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A neural network *Dst* index model driven by input time histories of the solar wind–magnetosphere interaction

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ABSTRACT

A model to forecast 1-hour lead *Dst* index is proposed. Our approach is based on artificial neural networks (ANN) combined with an analytical model of the solar wind–magnetosphere interaction. Previously, the hourly solar wind parameters have been considered in the analytical model, all of them provided by registration of the ACE satellite. They were the solar wind magnetic field component B_z, velocity V, particle density n and temperature T. The solar wind parameters have been used to compute analytically the discontinuity in magnetic field across the magnetopause, denoted as $[B_t]$. This quantity has been shown to be important in connection with ground magnetic field variations. The method was published, in which the weighted sum of a sequence of $[B_t]$ was proposed to produce the value of *Dst* index. The maximum term in the sum, possessing the maximum weight, is the one denoting the contribution of the current state of the near-Earth solar wind. The role of the older states is less important – the weights exponentially decay. Moreover, the terms turn to zero if $B_z \ll 0$. In this study, we set up a more comprehensive model on the basis of the ANNs. The model is driven by input time histories of the discontinuity in magnetic field $[B_t]$, which are provided by the analytical model. At the output of such revised model, the *Dst* index is obtained and compared with the real data records. In this way we replaced those exponential weights in the published method with another set of weights determined by the neural networks. We retrospectively tested our models with real data from solar cycle 23. The ANN approach provided better results than a simple method based on exponentially decaying weights. Moreover, we have shown that our ANN model could be used to predict *Dst* 1 h ahead. We assessed the predictive capability of the model with a set of independent events and found correlation coefficient $CC = 0.74 \pm 0.13$ and prediction efficiency $PE = 0.44 \pm 0.15$. We also compared our model with the so-called *Dst*-specification models. In those models, the *Dst* index was derived directly through an analytic or iterative formula or a neural network-based algorithm. We showed that the performance of our model was comparable to that of *Dst*-specification models.

1. Introduction

Nowadays, there is an increasing demand to understand and predict conditions in the near-Earth space driven by the solar activity. Global magnetohydrodynamic (MHD) computational models based on first principles (Baker et al., 2004; Gombosi et al., 2001; Goodrich et al., 2004; Odstrčil et al., 2004; Siscoe et al., 2004; Tóth et al., 2012; Tsyganenko, 2013) are some examples of major thrusts in this effort. On the other hand, the use of empirical models for the purposes of forecasting has the advantage of being less computationally demanding than the MHD models. The goal is to develop short-term models which can take into account the observed features of the solar wind–magnetosphere interaction while being computationally simple and possessing real-time forecasting capability.

In Alexeev and Feldstein (2001), the dynamic paraboloid magnetospheric field model has been developed and applied for the evaluation of a variety of magnetospheric current systems and their contribution to the ground magnetic field variations during magnetic storms. In later studies by Romashets et al. (2005) and Romashets et al. (2008), a 3D paraboloid model of the solar wind–magnetosphere interaction has been proposed to evaluate the magnetic field in the near-Earth space environment. In Romashets et al. (2005), an attempt has been made to describe the magnetosheath field as given by a scalar potential, which implies a current-free approximation. In order to involve finite currents, in Romashets et al. (2008), the magnetic field has been determined

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by a vector potential. The model studied in Romashets et al. (2008) has been also shown to be useful for studying the solar wind–magnetosphere interaction. As a result, a function measuring the discontinuity in magnetic field across the magnetopause, denoted as $[B_t]$, has been expressed analytically. In Romashets et al. (2008), this quantity has been pointed out to be important in connection with ground magnetic field variations.

Geomagnetic activity can be characterized by geomagnetic indices, the most common being the *Dst* index. This index serves as a good measure of the overall strength of the near-Earth global electric currents, especially the ring current, thereby providing a good measure of geomagnetic storm intensity. Correlations between the *Dst* index and possible external drivers can provide the basis for empirical prediction (Burton et al., 1975; Siscoe et al., 2005).

The use of advanced techniques such as ANNs is found to be effective in predicting *Dst*. The modeling capability of an ANN lies in its ability to learn the mappings of underlying input–output features. If the network is designed and trained properly, it can perform generalization rather than simple fitting of the function, see Gurney (1997) and Hertz et al. (1991). This approach is rather useful when information and understanding of a physical system are lacking.

The ANN can be fed with the data on solar wind or solar activity (input data) and it can be trained to provide the caused geomagnetic activity (output). The ANNs are thus usable for the forecasting of the geomagnetic activity (e.g. Andrejková et al., 1997; Valach et al., 2007, 2009). This method has been widely used for the real-time modeling of the geomagnetic responses to solar wind disturbances, e.g. Boberg et al. (2000), Lundstedt (1992), Lundstedt et al. (2002), and Wu and Lundstedt (1996). For instance, the model developed by Lundstedt et al. (2002) consists of a recurrent neural network that requires the hourly averages of the solar wind parameters as inputs and predicts the *Dst* index in almost real-time.

The underlying study is a contribution towards the *Dst* index modeling on the basis of the model proposed in Romashets et al. (2008). We employ the method of ANN to develop a revised version of the model, hereafter referred to as the revised RPV model. Unlike the approach by Lundstedt et al. (2002), where the solar wind parameters are used directly as the ANN input, here we feed the ANN with past hourly means of the function $[B_t]$ known from Romashets et al. (2008). As such, the presented ANN model can be thought as driven by input time histories of the solar wind–magnetosphere interaction. We obtain the *Dst* index series as the ANN output and compare it with the real data records. We evaluate the model for the set of intense geomagnetic storms of the 23-rd solar activity cycle. This study concerns strong geomagnetic storms because the intense events and their impacts on the terrestrial environment interest the space weather community (e.g. Echer et al., 2010; Gopalswamy et al., 2005; Siscoe et al., 2006; Srivastava, 2005b; Srivastava and Venkatakrishnan, 2004; Szajko et al., 2013; Zhang et al., 2003). Nevertheless, we must also admit a disadvantage of such a treatment: The downside of focusing on extreme storms is the limited number of the observed events, which partly reduces the potency of our arguments when drawing conclusions.

The paper is organized as follows. In Section 2, the data resources are specified. Development of the revised model for the *Dst* index and the results are presented in Section 3. The main findings are summarized in Section 4.

2. Data used

In Romashets et al. (2008), the *Dst* index for the so-called Bastille day event, on 14–15 July 2000, has been computed using the hourly solar wind parameters: the solar wind magnetic field component B_z, velocity V, particle density n and temperature T; all of them provided by registration of the ACE satellite operating at the libration point L1.

In this study, 16 major geomagnetic storms from solar cycle 23 are considered, as listed in Table 1 (according to Table 1 in Tripathi and Mishra, 2006). Note, that two successive storms of November 2004 are treated as a single event. For each of the events considered, the series of the model *Dst* index is computed. The observed true *Dst* values, required to compare with the model values, were obtained from the World Data Center for Geomagnetism, Kyoto.

3. Models and results

In what follows, the revised model for the *Dst* index will be developed by combining the original analytical model by Romashets et al. (2008) with the approach of ANN. First, the analytical expression for the jump in magnetic field $[B_t]$ will be shown. The original model by Romashets et al. (2008) will be referred to as *the primal RPV model*, with its output denoted as Dst^p. This model will be evaluated for the set of geomagnetic storms considered and the need for its revision will be argued. As a preliminary step, a neural network model without hidden neurons will be presented, referred to as *the preliminary revised RPV model*, with its output denoted as Dst^n. The final revised version of this model will be constructed involving the neural network possessing hidden layer and will be referred to as *the revised RPV model*, with its output denoted as Dst^{nn}. Hereafter, the notation *Dst* will stand for the observational data record.

3.1. Analytical expression for the jump in magnetic field

Considering the magnetopause as paraboloidal in shape, Romashets et al. (2008) constructed an analytical representation of magnetic fields in the region where the solar wind interacts with the Earth's magnetosphere. The paraboloidal coordinates (σ, τ, φ) were adopted, defined by

$$x = \tfrac{1}{2}(\sigma^2 - \tau^2), \tag{1}$$

$$y = \sigma\tau \cos\varphi, \tag{2}$$

$$z = \sigma\tau \sin\varphi, \tag{3}$$

where x, y, z are solar ecliptic coordinates, with axis x pointing to the Sun. The components of magnetic field have been expressed analytically in paraboloidal coordinates. The full development of this analytical model can be found in Romashets et al. (2008) and will therefore not be reproduced here.

Magnetic field exhibits a discontinuity in tangential component when moving across the magnetopause from the solar wind (the IMF) to the magnetosphere (the internal field). There is no normal component of the magnetic field at the magnetopause. Romashets et al. (2008) used the notation $[B_t]$ for the magnitude of the jump in magnetic field across the magnetopause and argued for the relevance of this quantity for modeling the geomagnetic activity. We refer to the final expression for $[B_t]$ (Section 5 in Romashets et al., 2008) which reads

$$[B_t] = B_z\left[4.2629\left(\frac{V_\infty}{500}\right)\left(\frac{10^6}{T_\infty}\right)^{1/2} - 1\right] - 34.2109\left(\frac{n_\infty}{5}\right)^{1/2}\left(\frac{V_\infty}{500}\right). \tag{4}$$

Here, the subscript ∞ stands for the undisturbed solar wind parameters far before the interaction with the magnetosphere, V_∞ is the velocity measured in km s^{-1}, n_∞ is the particle density measured in cm^{-3}, T_∞ is the temperature measured in K, B_z