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The Rule of Artificial Neural Network Algorithm in Geomagnetic Storms Prediction

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Abstract

While relativistic electrons can completely destroy a spacecraft when the solar wind-magnetospheric interactions are enhanced, the Dst index is considered to be an indicator of any geomagnetic storm. The more negative the Dst index values, the stronger the magnetic storm. Every relativistic electron event was associated with a magnetic storm, but, magnetic storms could occur without appreciable enhancement of the relativistic electron fluxes. The problem thus arises, which one should be predicted: the Dst index or relativistic electron enhancements (REE), in order to be more logic? and which is more effective for prediction: the use of statistical relationships or Artificial Neural Networks? Reproduction (or simulation) of the Dst index using a neural network algorithm would solve the problem.

An Artificial Neural Network Algorithm was adopted in the present study for the reproduction of the Dst index of geomagnetic storms having the training concept "Train to Gain" in mind. The ANN was well trained using a data set of 37 storms of different intensities as input to the network. A well trained ANN would yield an extremely good correlation between the measured Dst and the predicted Dst.

The applied ANN algorithm in the present study shows an excellent performance. About 97% of the Dst have been reproduced, at least, for both the main and recovery phases. Efficient forecast of the oncoming relativistic electron flux enhancements (REE) can thus - under certain conditions - be issued.

Keywords: Geomagnetic storms, Geosynchronous orbit, Solar cycle-23, Dst index, Relativistic Electron Enhancement, Artificial Neural Network.

1 Introduction

Intense geomagnetic storms seem to be related to intense interplanetary magnetic field (IMF) with a southern component for a long time (Gonzalez & Tsurutani 1987; Tsurutani 2001). Dungey (1961), Tsurutani & Meng (1972), Akasofu (1981), Gonzalez & Mozer (1974) and Gonzalez *et al.* (1989) pointed out the reconnection between a southern IMF and the magnetospheric magnetic field as the physical mechanism responsible of Sun-Earth connection.

When the electric field is intense enough as to enhance the current of the ring current above a value, a geomagnetic storm is produced. The Dst index is considered to be an indicator of the current of the RC (Kamide *et al.* 1998; Daglis *et al.* 1999).

This hourly index is calculated as the horizontal variation of geomagnetic field measured at four different observatories distributed in longitude and near Earth equator. Then, if Dst index reaches -50nT, the event is considered as a geomagnetic storm and if it passes -100nT the storm is considered as intense. Major geomagnetic storms can reach more that -300nT (Cerrato *et al.* 2003).

2 Magnetic Storm Forecasting

Magnetic storm forecasting is one of the most important problems of solar-terrestrial physics and the keystone of space weather science.

Burton *et al.* (1975) proposed an empirical linear relationship for predicting the Dst index from the knowledge of the solar wind velocity, density, and the southward component of IMF. Gonzalez *et al.* (1994), Murayama (1982), Thomsen *et al.* (1998), Klimas *et al.* (1998) and O'Brien & McPherron (2000) have tested, improved, or attempted to improve the prediction by modifying the driver and decay terms. Other innovative techniques were introduced by Vassiliadis *et al.* (1999). Wu & Lundstedt (1996; 1997), Kugblenu *et al.* (1999) and Watanabe *et al.* (2002) used neural network methods.

In a geomagnetic storm, two phases can usually be distinguished. The first one, the main phase, when energy passes from solar wind to magnetosphere enhancing the current of the RC and producing a strong decrease of Dst index. After, a recovery phase, when the magnetic field on the Earth surface goes back to the value of quiet time because of a decay of the current of the RC. This decay is due basically to loss processes as exchange of charge (Gonzalez *et al.* 1994; Jordanova *et al.* 1996), Coulomb interaction (Kozyra *et al.* 1998), and particle-wave interaction (Kozyra *et al.* 1997). Each process is sensitive to ions energy, composition, pitch angle, distribution, etc. Then, decay time is a mean value in the RC as a whole that includes all these contributions (Cerrato *et al.* 2003).

Successful magnetic storm forecasting is one of the main aims of the space weather investigations. Forecasting methods can be classified into short-term (about 1 hour in advance, using spacecraft data), medium-term (about 1-4 days), and long-term (>7 days, solar cycle intensity predictions). The short-term forecasts are rather exact, up to ~90%, but their alert time (ΔT ~1 hour) is too small for preventing of storm hazard (Khabarova 2007).

3 Problems of Magnetic Storm Prediction

3.1 Statistical relationships

Statistical relationships between the solar wind and IMF parameters have turned out to differ, sometimes significantly, at various solar cycle phases. This fact may indicate that intrinsic properties of the solar wind and IMF, as well as their magnetospheric response, vary during a solar cycle. Prediction algorithms must adapt to these variations, otherwise they would be not equally effective during various phases of solar cycle (Khabarova *et al.* 2006).

3.2 Medium-term geomagnetic storm prediction

Predictions on growing and decay of geomagnetic storms from solar wind conditions follow on improving. Nowadays, it is possible to reproduce roughly the hourly variation of the index Dst from solar wind data by several techniques (linear and non-linear). The problem arises when a storm is made of several substorms nearly in time. Then, the main phase of Dst index is not properly reproduced by any technique. Moreover, the relative importance of storms and substorms in building of RC is still an open problem.

Therefore the main problem of medium-term geomagnetic storm forecast is: in spite of our growing knowledge we can predict only 75% of geomagnetic storms with Dst <-80nT, *i.e.* we can predict only 75% from 10% of the total number of magnetic storms, *i.e.* we can predict only 7.5% of all geomagnetic storms, *i.e.* we can predict almost nothing (Khabarova 2007).

3.3 The Dst index and relativistic electron enhancement (REE) prediction

The Dst index is widely used as a measure of the strength of the ring current and is generally used to define the disturbed magnetospheric conditions that we call "magnetic storms".

Wrenn *et al.* (2000) has shown a solar-cycle dependence of the intensity of relativistic electron enhancements. The relativistic electrons in the outer radiation belt exhibit a decrease in flux when monitored at a geosynchronous orbit during the main phase of a magnetic storm. Then the flux level increases during the recovery phase (Hwang *et al.* 2004). Baker *et al.* (1994) explained that enhancement of high energy electron flux has harmful effects on satellite operations, weather observations, and valuable services to human societies. Lam (2004) predicted the relativistic electron fluence based on its relationship with geomagnetic activity.

Every relativistic electron event was associated with a magnetic storm in the Dst index, but, magnetic storms could occur with no appreciable enhancement of the relativistic electron fluxes. The solar wind conditions that are necessary to generate a ring current response are also necessary to generate a strong relativistic electron response but that there is some additional factors, either in the solar wind or in the magnetosphere, that determine whether a given storm will produce relativistic electrons or not and how strong that response will be (Reeves 1998).

4 Artificial Neural Networks

A neural network is a mathematical algorithm that can be trained to solve a problem that would normally require human intervention.

Neural networks can be thought of multi-channel processing systems which attempt to learn and generalize a set of processing rules given a number of known inputs and, optionally, known outputs. Although there are many different types of neural networks, there are two ways in which they are categorized: by the type of problem that they can solve and by their type of learning (Russell 2005).

One of the most unique properties of these Artificial Neural Networks is their ability to generalize to new situations after having been trained on a number of examples of a relationship. They can then induce a complete relationship that interpolates and extrapolates from the examples. ANNs therefore offer the possibility to study large complex nonlinear systems of highly inter-correlated data (Kugblenu *et al.* 1999).

4.1 Neural networks learning

The most common example of the supervised learning neural network is the multi-layer perceptron, or *MLP*, which has become almost synonymous with the term neural network, and is illustrated in Figure 1.

The *MLP* shown in Figure 1 consists of three layers, and the lines between the layers represent weights that are applied to the outputs of each layer. The circles in the first layer represent the inputs, but in the other two layers are nonlinear functions which are applied to the weighted outputs. The weights in the MLP are determined by back-propagating the errors between the inputs and the outputs, and this is both time consuming and potentially non-repeatable

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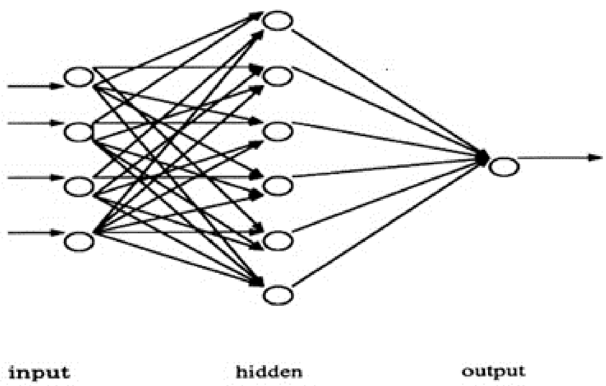

Figure 1 A multi-layer perceptron neural network.

With a desire to learn how predictable the magnetosphere is and in an attempt to make a better prediction, the present authors applied the artificial neural network method for network training and prediction following Kugblenu *et al.* (1999). This network belongs to the class of supervised networks, *i.e.* it learns from known answers. Detailed explanation is given in their paper.

5 Data Sets and Network Training

An artificial feed-forward neural network with multi-layer network and error back-propagation learning is used to predict the geomagnetic activity index (Dst). This network structure is flexible to configure since all parameters are commutative. The model is a feed forward multi-layer network with error-back-propagation learning, and applied as a nonlinear, multi-variable least squares algorithm. It was trained using a data set consisting of minimum Dst (Dst_{min}) value in the main phase for each storm, the corresponding solar wind data (IMF southward component Bz, the velocity of the solar wind (Vsw), and dynamic pressure $\sqrt{nV^2}$) for that hour, and 3 consecutive preceding hourly Dst values in the main phase as input to the network. A data set for one storm thus consists of a six-parameter input and a corresponding one parameter output. This is presented to the net during training. In other words, only the main phase information was used for the network training. This trained network was thus able to reproduce the recovery phase with high accuracy.

For both network training and prediction, the network is trained on OMNI data set from the database of the National Space Science Data Center of NASA and the WDC-2 Data Center of Kyoto University covering a total of 1370 hours, extracted from the 9-year period from 1998 to 2006, *i.e.* they are distributed along Solar Cycle 23. These data sets consist of hourly averages of the solar wind plasma and IMF data from various spacecraft.

5.1 Selection of events

Dst is an important space weather parameter since it is the main indication of magnetic storms. Due to the incompleteness of solar wind data, selection of storm events was, however, limited. Storms with large and sustained southward IMF were given priority in the selection process provided that the storm has been preceded by a relatively quiet period of Dst activity as well as sudden increases in the velocity of solar wind, mostly above 450 $km.s^{-1}$.

Thirty seven storms of different intensities were selected considering the intense and severe geomagnetic storms that occurred during Solar Cycle 23 by setting a value of Dst_{min} ≤-100nT as threshold, provided that the 1-minute average electron fluxes energies are >2MeV. When the solar wind data set corresponding to the minimum value of Dst is not available in the database, the nearest hour having a complete data set was considered.

6 Network Prediction

For prediction, the six parameters were used with no corresponding output parameter. This includes three preceding previous Dst values and the solar wind data set for each hour of a storm event. Different network architectures with various numbers of hidden nodes have frequently been used. In the present study, 6 nodes for the hidden layer with a corresponding one parameter output were satisfactory.

The purpose of the present study is to reproduce the Dst index for the recovery phase using data from the main phase, nevertheless the trained ANN were applied to the period starting with several hours before the beginning of the initial phase. It is worthwhile to mention that the recovery phase, which is more dependent on the internal processes of the magnetosphere, is bound to be represented by the Dst history. The Dst_{min} marks the beginning of the recovery phase during which the ring current decays.

Three intense and severe magnetic storms of Solar Cycle 23 were chosen to represent the application of ANNs prediction technique in the present study.

6.1 October 22, 1999 magnetic storm

The interplanetary and geomagnetic observations for October 21-23 show that there is an increase in both plasma density and flow speed between 04:00 UT and 07:00 UT on October 22, 1999 (which is the storm day). This is coincident with a sharp turning of Bz to a minimum peak value of -29nT within the same time interval on October 22. These are all indicative of arrival of a shock in the planetary medium. However, there is rarely a forward shock of geomagnetic storms associated with co-rotating interaction region (CIR) – like plasma signatures that rarely have a Dst_{min} <-100nT. Therefore, the compression is gradual with no "sudden impulse" or SSC (Adebesin 2008).

The selected 120 data points were extracted from SPIDR for the application of ANNs prediction technique. The Dst plot (Figure 2) shows a rather quiet observation until around 00:00 UT on October 22, when it falls sharply from a value of +21nT reaching a peak value of -231nT at 07:00 UT on the same day. This sharp decrease is coincident with a southward turning of Bz to a peak value of -31nT (as recorded by OMNI) before it and thereafter turns northward and recovers throughout October 23, 1999 until 1400 UT hour. The electron flux of >2MeV reached a maximum of 38700 Particles/cm^2-s-sr at 1820 UT on the 25th October, 1999.

A good agreement between the measured Dst and the predicted one does exist (Figure 2).

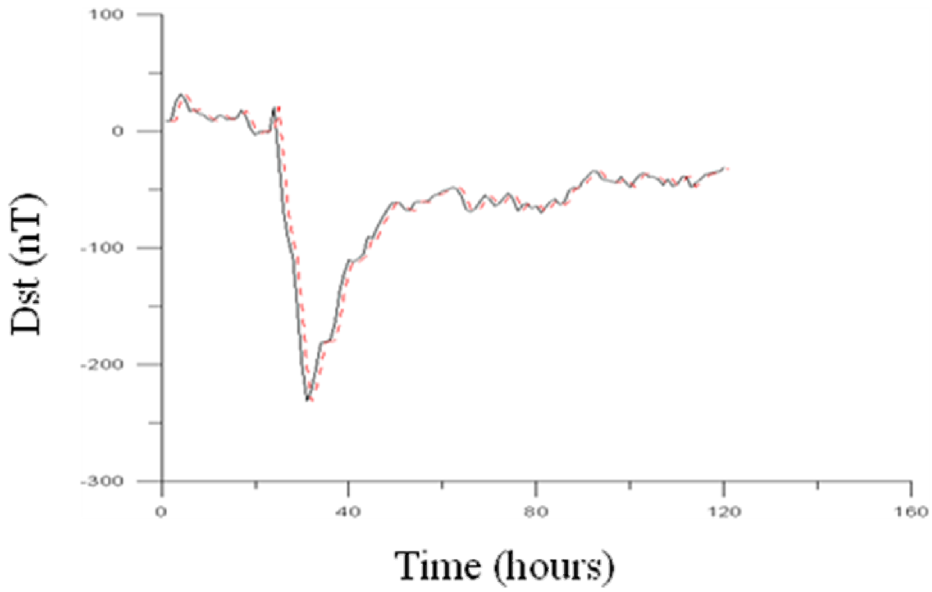

Figure 2 Observed and predicted Dst plot of October 22, 1999 storm. The x-axis represents time from 0000 UT, October 21, 1999.

6.2 November 20, 2003 magnetic storm

This magnetic storm is the most intense magnetic storm of the current solar cycle where Dst_{min} has reached -472nT.

The number of data points which were selected for the application of ANNs prediction technique were 144 (recorded by GOES-10). Figure 3 shows the observed and predicted Dst plot of the present event. The description of which was published by Rawat *et al*. (2007) and briefed as follows: On 20 November 2003, an interplanetary shock, observed by ACE at 0720 UT, featured by sudden increase in solar wind parameters such as solar wind velocity (Vsw) ~620km.s^{-1}, proton density (Np) ~18cm^{-3} and and IMF |*B*| ~22nT. After the shock IMF |*B*| increased to larger values peaking later to values as high as ~56nT and IMF *Bz* was predominantly southward just after the shock till 0955 UT on 20 November 2003, when it turned sharply northward followed shortly by southward traversal at 1050 UT. Southward orientation prevailed for ~13 hours with a peak of -50nT. After ~45 minutes from interplanetary shock (IPS) at ACE, the increase in solar wind dynamic pressure (~12nPa) produced magnetopause compression marked by storm sudden commencement (SSC) at 0805 UT with amplitude ~25nT. Main phase depression started shortly after the SSC in consistence with southward *Bz* on 20 November 2003 and the main phase (1156-1911 UT) prevailed for ~7 hours followed by rapid recovery. Main phase for this intense storm event reached a maximum magnitude of ~626nT at Alibag when Dst attained a peak of -472nT. This storm although intense, it is a non REE storm. The electron flux of >2MeV reached a maximum of 27700 Particles/cm^2-s-sr at 0004 UT on 20th November, 2003.

A good agreement between the measured and predicted Dst can be observed in Figure 3. To test the credibility of the present ANNs prediction technique, the average relative variance (*ARV*) was also calculated, *i.e.* the mean squares error normalized by the variance of the data,

$$ARV = \frac{\sum_{t=1}^{N}(D(t)-O(t))^2}{\sum_{t=1}^{N}(D(t)-(D))^2} \quad (1)$$

and the root mean squares error (*RMSE*):

$$RMSE = \left[\frac{1}{N}\sum_{t=1}^{N}(D(t) - O(t))^2\right]^{1/2} \quad (2)$$

for the same interval, where *D(t)*, (*D*) and *O(t)* denote observed, its averaged, and predicted Dst, respectively (Kugblenu *et al.* 1999).

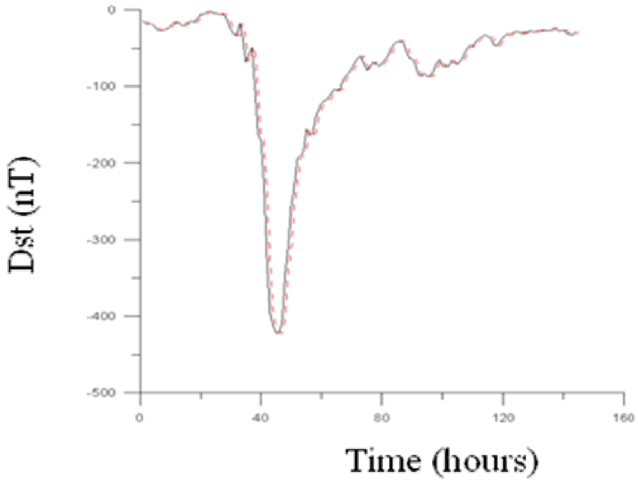

Figure 3 Observed and predicted Dst plot of November 20, 2003 storm. The x-axis represents time from 0000 November 19, 2003.

As a resembling sample, the correlation coefficient between the measured and predicted Dst for this event, over the recovery phase is 0.99 (Figure 4), demonstrating a very fine agreement. The diagnostic parameter *ARV* has been calculated to be 0.03, indicating that ~97% of the observed Dst variance is predictable. The value of *RMSE* is 2.2nT, which is very small compared with the lowest peak value of Dst.

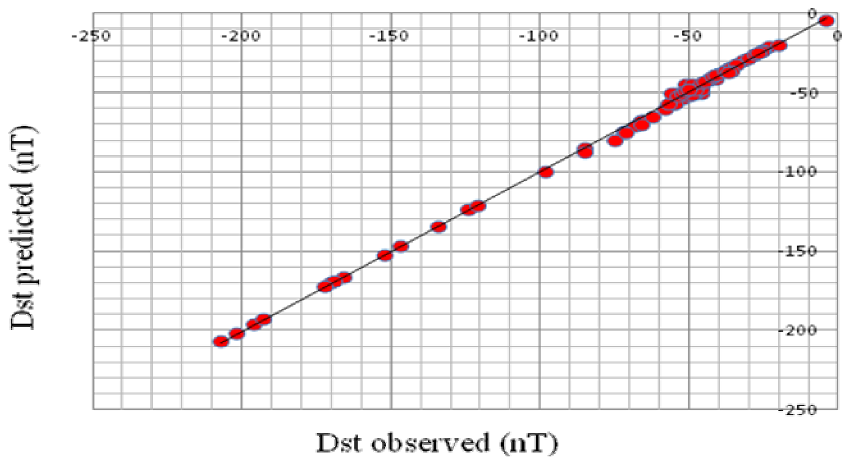

Figure 4 Correlation plot of Dst observed and Dst predicted of November 20, 2003 storm.

6.3 November 10, 2004 magnetic storm

This magnetic storm is a part of a magnetic storm consequence that started at November 7, 2004 and lasted on November 13, 2004. November 10, 2004 magnetic storm event is characterized by the highest electron flux (85900MeV) among this consequence, thus it was selected in the present study. It commenced at the 0159 UT of 10th day of November, 2004.

From a value of -146nT, Dst decreased to a low value of −289nT to comprise the main phase. The Dst index began a disturbed, long-lasting and slow recovery until the 1710 UT of 11th day of November, 2004, which was the onset of another magnetic storm. The electron flux of >2MeV reached a maximum of 98900 Particles/cm^2-s-sr at 2202 UT on 11th November, 2004.

For the application of ANNs prediction technique 192 data points were chosen from OMNI Data Documentation. The agreement between measured and predicted Dst is rather satisfactory for this magnetic storm consequence (Figure 5).

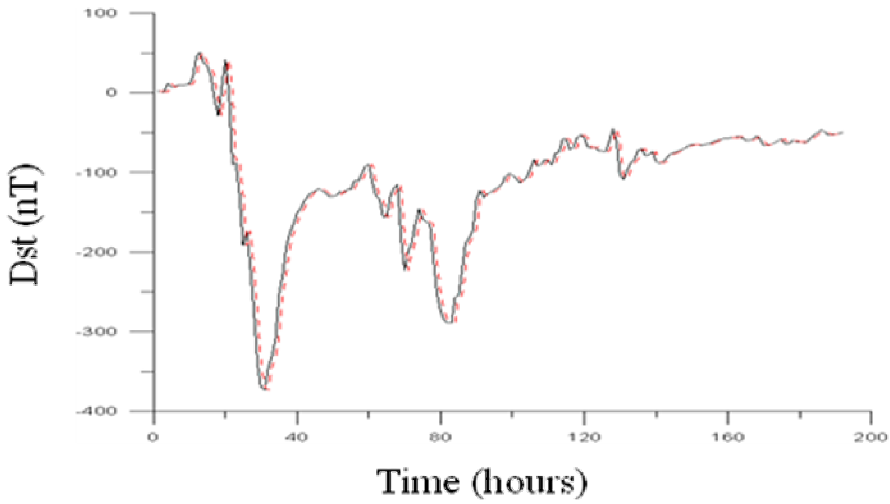

Figure 5 Observed and predicted Dst plot of November 10, 2004 storm. The x-axis represents time from 0000 November 7, 2004.

7. Conclusion

The present research was commenced intending to make an accurate and effective magnetic storm forecasting. Most of the storm events studied (which spans between 1998 and 2006) are characterized by Dst_{min} ≤-100nT, electron flux of >2MeV and a southward interplanetary magnetic field. The number of preceding hourly Dst values included beside the solar wind data as input to the network was significant in reproducing the current Dst . Our model starts from 0000hr of the preceding day of the event's Dst_{min}.

The applied ANN for reproducing the recovery phase Dst index in the present study shows an excellent performance. About 96-97% of the observed Dst variance is predictable from both solar wind and Dst history. With the Dst_{min} calculated three hours before the minimum in the main phase, the herein applied ANNs prediction technique can provide real-time and accurate recovery phase alerts at the very beginning of the main phase of a magnetic storm even though it is not yet over. This model has greatly improved the prediction accuracy and enhanced the recovery phase reproduction. It seems that the training concept "Train to Gain" is true even for an artificial neural network.

Efficient forecast of the oncoming relativistic electron flux enhancements (REE) can thus be issued if the solar wind speed is higher than average (*i.e.* >450km/s) and the interplanetary magnetic field is southward.

A well trained Artificial Neural Network Algorithm is thus one of the most important techniques of solar-terrestrial physics and a keystone for space weather forecasting.

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