	1.86

Case 2: **Mean value of the day**

Mean Value at day $d = (\sum_{h=1}^{24} V(h,d))/24$ (11)

where $V(h,d)$ is the geomagnetic data value at hour h on day d.

The topology of the ANN for the mean value forecasting is as follows;

Input neurons : V(k-7), V(k-6), V(k-5), V(k-4), V(k-3), V(k-2), and V(k-1)
Hidden neurons : 14 hidden neurons
Output neuron : V(k)

where
k = day of predicted value,
V(k) = *mean value* at day k.

Table 3 shows the error (%) of each day in the test sets. The average error for all 5 sets is 1.51 %.

Table 3 Error (%) of Daily Mean Forecasting

days	set1	set2	set3	set4	set5
day1	0.82	3.59	2.28	2.22	0.70
day2	2.49	2.57	2.49	2.26	1.42
day3	0.18	2.24	2.50	2.17	2.91
day4	1.32	0.92	1.84	2.44	0.53
day5	2.05	1.76	4.14	1.98	2.37
day6	2.58	0.95	2.66	0.44	0.62
Avg.	1.57	2.01	2.65	1.92	1.42

Case 3: **Hourly pattern of one-day**

The ANN was trained to forecast hourly patterns for future days. The topology of the ANN for one day ahead forecasting is as follows;

Input neurons : $V(i)$, $i = 1, 2, \ldots, 24$
Hidden neurons : 24 hidden neurons
Output neuron : $V(k)$, $k = 1, 2, \ldots, 24$

where i = hour of input data,
$V(i)$ = input pattern at hour i,
k = hour of predicted value,
$V(k)$ = *predicted pattern* at hour k.

Table 4 shows the error (%) of each day in the test sets. The average error for all set is found to be 2.02 %. Note that each day's result is averaged over a 24 hour period .

Table 4: Error (%) of Hourly Load Forecasting

days	set1	set2	set3	set4	set5
day1	1.35	1.39	1.41	1.37	1.41
day2	2.11	2.11	2.12	2.04	1.94
day3	2.46	2.44	2.50	2.58	2.59
day4	1.66	1.68	1.62	1.60	1.58
day5	1.96	1.90	1.89	1.91	1.93
day6	2.53	2.60	2.66	2.65	2.69
Avg.	2.01	2.02	2.03	2.02	2.02

Fig.5 shows two examples of the hourly actual and forecasted patterns (short-term forecasting) for one day ahead.

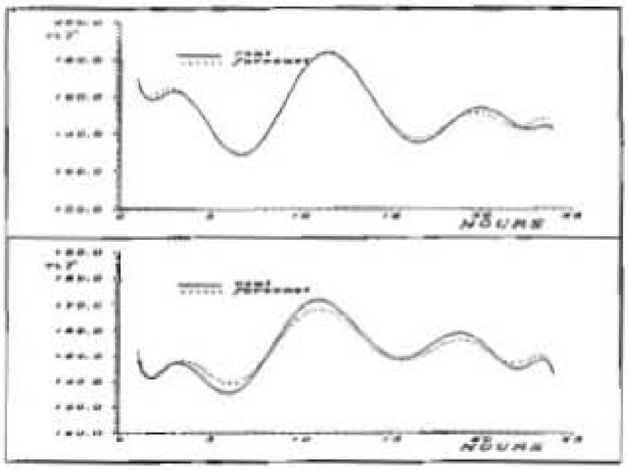

Fig. 5 Hourly patterns of real and forecasted days

IV.2 Long-Term Forecasting

The ability of the network to make longer-term predictions was also tested. To do this, the network is given input hourly pattern of one-day from the test data set. The output of the network, which is the predicted future hourly pattern, is then used as the next input data set. The output from the second prediction is likewise used as the third input data set. Continuing the process in this way, the network recursively propagates the time series forward in time to make prediction for 30 days ahead.

Fig.6 shows the results of long-term forecasting for a period of one month ahead: actual data of one day (24 hour) only are used as an input and the successive 29 days are predicted. Fig.7 illustrates the results of day 5, day 15 and day 20 for the same month. The percentage error is less than 10%. The validity of the predicted data are also confirmed by comparing the total power, amplitude distribution, and the number of zero crossings of the real and predicted records. A good agreement of the actual and predicted values is obtained.

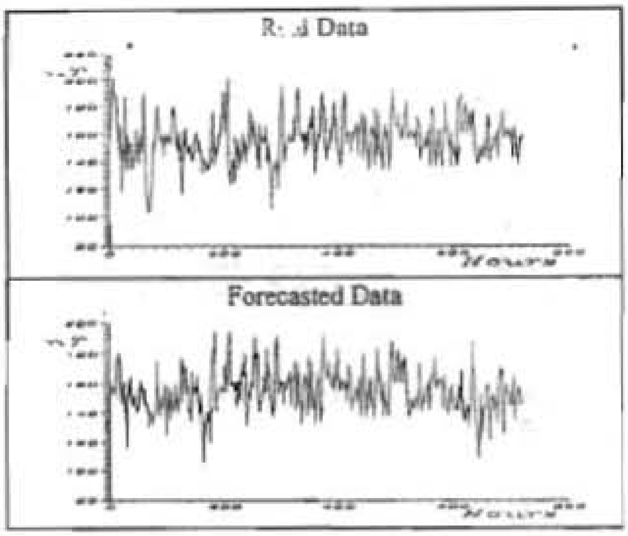

Fig. 6 Results of long-term forecasting for a period of 30 days

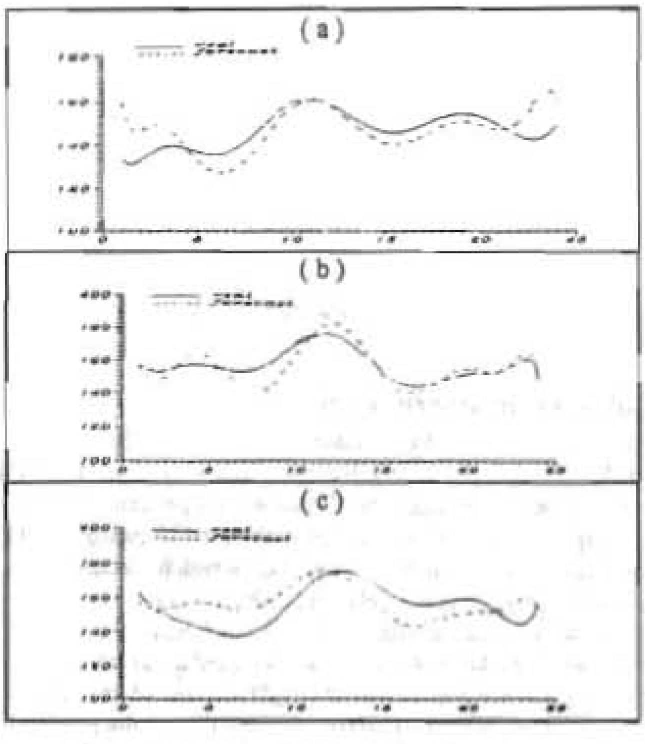

Fig.7 The results of long-term forecasting
of (a) day 5, (b) day 15, and (c) day 20

V. CONCLUSION

We have presented a neural network approach to forecasting geomagnetic time series. In our work real and simulated data have been used to train and test the predictive power of the artificial neural networks. Remarkable success has been achieved in training the networks to learn the data patterns and thereby to make accurate data predictions; we obtain a very close fit during the training phase. The average error does not exceed 3% in our test on actual data. Our results show that the neural network approach gives good estimates for short-term and long-term forecasting.

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