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Prediction of Geomagnetic Storm using Multi-layer feed-forward Neural Networks

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Abstract

The geomagnetic storm plays an important role over the variations of different parameters of magnetosphere and ionosphere. In this paper, an attempt is made for prediction of geomagnetic storm using multi layer feed forward artificial neural network using D_{st} and solar wind data. The D_{st} and solar wind data in this research are selected from the period 1998 to 2013. The input data consist of solar wind B_z component. A few case studies made by application of this technique are presented in this paper.

Key words: *1; ionosphere. 2; geomagnetic storm. 3; artificial neural network.*

1. Introduction

The solar wind, interplanetary magnetic field and terrestrial magnetosphere play an important role in the dynamics of the magnetosphere. Gonzalez et al. (1994) defined that "The geomagnetic storm is an interval of time when an adequately strong and long lasting interplanetary electric field leads, through a considerable energization in the magnetosphere-ionosphere system, to an intensified ring current strong enough to exceed some key threshold of the quantifying storm time DST index". The geomagnetic index D_{st} was introduced by Sugiure in 1964 as a measure of the ring current magnetic field. This index is defined as the reduction of the horizontal magnetic field component at the geomagnetic discipline at equator, and has often been used in studies of solar wind magnetosphere coupling. The development of D_{st} can be described in terms of source and loss mechanism [Burton et al., 1975]:

$$\frac{d(Dst)}{dt} = Q - \frac{1}{\tau} Dst$$

where Q is the coupling function and τ is the decay time of the ring current.

Various techniques have been utilized to study relationship between solar wind and magnetospheric response and to predict geomagnetic storm based on observational data and solar wind data. Feldstein et al. [1984] has proposed ring current simulation and Burton et al. [1995] proposed a prediction algorithm for D_{st}. Linear prediction filtering method was first applied to a study of solar wind magnetosphere coupling by Iyemore et al. [1997], supposing that a geomagnetic disturbance and a solar wind input can be related by a liner time interval filter. From those studies using linear prediction filtering method it has been shown that solar wind magnetosphere coupling is nonlinear since the filter or the impulse response function evolves with varying geomagnetic activity level. Recently, predictions of geomagnetic activity have been improved by developing nonlinear dynamical analogue models [Barker et al., 1990, Klimas et al., 1992, 1994] or by using nonlinear prediction filtering methods [Price et al., 1993,1994, Vassiliadis et al., 1995].

Artificial Neural Networks(ANN) have often been used as an alternative to the techniques of standard nonlinear regression and cluster analysis to carry out statistical analysis and data modeling [*Cheng and Titterington, 1994*]. In addition, computer scientists and engineers have seen ANNs, as providing a new experimental paradigm for Parallel Distributed Processing, rather than the algorithmic paradigm that dominated the field of machine intelligence prior to the ANN revolution *[Gurney, 1999]*. There have already been some applications of ANN to predicting geomagnetic activity [Kugblenu et al.,1999, Lundstedt et al., 2002]. In this paper, an attempt is made for prediction of geomagnetic storm using multi layer feed forward artificial neural network using D_{st} and solar wind data. In this study, the hourly data of solar wind and geomagnetic index are obtained from the National space science data center OMNI database.

2. Analysis and techniques

For the artificial neural network model the geomagnetic storm events of 1998 to 2013 are considered for prediction. Here the Bz component of solar wind is considered as input and D_{st} is considered as target for the network. In the experiment, multi-layer feed-forward neural networks with 24 input nodes, variable number of hidden nodes as well as layers and one output layers are considered. To train the network error back propagation algorithm has been utilized. The system is checked with number of hidden nodes and layers for better accuracy in terms of prediction of geomagnetic storm. But with increasing number of hidden nodes, the time required for convergence is also increased. Considering all parameters, it has been notified that multilayer perceptron with 3 layers (two hidden and one output) give optimal performance for prediction of geomagnetic storm.

2.1 Multi-layer feed-forward neural networks

Multi-layer feed-forward neural networks with error back propagation learning algorithm are most popular technique for prediction modeling. It consists of neurons that are ordered into three layers which are input layer, output layer and the hidden layer. For formal description of neurons suppose Γ is the mapping function which assigns for each neuron i, a subset $\Gamma(i) \subseteq \gamma$ which consist of all ancestors of the given neuron. Each neuron in a particular layer is connected with all neurons of the next layers. If w_{ij} is weight coefficient of the i^{th} and j^{th} neuron and for i^{th} neuron the threshold coefficient is γ_i , the output value of the i^{th} neuron X_i is determined by

$$X_i=f(\varepsilon_i)$$

$$\text{where } \varepsilon_i = \gamma_i + \sum_{j \in \Gamma_i^{-1}} w_{ij} X_j$$

Here ε_i is the potential of the i^{th} neuron and $f(\varepsilon_i)$ is the transfer function

The threshold coefficient can be describes as a weight coefficient of the connection with formally added neurons added j where $X_j=1$(bias).

For transfer function it can be represented mathematically as follows

$$f(\varepsilon i) = \frac{1}{1+\exp(-\varepsilon)}$$

The supervised adjustment process varies on the value of γi and w_{ij} to minimize the sum of the squared differences between the computed and required output values. This is accomplished by minimization of the objective function ϵ

$$\epsilon = \sum_{0} 1/2(X_0 - X_0)^{2}$$

Where X_0 and $\hat{X}_0$ are vectors computed and required activities of the output neurons and summation runs over all output neurons o.

2.2 Network Training

Training a network defines finding a set of weights that minimizes the average error on the training set. The training is done iteratively by presenting the network known input output pairs, calculating the error and updating the weighting consequently. Here, for training the network the error back propagation training algorithm is used.

In the error back propagation training algorithm, the error in the network when training pair p is presented is defined as

$$E_p = {}^{1}/_{2} \sum (t_{pj} - o_{pi})^2$$

where t_{pj} is the target value for the j^{th} element of the output pattern from the training pair p.

o_{pj} is the actual value provided by the network for the j^{th} element of the output pattern when the input pattern from the training pair p is presented to its input.

Therefore the overall error is $E = \sum_p E_p$

The input node j is $\mathrm{net}_{inp} = \sum_i w_{ji}\, o_{pi}$

Where w_{ji} is the weight from i^{th} node of the previous layer to the j^{th} node at time than the input/output pair p is presented to the network. O_{pi} is the output of the i^{th} node of the previous layer. To implement a gradient descent the native derivative of E_p with respect to the w_{ji} must be proportional to the change in the weight w_{ji}, $\Delta_p w_{ji}$. Therefore,

$$\Delta_p wji \propto -\frac{\delta E_p}{\delta w_{ji}} \qquad (1)$$

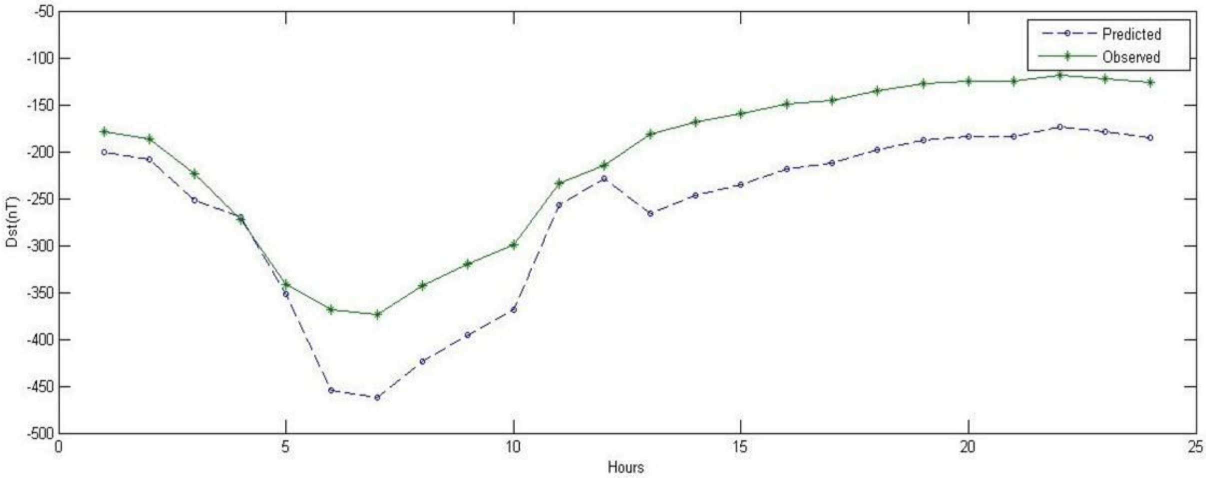
Solving equation (1) based on *S. Karpagavalli et al.* [S. Karpagavalli, et. al., 2012.]

$$w_{ji}(t+1) = w_{ji}(t) + \eta \boldsymbol{\delta}_{pi} f'_j(\mathrm{net}\ p_j o_{pi})$$

where $w_{ji}(t+1)$ is the weight from the i^{th} node to j^{th} after adjustment. Equation (1) is known as the standard delta rule and defines how weights are changed after presentation of a training pair.

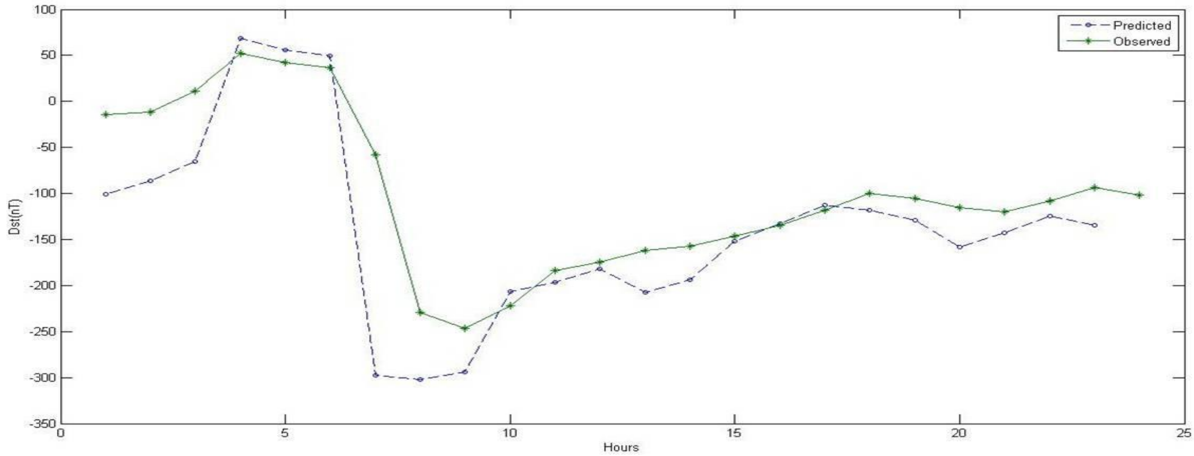
3. Results

Figure 1, 2 and 3 shows the predicted and observed D_{st} for 24 hours of a geomagnetic event. Figure 1 shows the prediction result for the storm of November 8, 2004 compared with observed D_{st}. The solid and broken line represents the observation and prediction, respectively. In the geomagnetic event of November 8, 2004 it is observed that the D_{st} become minimum at 07.00 hour and observed D_{st} is -375 nT and predicted D_{st} is -460 nT. From the figure it is also observed that the model predicted similar trend of D_{st} with the observed with respect to time.



08 November 2004

Figure 1: Observed and predicted D_{st} plot of November 8, 2004 storm.

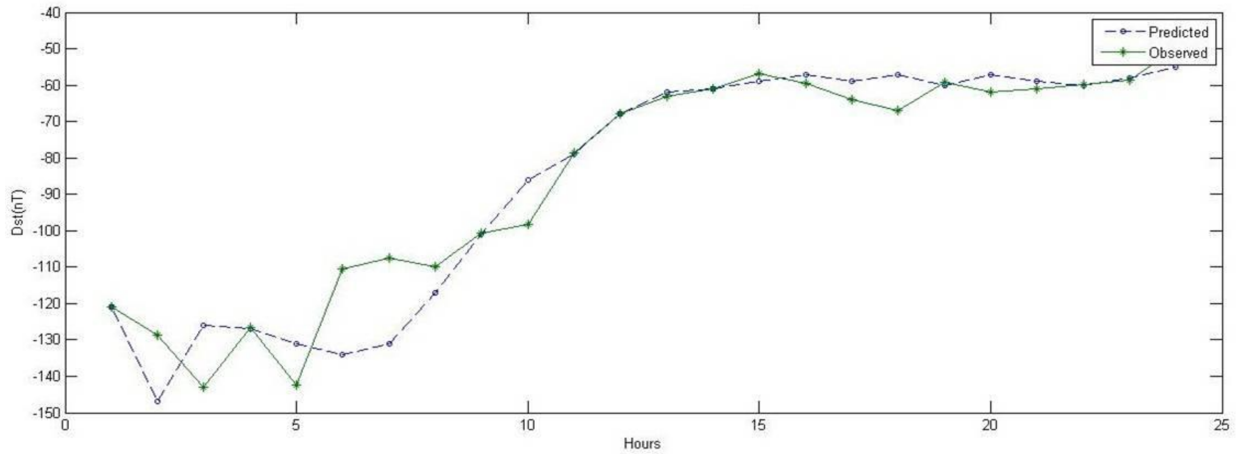


15 May 2005

Figure 2: Observed and predicted D_{st} plot of May 15, 2005 storm.

Similarly, Figure 2 represents the predicted and observed D_{st} for the storm of May 15, 2005. In the figure, the value of observed D_{st} increases at 04.00 hour to 50 nT and suddenly decreases at 09.00 hour to -250 nT. Again the predicted D_{st} values also increases at 04.00 hour to 70 nT and become minimum at

07.00 to 09.00 hour to about -300 nT. The result also shows a good relation between the predicted and observed D_{st}.



25 October 2011

Figure 3: Observed and predicted D_{st} plot of October 25, 2011 storm.

Next in the Figure 3, the value of observed D_{st} decreases to -145 nT at 3.00 hour. The predicted D_{st} value is also decreases to -148 nT at 2.00 hour. The predicted result shows similar trend of D_{st} with the observed with respect to time.

One of the disadvantages of using a large input data is that the number of input nodes and number of weights become large. If we want the number of weights to be a exact fraction of the number of training data, then we have to eliminate hidden nodes as the size of input data sequences increases. There could be then risk that the network looses its ability to model the full complexity of the problem.

4. Conclusion

In this paper, an attempt is made for prediction of geomagnetic storm by means of multi layer feed forward artificial neural network using D_{st} and solar wind data. This is the first step for utilizing this approach for prediction of geomagnetic storm. The model can predict nicely the D_{st} profile for 24 hours for the solar wind Bz component. However the limitation is that it cannot resolve fine structure because the enormous increase in size of the necessary matrix for computation such changes. It is planned to adapt, in future, other parameters like solar wind density, velocity and Bs component of solar wind as input to the system and use Nonlinear Autoregressive models with eXogenous input recurrent neural network for prediction of D_{st}.

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