STATISTICAL MODELLING OF EARTH'S PLASMASPHERE

by

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Dedication

I dedicate this dissertation to ... I dedicate this dissertation to ... I dedicate this dissertation to ... I dedicate this dissertation to ... I dedicate this dissertation to ... I dedicate this dissertation to ... I dedicate this dissertation to ...

Acknowledgments

I would like to thank the following people who made this possible ... I would like to thank the following people who made this possible ...

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Abstract

STATISTICAL MODELLING OF EARTH'S PLASMASPHERE

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George Mason University, 2016

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This dissertation intends to first: be a survey of current forecasting capabilities of statistical and magnetohydrodynamic (MHD) methods of Earth's magnetosphere, and second: attempt to improve upon forecasting methods by investigating the usefulness of various new models on both real and modeled data. The forecasting will be separated into two parts: that focusing on rare, but significant events (e.g. geomagnetic storms), and that focusing on general day-to-day predictions. It will encompass three main methods of forecasting: impulse response functions (IRF), nonlinear methods, and statistical methods that attempt to forecast MHD.

Chapter 1: Introduction

1.1 Background

1.1.1 Magnetosphere

Discovery

The dynamic processes of Earth's magnetosphere and their various impacts on the planet and its inhabitants have been studied for centuries: from Celsius and Hiorter who noted a correlation between compass orientation and aurora [1], and the Carrington event in 1859 established the connection between solar output and electromagnetic effects on Earth [2].

It wasn't until Van Allen did his rocket sounding and satellite measurements of high altitude cosmic rays, finding the eponymous Van Allen Radiation Belt, that the structure of the magnetosphere was generally accepted to be more complex than that of a basic dipole magnet [3]. Showing that charged particles in solar wind plasma could be broken into constituent parts and directed into currents led to a deeper understanding of the behavior the magnetosphere and its interconnectivity with structures both inwards and outwards, which in turn allowed for better forecasting of ground-based effects based on solar wind conditions.

Our current computational technology, combined with over 50 years' worth of satellite and ground based measurements [4], allows for a much stronger statistics-based forecasting method to be performed and long-term analyses of the capabilities of computationally intensive forecasting methods.

Processes

The complex structure of the magnetosphere and plasmasphere lead to a number of distinct behaviors and processes such as ring currents, geomagnetic storms, and magnetospheric substorms.

Ring Current The Ring Current, shown in Figure 1.1 is a formed when the magnetosphere splits the neutral solar wind into positive and negative components, where they circle the earth moving along magnetic field lines until they either connect with particles in the upper atmosphere/ionosphere and fall out, or remain trapped in the magnetosphere and slowly drift in opposing directions around the magnetic equator. With enough energetic particles drifting together, a current is generated that can significantly affect the Earth's magnetic field and is labeled the Ring Current. These particles in the current are injected into the magnetosphere via conditions that cause the solar wind's magnetic field to connect with that of Earth, which is often exacerbated by the surge of energy created by geomagnetic storms.

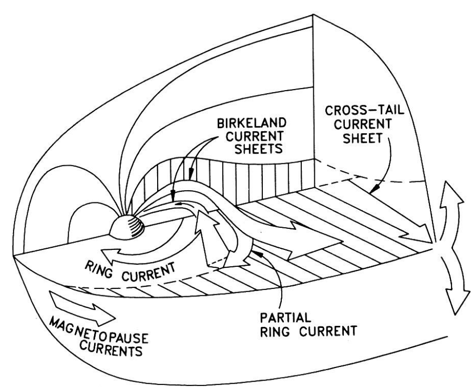

Figure 1.1: Currents in/around the magnetosphere [5]

Geomagnetic storms occur when the solar wind interacts with the Earth's magnetosphere in such a way as to produce significant disruptions in its normal, quiet-time, behavior. It is generally defined by a significant change to the magnetic field measured by multiple ground-based magnetometer measurements from stations spread around the world, in the case of the K_P index, or around the geomagnetic equator in the case of the Disturbance storm-time

(D_{st}) index. By using these indices, storms can be classified into categories of severity [6]. The definition of storms in the literature varies slightly between authors [7], but most agree that sustained and abnormally perturbed near-earth magnetic field strengths over several hours or more constitutes a geomagnetic storm [8].

Geomagnetic substorms, in contrast with storms, are much shorter; typically only existing for an hour or two, and potentially happening soon after one another. They tend to have a less appreciable effect on the amount of particles/energy in the ring current, and are associated with sudden changes in energy coming from the tail of the magnetosphere rather than the dayside reconnections associated with storms, and is often directly injected into the polar regions.

Geomagnetic storms and substorms can have significant impacts on Earth and space systems, from inducing currents in large power grids to harming satellite circuitry and onboard data [9]. Because of the potential damage of such events, any ability to forecast a storm could allow operators to prevent or mitigate problems in their systems. Becuase of the large correlation of CMEs with geomagnetic storms [7], it can be estimated that our forewarning time is the difference between observing a CME (via visual or X-ray methods) and its propagation time plus magnetospheric interaction time. This time can be anywhere from one to five days, depending on the speed of the CME and how it interacts with the interplanetary medium [10]. With a light delay of only eight minutes, this is ample time to see a storm approaching Earth and for operators to react, but a problem lies in the fact that storms are poorly predicted with such lead times [11]. Some storms have slow onsets, some spike suddenly; some have high velocities, and some coincide with large amounts of high-energy particles; no single factor has yet proven to be a good predictor for storms, and while prediction has gradually improved over the years, there remains room for further study.

Leave off with statement on how outer magnetosphere influences plasmasphere.

1.1.2 Plasmasphere

Discovery

Processes

Plumes, erosion, etc.

Leave off with list of things that are not well understood and how work in thesis approaches them.

1.1.3 Statistical Modeling of Magnetopshere and Plasmasphere

Initial forecasts were based on an observed time delay between sunspots and geomagnetic storms [12]. It then advanced to a basic theory involving electromagnetic interactions in the magnetosphere [13]. There now exist entire services dedicated to executing MHD-based models of the magnetosphere [14], as well as multi-year, multi-institution efforts to survey the general statistics of modeling and forecasting of extreme events [15].

The convergence of the advancement in both statistical and MHD-based simulation has led to a situation where the scientific community has the capacity for monitoring space weather in real time, and forecasting the near-Earth effects. There have been efforts to test the forecast performance of select models over a small number of geomagnetic events [7,16–18]. However no research has been done that involves the analysis of long-term forecasting performance of these models and comparison of the results with existing methods.

Make connection to each paper with a section in chapter 2.

Chapter 2: Methods

These are the methods that were used. No single method is ideal, and using many methods is better for insight, especially for nonlinear/complex systems.

2.1 Linear

2.1.1 Overview

2.1.2 Correlation

2.1.3 Impulse Response

Impulse response systems are systems in which the output (a response) is driven by a linear sum of coefficients of an input (a series of impulses). A simple example would be making a loud noise in a concert hall. The response will be the unique echoes and reverberations created by the initial driving sound, and with enough noise, a statistical model can be generated that will map the input sound to a response echo. In the magnetosphere, the most used example is an impulse of v_{B_s} driving the Auroral Electrojet (AE/AL) index [19], or the Disturbance Storm Time (D_{st}) index [20], also shown in Figure 2.1.

This plot shows how different models are used to predict magnetospheric variables with varying amounts of success. In this proposal, what starts as a simple Box-Jenkins model of the form [22]:

$$x(t) = c + \sum_{j=0}^{m} a_j f(t - j\Delta t)$$

can be modfied with an auto-regressive component to be an autoregressive model with

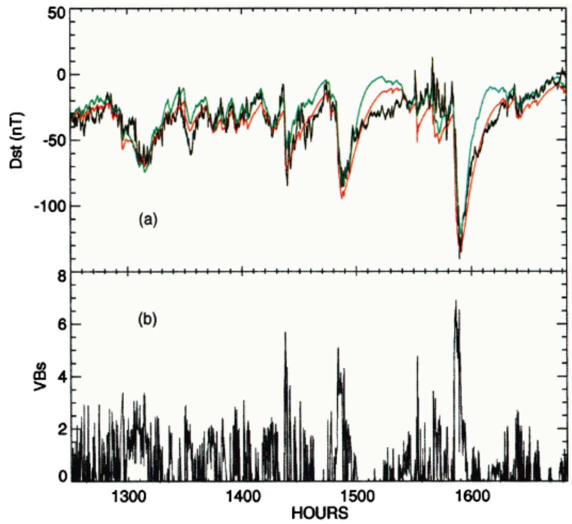

Figure 2.1: DST (black), nonlinear autoregressive exogenous (ARX) model (red), Burton et al 1975 model (green). (b) v_{B_S} impulse as input.[21]

exogenous inputs (ARX) such as that used in [21], taking the form:

$$\hat{x}(t + \Delta t) = \sum_{i=0}^{l} a_i \cdot x(t - i\Delta t) + \sum_{j=0}^{m} b_j \cdot f(t - j\Delta t) + c \tag{2.1}$$

Where m and l are the number of coefficients desired for including previous data points in the prediction, and c is a factor to remove the mean offset from the data. Note that in some cases the starting value of the iterators can be individually increased if there is a known delay in response time or there is a desire to predict further into the future. In [21], second order equations ($m = 2$) were used with anywhere from one to four driving coefficients, but in practice any number of coefficients and any number of driving variables can be used up to some fraction of the number of data points that allows the coefficient matrices to be solved for.

There generally is a limit to the usefulness of large-lag data [15]. By looking at a plot of the cross correlation relative to the number of coefficients, a limit will generally be seen where adding more coefficients no longer reduces error in the model. By creating a threshhold of change in fit per coefficient added (perhaps via a bootstrap method), the minimum number of coefficients needed to optimally model the system can be determined.

By constructing a linear system of equations from Equation 2.1, the coefficients can be solved for in a general matrix form (where, in this case, $l = m$):

$$\begin{pmatrix} x_0 & ... & x_{l-1} & f_0 & ... & f_{l-1} & 1 \\ x_1 & & x_l & f_l & & f_l & 1 \\ ... & & & & & & \\ x_{N-l} & ... & x_{N-1} & f_{N-l} & ... & f_{N-1} & 1 \end{pmatrix} \begin{pmatrix} a_0 \\ ... \\ a_{l-1} \\ b_0 \\ ... \\ b_{l-1} \\ c \end{pmatrix} = \begin{pmatrix} x_l \\ x_{l+1} \\ ... \\ x_N \end{pmatrix}$$

This is a linear model for the behavior of a system. However, it has been shown that the set of coefficients describing the response of a system can change with storm intensity [21], the time scale modeled [23], and even the time of day [19]. This creates a very large number of possible directions for research, from predicting storm onsets, to predicting storm intensities, to modeling the overall shape and behavior of a storm, as well as all of the other possible interactions outside of storm-time.

2.1.4 Caveats

There will be a number of things that, ideally, must come together to make this kind of data prediction work. For one: ARX methods can often be heavily dependent on a concept known as "persistence", whereby the best prediction for a variable at any time is that same variable at the last measured time step. For example, if the high temperature today is 70°, it is fairly likely that the high temperature tomorrow will be near 70°. Too much reliance on persistence forecasting, though, and predictions can lose their usefulness. Figure 2.2, for example, shows how a model can achieve high correlation with persistence, but be almost entirely useless for predicting events before they happen.

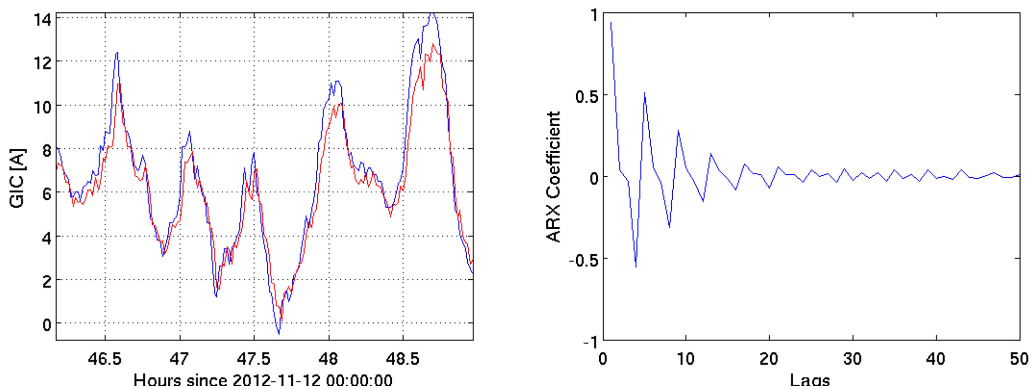

Figure 2.2: Persistence forecast; model in red

In this case, it is clear that the largest auto-correlation coefficient comes at 1 time lag, meaning the most recent measurement has the most weight in a forecast. For day-to-day behavior, this is acceptable as being part of the behavior of the system. For the forecasting of extreme events, however, another metric must be used that measures the ability of the model to predict events at or before their actual occurrence, while simultaneously avoiding predicting events that do not happen. One method for comparing models in this fashion is by using the Heidke Skill Score [24, 25], which is based on the quantity:

$$S = \frac{R - E}{T - E}$$

where R is the number of correct forecasts, T is the total number of forecasts, and E is the number expected to be correct by, in this case, a persistence forecast. This can be adapted to either consider a range of "correctness", or a binary threshold to be met. It may also be desired to assign a cost-weighting to success rates. If, say, it costs $1 million to prepare a power grid for a storm, 10 false alarms to every one storm gets costly unless successfully preparing for that one storm saves $1 billion. To do this, a measure of the utility of a forecast can be quantified [11]:

$$U_F \equiv BN_H - CN_{\bar{H}} > 0$$

Where N_H is the number of correct forecasts, $N_{\bar{H}}$ is the number of false alarms, C is the cost of taking mitigating action, and B is the benefit from correctly taking mitigating action. This method has caveats discussed in [11], but is a useful metric for forecast utility when costs are known, and some measure of success can be determined.

The other major problem in forecasting is that of lead time. Being able to forecast a storm one minute in advance is generally not enough time for operators to take mitigating action.

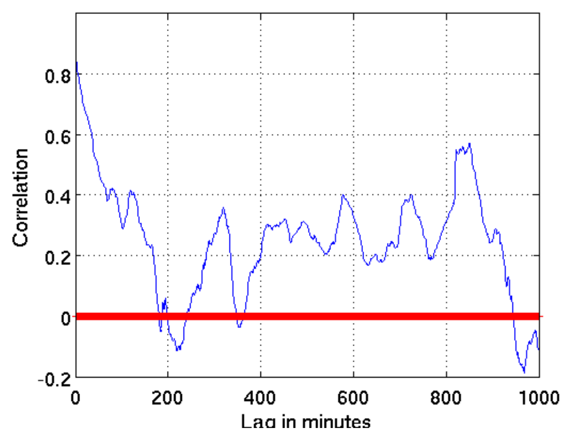

Figure 2.3: Correlation vs lags

Figure 2.3 shows a set of predictions made for autocorrelation in geomagnetically-induced currents (GIC). This metric is a measure of how much electric currents in the magnetosphere induce currents in ground-based electrical systems. The predictions were made further and further in time from the current magnetic field and GIC measurements, with decreasing accuracy as the predicted time got further from the current time. While an accurate prediction can be made one minute in advance, a prediction 3 hours in advance has almost no correlation with what actually happens. This is the main problem that this dissertation hopes to address.

2.2 ARMAX

2.2.1 Overview

2.2.2 Applicability

2.2.3 Caveats and Biases

2.2.4 Mean vs Median

2.2.5 Effects of time averaging

2.2.6 Results and Analysis

2.3 Nonlinear

2.3.1 Overview

Other models will be devised to test nonlinear approaches to forecasting. One common choice are models based on neural networks [16, 26] which allow for a model that can approximate a non-linear system. The usefulness of this is apparent in a few key points: the weights of contribution of any particular variable to a system will likely be nonlinear in some fashion (e.g. a ground station's measurements will depend on sunlight heating the ionosphere which depends on latitude, time of year, and time of day), and allowing for the non-linear effects of saturation where perhaps the magnetosphere will behave differently after reaching certain levels of particle density or electric potential.

Another algorithm known as Principal Component Analysis (PCA) can be used to take the large number of possible variables and define an orthogonal set of vectors that most efficiently encapsulate the variance in the data. By doing this, the number of variables needed for computing any linear or non-linear algorithm can be reduced and optimized, making predictions quicker while maintaining most of the predictive benefits of using all possible data.

2.3.2 Neural Networks

Applicability

Caveats and Biases

Parameters and Inputs

Results and Analysis

Comparison to Linear Model

Note that you always compare performance relative to linear model as a reference point. Useful for determining how important nonlinearity is.

Appendix A: An Appendix

This is an appendix. Here is a numbered appendix equation:

$$a^2 + b^2 = c^2. \tag{A.1}$$

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