

# Analogue model, relating $K_p$ index to solar wind parameters

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## Abstract

In a previous work the authors have developed a model, providing  $K_p$  as a function of the interplanetary magnetic field  $B_z$  component. They introduced a modified  $B_z$  function (denoted as  $B_{zm}$ ), exhibiting a delayed reaction to  $B_z$  changes. The modified function  $B_{zm}$  was defined by using the analogy with a damping RC-circuit output voltage. The delaying reaction of  $B_{zm}$  to  $B_z$  was characterized by two time constants, one for rising and one for decreasing parts of  $B_z$ . The cross-correlation between  $K_p$  and  $B_{zm}$  has increased to 0.7, compared with  $-0.4$  between  $K_p$  and  $B_z$ . In this paper, new dependences of  $K_p$  on solar wind velocity and dynamic pressure are included in the model to improve its accuracy. These solar wind parameters are found to correlate best with  $K_p$ . The hourly interpolated values are also added to the 3-h  $K_p$  values to increase the statistics. The new  $K_p$  data set is denoted as  $K_{p1}$ . The mean dependence of  $K_p$  on  $B_{zm}$  and dynamic pressure are approximated with parabolas, while the dependence on the velocity is linear. The constants in the model expression are obtained by using ACE data (1998–2000). The overall model error is estimated at 0.63 units  $K_p$ . The improvement over the previous simpler dependence in terms of the model error is about 30%.

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## 1. Introduction

The planetary indices of geomagnetic activity reflect the complex non-linear transfer of energy deposited by solar wind into magnetosphere with a subsequent interaction with polar ionosphere. To avoid complexity of the physical processes in modelling this transfer, many investigators use empirical relations between solar wind and geomagnetic activity parameters, which are based on some well-known physical analogues. Hones (1979) and Klimas et al. (1992) have used the dripping-faucet analogue to describe the plasmoid formation in the magnetosphere tail, the main transporter of solar wind energy into substorm activity. Baker et al. (1990) and Vassiliadis et al. (1993) have used an electric LRC circuit as a damped linear oscillator to represent the return of a “perturbed” magnetosphere to its “quiet” state.

Muhtarov and Andonov (2000), further denoted as MA, developed a model relating  $K_p$  to the interplanetary

magnetic field (IMF)  $B_z$  component by using an electric diode rectifier circuit (DRC) analogue. The circuit they used is similar to that of Vassiliadis et al. (1993), in which the inductance part was replaced with a half-wave diode rectifier. MA used  $B_z$  as an input voltage, while the output voltage they defined as a “modified”  $B_z$  ( $B_{zm}$ ) having positive variations only. The hourly values of the new quantity  $B_{zm}$  were correlated with the hourly interpolated  $K_p$  values to obtain the model parameters. Using 27 years of IMF data (1973–1999), MA estimated that  $B_{zm}$  improved the correlation between  $B_z$  and  $K_p$  from  $-0.4$  to 0.7. In this paper, we use the same approach as in MA, adding dependences on solar wind dynamic pressure and velocity. For this purpose, we use a database containing ACE data collected between 1998 and 2000.

## 2. The DRC circuit model

It is well accepted that  $B_z$  is a main driver of geomagnetic activity and of  $K_p$  variations, in particular (see Kamide

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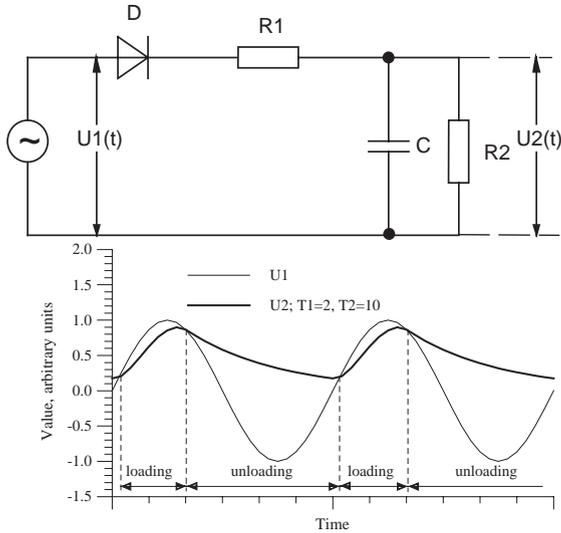


Fig. 1. (a) Equivalent electric circuit DRC, giving the delayed reaction of the output voltage  $U_2$  to the input voltage  $U_1$ .  $D$  is a half-wave diode rectifier,  $C$  is a capacitor,  $R_1$  and  $R_2$  are resistors; (b) a sample of a sinusoidal input voltage  $U_1$  and the resulting output voltage  $U_2$ . Loading and unloading phases are marked with horizontal bars.  $T_1$  and  $T_2$  are assumed arbitrary to demonstrate the functioning of the circuit and do not relate to the values considered in the paper.

et al., 1998 and references therein). The negative turning of  $B_z$  causes an increase of  $K_p$ , known as “driven” response (Klimas et al., 1991). The increase of  $B_z$  or turning positive is not followed by an immediate and proportional decrease of  $K_p$ . The changes of  $K_p$  appear more gradual and delayed. MA found that the cross-correlation between  $B_z$  and  $K_p$  had a maximum at a time lag of about 2 h. This means that  $K_p$  best correlates with  $B_z$  from the previous 2 h. In order to improve the dependence of  $K_p$  on  $B_z$ , MA introduced a new function of  $B_z$  (denoted as  $B_{zm}$ ), which is positive and contains a delayed reaction to  $B_z$  changes. To do this, they used an analogy with another inertial system, which involves loading and unloading processes with different time constants. An electrical circuit shown on Fig. 1a can represent such a system. The circuit includes a half-wave diode rectifier  $D$ , a smoothing capacitor  $C$  and two resistors  $R_1$  and  $R_2$ . MA considered that the input voltage  $U_1$  was a step-like function, formed by discrete values at arbitrary moments of time. If  $R_2 \gg R_1$ , the output voltage  $U_2$  within the time-step  $[t_i, t_{i+1}]$  is given by a well-known relationship:

$$U_2(t_{i+1}) = \begin{cases} (U_2(t_i) - U_1(t_i)) \exp\left(-\frac{t_{i+1} - t_i}{T_1}\right) + U_1(t_i); & U_2(t_i) < U_1(t_i) \\ U_2(t_i) \exp\left(-\frac{t_{i+1} - t_i}{T_2}\right); & U_2(t_i) > U_1(t_i), \end{cases} \quad (1)$$

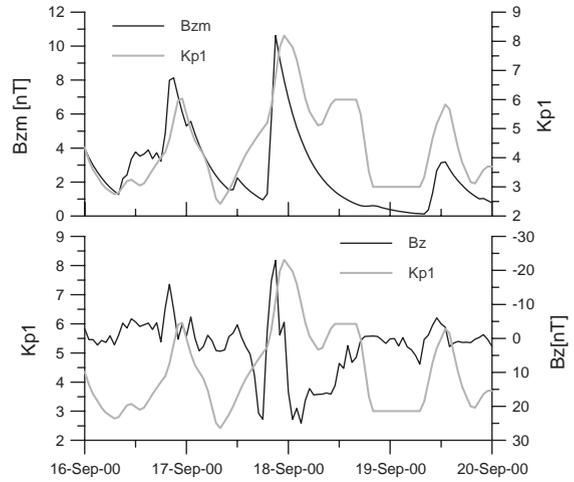


Fig. 2.  $B_z$ ,  $B_{zm}$  and  $K_{p1}$  variations during 16–19 September 2000. Upper panel:  $B_{zm}$  and  $K_{p1}$  (scale on the right); lower panel:  $K_{p1}$  and  $B_z$  (scale on the right).

where  $T_1 = R_1 C$  and  $T_2 = R_2 C$ . Expressions (1) have recurrent feedback: the voltage  $U_2$  obtained from the previous step  $[t_{i-1}, t_i]$  is placed on the right-hand side of the equations for obtaining  $U_2$  in the next step  $[t_i, t_{i+1}]$ . The first expression in (1) represents a process of loading the capacitor  $C$  with a time constant  $T_1$ , while the second expression represents the unloading process with a time constant  $T_2$ . The loading takes place while  $U_1$  is higher than  $U_2$  and the diode is open. If  $U_1$  becomes lower than  $U_2$ , the diode is closed and the capacitor starts discharging through the resistor  $R_2$ . The whole process is schematically presented on Fig. 1b. The input voltage  $U_1$  is represented as a simple sinusoid (thin line) and the output voltage  $U_2$  is given by the solid line. The loading takes place when  $U_1 > U_2$ . The output voltage  $U_2$  accepts now only positive values, gradually decreasing when  $U_1$  is lower. The time constants  $T_1$  and  $T_2$  shown in Fig. 1b are arbitrary, just to demonstrate the functioning of the circuit, and do not relate to the values considered later in the paper. Making use of the analogy with this electrical scheme, MA defined  $B_{zm}$  through Eq. (1) with a replacement of  $U_1$  with  $-B_z$  and  $U_2$  with  $B_{zm}$ .

As MA, here we also add the hourly  $K_p$  values, obtained by a linear interpolation between the observed 3-h  $K_p$  index, to the  $K_p$  data set. The only reason for that is to increase statistics, while we use the hourly values of the solar wind parameters  $B_z$ , velocity and dynamic pressure. In order to distinguish between the new data set and the observed 3-h  $K_p$  index, we denote hereafter the new data set as “ $K_{p1}$ ”. Fig. 2 shows a sample of  $B_z$ ,  $B_{zm}$  and  $K_{p1}$  variations during the period 16–19 September 2000.  $B_{zm}$  is calculated by using Eq. (1), setting  $T_1 = 0.8$  and  $T_2 = 9$  h, as obtained by MA. MA has obtained these values through a procedure explained below, using IMF data.  $B_z$  and  $K_{p1}$  variations are compared in the lower panel, while  $B_{zm}$  and  $K_{p1}$  variations

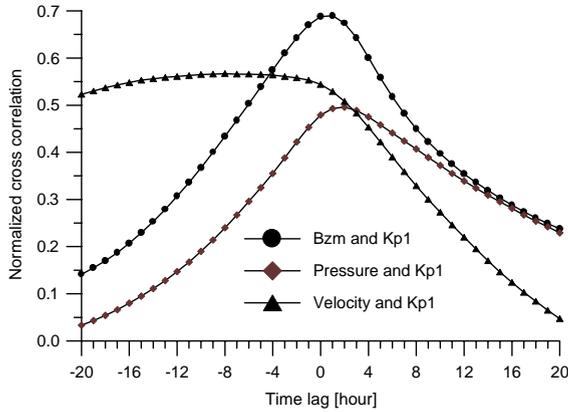


Fig. 3. Normalized cross-correlation of  $K_{p1}$  with  $B_{zm}$  (dots), solar wind dynamic pressure (diamonds) and velocity triangles.

are shown in the upper panel.  $B_z$  scale is reversed, with negative  $B_z$  upward. Two spikes of negative  $B_z$  occur on 16 and 17 September, followed by a delayed decrease of  $B_{zm}$ .  $B_{zm}$  changes resemble those of  $K_{p1}$ . In this particular sample,  $B_{zm}$  increase faster than  $K_{p1}$ , which means that  $T_1$  is assured smaller than needed. In the unloading phase,  $B_{zm}$  decrease matches better than  $K_{p1}$  changes. It is worth noting, that MA has determined  $T_1$  and  $T_2$  by using 27 years of data, but obviously these average time constants do not assure the best agreement between  $K_{p1}$  and  $B_{zm}$  in any individual case.

Using ACE solar wind data, we calculated the cross-correlation between  $K_{p1}$  and the hourly values of  $B_{zm}$ , solar wind velocity  $V$  and dynamic pressure  $P$  ( $P = 1.673 \times 10^{-6} nV^2$ ,  $n$  is the ion density). Here  $B_{zm}$  is in nanotesla,  $P$  in nanopascal,  $n$  in  $\text{cm}^{-3}$  and  $V$  in  $\text{km/s}$ . The cross-correlation functions are shown in Fig. 3 as functions of the time lag in the range  $(-20, 20)$  h.  $B_{zm}$  (calculated with  $T_1 = 3$  and  $T_2 = 7$  h, as will be shown later) has the highest correlation with  $K_{p1}$ , reaching 0.7 at the time lag of 1 h. The correlation of  $K_{p1}$  with solar wind dynamic pressure has a peak of 0.5 at the time lag of 2 h, while the correlation with solar wind velocity has a broad maximum of 0.57 in the negative time lags. The cross-correlation of  $K_{p1}$  with solar wind density has a maximum value of 0.25 at the time lag of 3 h and is practically insignificant. Fig. 3 shows the cross-correlation at both positive and negative time lags because formally this function is not symmetric. Positive time lags indicate forecasting capabilities, while the negative time lags do not. For these particular dependences, however, when we consider a cause–effect relationship between solar wind parameters and  $K_{p1}$ , negative time lags are meaningless. The high cross-correlation between velocity  $V$  and  $K_{p1}$  at negative time lags possibly is due to the different time scale variations of the velocity and  $K_{p1}$ . Data show that over the large time scale, e.g. days, both quantities correlate fairly well, but for the time scale of hours correlation is poor. In this latter case  $K_{p1}$  spikes are observed to precede those of  $V$ ,

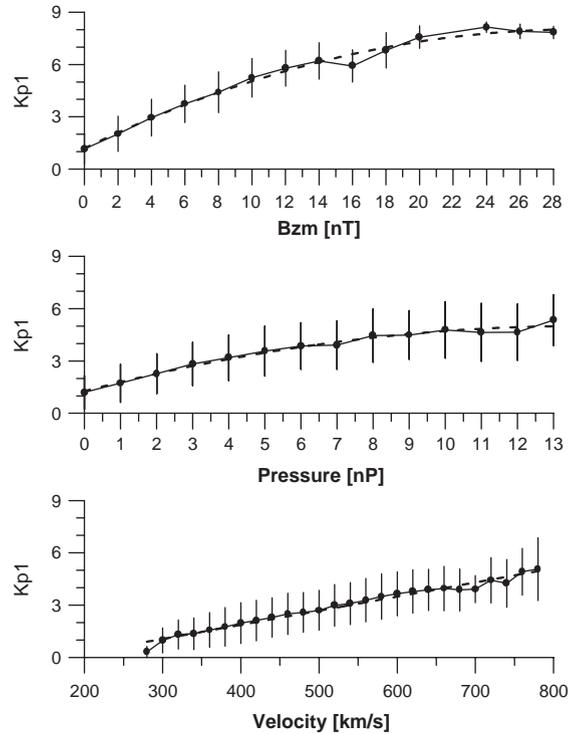


Fig. 4. Mean dependences of  $K_{p1}$  on  $B_{zm}$  (top), solar wind dynamic pressure (middle) and velocity (bottom). Dots show the mean values in the bins along  $X$  axis, vertical bar length represents  $\pm$  standard deviation, while the dashed lines show the approximation of the mean values.

which obviously reflects in the cross-correlation. In this paper we do not attempt to resolve this relationship. We rather use the cross-correlation as a criterion of how significant the corresponding solar wind parameter to the model of  $K_{p1}$  is based on this figure, we conclude that the main dependence of  $K_{p1}$  should include, besides  $B_{zm}$ , solar wind velocity and dynamic pressure as well. Fig. 4 shows the mean dependence of  $K_{p1}$  on each of these solar wind parameters. The solid dots represent the mean values, obtained by averaging all available data within the corresponding bins, and are placed on the left border of each bin. The vertical bars represent the scatter of the data and their length is equal to twice the standard deviation of data around the mean. The dashed lines show the best approximations to the mean dependences: parabolic between  $K_{p1}$  and  $B_{zm}$  and between  $K_{p1}$  and the dynamic pressure, and linear with the ion velocity. We therefore consider the  $K_{p1}$  model in the form:

$$K_{p1} = a_0 + a_1 B_{zm} + a_2 P + a_3 V + a_4 B_{zm}^2 + a_5 P^2. \quad (2)$$

As was mentioned above, the  $K_{p1}$  model of MA contained the dependence on  $B_{zm}$  only and the time constants  $T_1$  and  $T_2$  they calculated reflected that dependence. We expect that the new expression (2) will define different values of the time constants. Following the same approach as MA, we

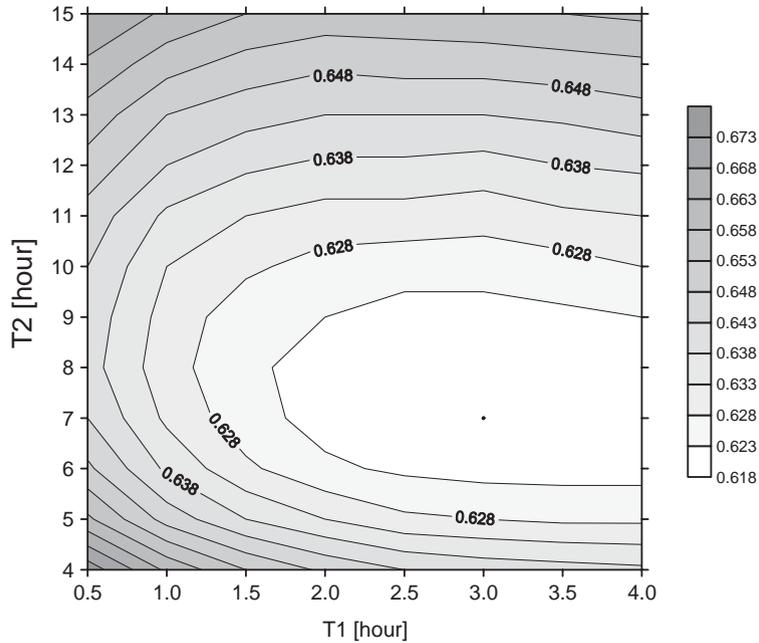


Fig. 5. Contours of constant model error, calculated by using variable values of time constants  $T_1$  and  $T_2$ . It is assumed that the time constants  $T_1 = 3$  and  $T_2 = 6$  h, yielding the lowest model error, best represent the delayed reaction of  $B_{zm}$  to  $B_z$  changes.

now calculate  $K_{p1}$  fitting Eq. (2) to the values of  $B_z$ ,  $P$  and  $V$  at each hour within the whole ACE database, compare it with the corresponding observed  $K_{p1}$  and calculate the model error as the root mean square deviation. Every fit uses a pair of time constants ( $T_1$ ,  $T_2$ ) and yields its own set of constants  $a_i$  and a model error. For a given hour, the fitting is repeated for a grid of pairs of  $T_1$  (step 0.2 in the range 0.2–4.0 h) and  $T_2$  (step 1.0 h in the range 4–24 h) which equals to  $20 \times 20 = 400$  grid points. Model errors, obtained for each pair of time constants over the whole database, are accumulated and averaged. Fig. 5 shows a contour plot of the averaged model errors along  $T_1$  and  $T_2$  axes. Contours of constant error magnitudes are drawn with solid lines. We assume that the pair of time constants with the lowest model error best represents the delayed reaction of  $B_{zm}$  to  $B_z$  changes. Therefore, for further analysis we take  $T_1 = 3.0$  h and  $T_2 = 7.0$  h. With these time constants, the model expression for  $K_{p1}$  becomes:

$$K_{p1} = -2.3 + 0.64B_{zm} + 0.31P + 0.007V - 0.24B_{zm}^2 - 0.01P^2. \quad (3)$$

The coefficients  $a_i$  are obtained by fitting (2) to the whole database, with  $T_1 = 3$  and  $T_2 = 7$  h. Fig. 6 shows a comparison between  $K_{p1}$  observed during 1–19 August and 16–28 September 2000 and the corresponding model values. The thin line shows  $K_{p1}$  values and the solid line presents the model prediction. The agreement between the model and observations in these samples is acceptable. The model over-

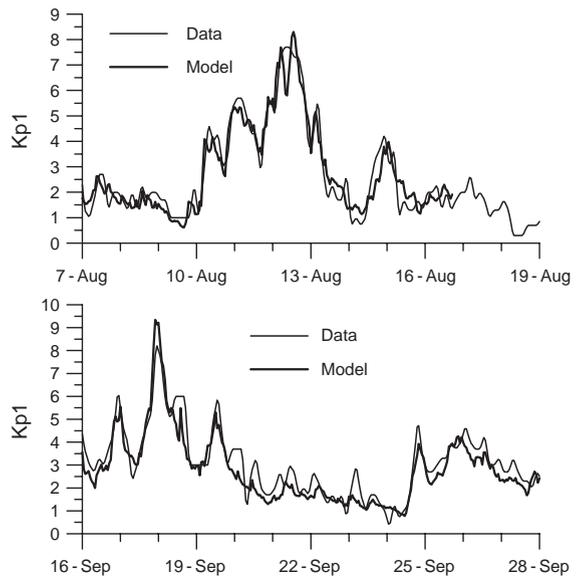


Fig. 6. Observed (thin line) and modelled (solid line)  $K_{p1}$  for the periods of 7–18 August 2000 (a) and 16–27 September 2000 (b).

estimates the peak values of  $K_{p1}$  during its sharp increase on 12 August and 18 September 2000. Both increasing and decreasing parts of  $K_{p1}$  changes, however, are well reproduced. The average root mean square deviation between the

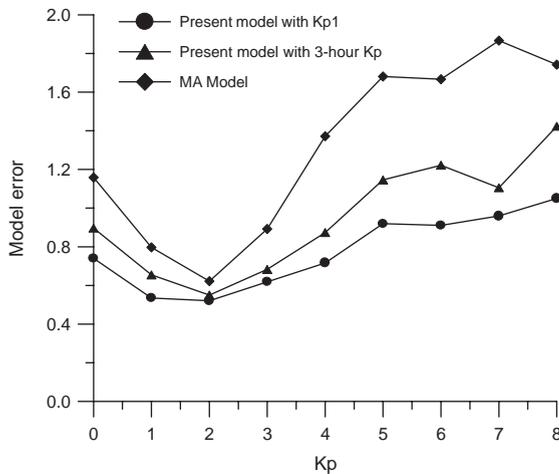


Fig. 7. Model error (diamonds) calculated for each a-unit-wide bin of the  $K_p$  magnitude.

observed and model  $K_{p1}$ , estimated over the whole database (overall model error) is  $0.63 K_p$  units. Fig. 7 compares the model error of MA with that of the present model, calculated separately in a-unit-wide bins of  $K_p$  magnitude. The model error estimated from the 3-h  $K_p$  data set only is  $0.72 K_p$  units, or about 14% higher than that estimated from the whole  $K_{p1}$  set. The difference obviously is due to the contribution of the interpolated  $K_{p1}$  values having lower standard deviation. The model error of MA is  $0.96 K_p$  units. The minimum  $K_{p1}$  error of  $0.52$  is found around  $K_p = 2$ , which coincides with the most likely  $K_p$  value. At  $K_p = 8$ , the error increases to  $1.05$ . Corresponding errors, when the model is applied to the 3-h  $K_p$  values only, are  $0.55$  and  $1.7$ , respectively. The present model error is less than that of MA with  $0.1$  at  $K_p = 2$  and with  $0.9$  at  $K_p = 8$ .

### 3. Discussions

Using the analogy with an electric circuit scheme, the so-called DRC circuit, MA obtained an analytical expression of the delayed reaction of  $K_{p1}$  to the faster changes of IMF  $B_z$ . The new quantity  $B_{zm}$  correlates much better with  $K_{p1}$  (reaching a maximum cross-correlation of  $0.7$ ) than  $B_z$  does (maximum of  $-0.4$ ). In the present paper we improve the model by adding dependences on solar wind velocity and dynamic pressure, whose cross-correlations with  $K_{p1}$  are also significant. The mean dependences of  $K_{p1}$  on these three quantities determine how each of them enter the model expression:  $B_{zm}$  and  $P$  as parabolas and  $V$  as a linear function. The constants  $a_i$  are obtained by fitting expression (2) to the data from the whole available ACE database. The inclusion of additional terms to  $K_{p1}$  model requires obtaining of new values of the time constants  $T_1$  and  $T_2$  in the expression of

$B_{zm}$  (1). Fig. 5 shows that expression (3) with  $T_1 = 3.0$  and  $T_2 = 7.0$  h fits best to the data. These values differ from those obtained by MA ( $T_1 = 0.8$  and  $T_2 = 9$  h) using an expression on  $B_{zm}$  only. The new terms in linear regression (2) now capture some of the deviations between the data and  $B_{zm}$ , which in MA analysis have been assigned to the time delayed process. It is clear that the present approach cannot define a physically meaningful time delay between the force from solar wind parameters and  $K_{p1}$  reaction. This time delay will depend on the parameters included in the regression.

Della-Rose et al. (1999) have introduced “ $K$ -like” geomagnetic indices with variable time intervals (JD index), which were designed to represent geomagnetic activity with different time resolution. These authors found that the average value of their JD index strongly depends on the time window of averaging. At 1-h time-window the average JD value is about 30% less than the value averaged in the standard 3-h time window. Della-Rose et al. (1999) raised the question of how accurate is the standard 3-h  $K_p$  index in representing the geomagnetic activity within the time scales about an hour or less. In the present analysis we simplified the problem, formally increasing the number of  $K_p$  values. This hourly interpolation of the 3-hour  $K_p$  index is roughly equivalent to the averaging within a 3-h time window, sliding it with 1-h step. In the same way Della-Rose et al. (1999) have computed their 3-h index sliding it with 15-min step.

The overall model error, that is the mean root square deviation of model from the data, is estimated at  $0.63 K_p$  units. The model error depends on  $K_p$  magnitude, having minimum value of  $0.52$  at  $K_p = 2$  and increasing to  $1.05$  at  $K_p = 8$ . When the error is estimated only by the 3-h  $K_p$  values, with the moderate, interpolated values excluded, the error increases to  $0.72$ , or with 14%. A rough comparison of this error with another sources of  $K_p$  prediction shows a marked advantage of the present approach. Boberg et al. (2000) have shown a model error of  $0.60$  at  $K_p = 2$  and  $2.80$  at  $K_p = 8$ . Costello (1997) estimation showed values of  $0.60$  and  $1.50$ , respectively. The model error obtained here improves the accuracy achieved by MA by 30%.

### 4. Conclusions

A new model relating  $K_p$  to the solar wind parameters is developed, using the analogy with a time-delayed output voltage in a DRC electric circuit. The model includes the previously defined  $B_{zm}$  function, solar wind velocity and dynamic pressure. These quantities show the highest correlation with  $K_p$ . To enlarge the statistics, the model is derived by using the hourly interpolated  $K_p$  values, denoted here as  $K_{p1}$ . The regression fit with the data from 3 years of ACE measurements shows that the average root mean square deviation between the model and observations (model error) is  $0.63$ . The model error decreases with 14% when the 3-h  $K_p$  values only are used for testing. The accuracy of the present model compared with the previous MA model is increased

with about 30%. It is found higher than the accuracy of the models currently forecasting  $K_p$ .

## References

- Baker, D., Klimas, A., McPherron, R., Buchner, J., 1990. The evolution from weak to strong geomagnetic: an interpretation in terms of deterministic chaos. *Geophysical Research Letters* 17 (1), 41–44.
- Boberg, F., Wintoft, P., Lundstedt, H., 2000. Real  $K_p$  predictions from solar wind data using neural networks. *Physics Chemistry Earth* 25 (4), 275–280.
- Costello, K.A., 1997. Moving the Rice MSFM into a real-time forecast mode using solar wind driven forecast models. Ph.D. Dissertation, Rice University, Houston, TX, June 1997.
- Della-Rose, D.J., Sojka, J.J., Zhu, L., 1999. Resolving geomagnetic disturbances using “K-like” geomagnetic indices with variable time intervals. *Journal of Atmospheric and Solar-Terrestrial Physics* 61, 1179–1194.
- Hones Jr., E., 1979. Transient phenomena in the magnetotail and their relation to substorms. *Space Sciences Review* 23, 393–412.
- Kamide, Y., Baumjohann, W., Daglis, I., Gonzalez, W., Grande, M., Joselyn, J., McPherron, R., Phillips, J., Reeves, E., Rostoker, G., Sharma, A., Singer, H., Tsurutani, B., Vasyliunas, V., 1998. Current understanding of magnetic storms: storm–substorm relationships. *Journal of Geophysical Research* 103 (8), 17705–17728.
- Klimas, A., Baker, D., Roberts, D., 1991. Linear prediction filters for linear and nonlinear modeled geomagnetic activity. *Geophysical Research Letters* 18 (8), 1635–1638.
- Klimas, A., Baker, D., Roberts, D., Fairfield, D., Buchner, J., 1992. A nonlinear dynamic analogue model of geomagnetic activity. *Journal of Geophysical Research* 97 (A8), 12253–12266.
- Muhtarov, P., Andonov, B., 2000. Improved relationship between the IMF component  $B_z$  and  $K_p$  index. *Bulgarian Geophysical Journal* 26 (1–4), 165–172.
- Vassiliadis, D., Sharma, A., Papadopoulos, K., 1993. An empirical model relating the auroral geomagnetic activity to the interplanetary magnetic field. *Geophysical Research Letters* 20 (16), 1731–1734.