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A solar wind-based model of geomagnetic field fluctuations at a mid-latitude station

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Abstract

Anomalous quasi-DC currents known as geomagnetically induced currents (GIC), produced in electric power network infrastructure during geomagnetic storms, pose a risk to reliable power transmission and network integrity. The prediction of a geomagnetic field-derived proxy to GIC provides an attractive mitigation technique that does not require changes to network hardware. In this paper we present the development of two artificial neural network based models tasked with predicting variations in the X (northward) and Y (eastward) components of the geomagnetic field at Hermanus, South Africa, with only solar wind plasma and interplanetary magnetic field (IMF) parameters as input. The models are developed by iteratively selecting the best set of solar wind parameters to predict the fluctuations in X and Y. To predict the variation in X, IMF magnitude, solar wind speed, fluctuation in solar wind proton density and a IMF-B_Z derived parameter are selected. To predict the variation in Y, IMF-B_Z, solar wind speed, and fluctuation in IMF magnitude are selected. The difference between the sets of selected input parameters are explained by the dependence of eastward perturbations in geomagnetic field at middle latitudes on field aligned currents. Model performance is evaluated during three storms in 2012. The onset and main phases of storms are fairly accurately predicted, but in cases where prolonged southward IMF coincides with solar wind parameters that are slowly varying the model fails to predict the observed fluctuations.

Keywords: Geomagnetically induced currents; Solar wind; Forecast; Neural networks

1. Introduction

Perturbations of the geomagnetic field driven by the upstream solar wind (SW) and its coupling to the magnetosphere can cause geomagnetically induced currents (GIC) to flow in technological systems at the Earth's surface, such as electric power transmission networks, in which GIC may lead to a number of negative effects. Fluctuations in the geomagnetic field (**B**), prevalent during geomagnetic storms and substorms, induces an electric field (**E**) through $\partial \mathbf{B}/\partial t = -\nabla \times \mathbf{E}$. The induced E-field drives anomalous currents in grounded conductor networks.

The induced currents are low frequency (around 1 Hz) "quasi-DC" currents that may cause half-cycle saturation of transformers, possibly leading to heating and increased reactive power demand (Molinski, 2002). Increased reactive power consumption, in turn, can cause system instability leading to blackouts (see Molinski (2002), for an overview of GIC effects on transformers).

It is important to note that GIC events usually do not result in system-wide blackouts such as the famous failure of the Hydro-Quebec system in 1989 (see Bolduc (2002), for example). On the other hand, GIC hazards are not limited to high latitudes, where geomagnetic storms are the most intense, but GIC problems may also occur at mid-to-low latitudes. During the intense geomagnetic storms of October/November 2003 and November 2004, transformer damage was reported at a number of mid

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latitude locations (given in geomagnetic coordinates according to the 2010 epoch of the IGRF model), e.g. in South Africa (about 30° S) (Gaunt and Coetzee, 2007), Spain (42.96° N) (Torta et al., 2012), Brazil (about 12° S) (Trivedi et al., 2007) and Japan (about 46° N) (Pulkkinen et al., 2010). Less intense events systematically degrade transformer performance, resulting in decreased transformer lifetime (e.g. Gaunt and Coetzee (2007)).

Several options for the mitigation of the damage incurred due to GIC exist. Molinski (2002) analysed various mitigation methods. These involve (i) designing the system with GIC risk in mind by using appropriate types of transformers and voltage control devices that are capable of handling wide ranges of voltage; (ii) installing series capacitors capable of blocking GIC flow, especially in long lines; (iii) changing system operating guidelines to react to geomagnetic events and (iv) notification and prediction of GIC risk.

Forecasting of GIC is an attractive mitigation technique because the reconfiguration of the network power flow to minimise the impact of the GIC incurs significantly lower cost than altering the design of the distribution network (Molinski, 2002). Empirical models of GIC (e.g. Weigel et al. (2003), Wintoft et al. (2005)) are usually based on in situ solar wind plasma and magnetic field measurements taken by spacecraft near the first Lagrangian (L1) point upstream of the Earth (e.g. ACE and Wind). The spacecraft location affords a prediction lead time of about 30–90 min, depending on the bulk solar wind speed.

Pulkkinen et al. (2010) introduced the Solar Shield (<http://ccmc.gsfc.nasa.gov/Solar_Shield>) project that offers two distinct forecasts based on (i) solar wind observations at L1, and (ii) observations of the solar corona. Both levels of prediction use measured data to run MHD simulations that predict ionospheric currents (level i) and plasma transport from the Sun to the Earth (level ii).

In this paper we present an empirical neural network-based model of a GIC proxy, with solar wind-based input parameters. The structure of a feed-forward network, with a single hidden layer, may be visualised as a directed graph with input nodes linked with weighted connections to a layer of intermediate nodes, which are connected to the output node via weights. Network nodes are computational structures that apply a sigmoidal function (tanh() in this paper) to the sum of all incoming signals. Model development involves training the network by applying an optimisation algorithm that is tasked with minimising the error between measured and predicted output by adapting the connection weights. This procedure relies on large sets of historical input and output parameter data. In this study solar wind parameters serve as inputs and a GIC-related proxy as output. We use fully connected feed-forward NN's and the error back-propagation algorithm for optimisation. Books such as Fausett (1994), Bishop (1995), or Haykin (1994) may be consulted for a full treatment on NN's. The software used to simulate NN's is the Stuttgart Neural Network Simulator (SNNS) – see Zell et al. (1998). The developed model and the procedure followed is similar to the work done by Wintoft et al. (2005), who used neural networks to model fluctuations in B_X and B_Y at northern latitudes 55° and 59°. We use a large data set of solar wind plasma and interplanetary magnetic field (IMF) measurements, with coinciding geomagnetic field measurements at a middle-latitude station at Hermanus, South Africa (HER: geographic coordinates 34.43° S, 19.23° E), to train the artificial neural networks. The output (predicted quantity) of the models are two GIC-proxies, respectively derived from dB_X/dt and dB_Y/dt.

The paper is laid out as follows: In Section 2 the data sources are described. The input and output parameters, and the selection of data are discussed in Section 3. The development of the NN-based model is described in Section 4. In Section 5 we use the models developed in Section 4 to predict out-of-sample data and discuss the performance during three storms. The paper concludes with Section 6.

2. Data sources

The models developed here are based on training a number of artificial neural networks on a historical set of in situ solar wind measurements and geomagnetic field observations made at HER.

2.1. Solar wind data

The input parameters selected to drive the models are solar wind plasma and magnetic field parameters measured upstream of the bow shock. Data are retrieved from the High-Resolution OMNI (HRO) data set (<http://omniweb.gsfc.nasa.gov>). Measurements from the ACE, Geotail and Wind spacecraft were collected and shifted in time to correct for solar wind plasma flow from the location of the spacecraft to the bow shock nose. In this study we only use OMNI measurements of those parameters that are also available in near real-time from ACE at 1-min intervals – i.e. measurements taken by the SWEPAM (<http://www.swpc.noaa.gov/ftpdir/lists/ace/ace_swepam_1m.txt>) and MAG (<http://www.swpc.noaa.gov/ftpdir/lists/ace/ace_mag_1m.txt>) instruments. This model is the first iteration of what is intended to become an increasingly realistic prediction tool. The next version will use (quasi-) real-time ACE data as input. Parameters available in near-real-time from SWEPAM are proton density (N_p), ion temperature (T_i) and bulk solar wind speed (V_{sw}) and the GSM components of the IMF (B_X, B_Y, B_Z) are available from the MAG instrument.

2.2. Geomagnetic field data

The output of the model is derived from the X (geographic north) and Y (geographic east) horizontal components of the geomagnetic field measured at HER. The data are recorded by a fluxgate magnetometer at 1-s intervals,