

# Neural network model for $Kp$ prediction based on one-hour averages of solar wind data

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**Abstract:** In the paper a new neural network (NN) model for prediction of  $Kp$  indices during geomagnetic storms is proposed. The model consists of 34 individually trained three-layer networks that are fed with solar wind parameters  $B_z$ ,  $n$ , and  $V$  measured at libration point L1. One-hour averages of those are used. Four geomagnetic storm intervals (14–18 May 1997, 1–7 May 1998, 25–26 June 1998, and 24–27 September 1998) were used for the training and validation of the NNs. The final test was performed on three storm intervals (26–29 August 1998, 18–22 October 1998, and 7–11 November 2004). This test was compared with the results of simple NNs fed with three-hour averages of the solar wind data. As follows from this comparison, the NN model based on the one-hour averages gives more accurate predictions of  $Kp$  during the selected test storms, than the usually utilized model based on three-hour averages of solar wind parameters.

**Key words:** neural networks,  $Kp$  index, geomagnetic storm, solar wind

## 1. Introduction

The Earth's magnetosphere interacts with the ever-changing solar wind. Currents in the ionosphere and magnetosphere are generated during interaction processes. Their intensity and, generally, the near-Earth plasma dynamics are directly associated with the variable solar forcing (*Feldstein et al., 2003, 2005*). The chain of these complex phenomena including generated geomagnetic disturbances characterizes the changing space weather.

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Various types of geomagnetic disturbances which can be measured on the Earth's surface are known. A typical one is a magnetic storm. Three phases for this global disturbance are usually considered. When disturbed solar wind streams arrive, the dynamic pressure exposing on the magnetopause compress the dayside magnetosphere. In fact the increased solar wind dynamic pressure drives the magnetopause earthward as revealed by magnetic field and plasma measurements in space (*Siscoe et al., 1968; Ogilvie et al., 1968*). When the arrived shock wave is forcing on the magnetosphere a distinctive magnetic impulse (sudden commencement, SC) is produced as a consequence of the resulted magnetopause current intensification. An abrupt increase (SC) of the geomagnetic field horizontal component seen in magnetograms of magnetic observatories within the worldwide network is an initial phase of the magnetic storm, but not each storm begins with a SC. A gradual decrease of the geomagnetic field horizontal component, a main phase, follows. It is mainly caused by the dramatic enhancement of the ring current, the magnetic effect of which is opposite to the Earth's magnetic field of the interior origin (*Akasofu and Chapman, 1961*). Loss processes in the ring current lead to a slow recovery of the geomagnetic field to its undisturbed state, i.e. a recovery phase takes place (*Williams, 1983*).

In solar-terrestrial studies a planetary activity index  $Kp$  is often used (*Mayaud, 1980*). As a measure of geomagnetic activity  $Kp$  values range between 0 and 9, the differences among successive values being expressed in thirds. The 0 value means absolutely quiet conditions, 9 corresponds to most disturbed conditions. The calculated  $Kp$  values are based on measurements from 13 selected subauroral stations located at geomagnetic latitudes between  $48^\circ$  and  $63^\circ$ . The  $Kp$  data are usually available with a delay of about two month long, while a preliminary  $Kp$  index based on a subset of observatories is obtained in about a six-hour time lag.

Real time predictions of  $Kp$  as an indicator of the disturbed space weather are of great practical importance. That has dramatic impacts on high-tech systems. *Wu et al. (1999)* reported the possibility to use  $Kp$  as inputs in predicting increased risks for satellites. To determine the probability of high levels of geomagnetically induced currents in power grids *Boteler et al. (1990)* also used  $Kp$  as inputs.

To predict stormy conditions a neural network (NN) method (e.g. *Lundstedt, 1996*) is used recently. For providing real time predictions of the space

weather and its effects, the Lund Space Weather Model (*Lundstedt, 1999*) was developed. A neural network model to make real time three-hour predictions of the planetary magnetospheric  $Kp$  is one of the modules in the Lund Space Weather Model (*Boberg et al., 2000*). It consists of two expert networks. One of them makes low  $Kp$  predictions (i.e. within intervals of lower geomagnetic activity) and the latter makes high  $Kp$  predictions (i.e. within intervals of high geomagnetic activity). These two expert networks are joined to a hybrid model. The input parameters for the networks are the interplanetary magnetic field (IMF)  $B_z$  component, the solar wind density  $n$ , and the solar wind velocity  $V$  given as three-hour averages. The networks were trained with the error back-propagation algorithm. The optimum number of hidden units was found to be 10 for the both expert networks. The network specialized on making low  $Kp$  predictions uses only the current solar wind data as input. The second network on making high  $Kp$  predictions needs to take into account six-hour time interval, i.e. two inputs per parameter.

The NN method was successful in predictions of other geomagnetic indices, too. The  $Dst$  index was predicted by *Gleisner (1996)*, *Lundstedt (1996)*, and *Jankovičová et al. (2002)*. The prediction of  $AE$  index was reported by *Gleisner and Lundstedt (1999)*.

In this paper we present the NN predictions of  $Kp$  indices during magnetic storms. Instead of three-hour averages of the IMF  $B_z$  and solar wind parameters  $n$ , and  $V$ , we propose to use one-hour averages of them. Such an approach seems to express the time dependence links between solar wind parameters and the geomagnetic activity level more adequately. In fact a current one-hour input is most actual for a forthcoming three-hour interval to be predicted. In addition measurements at L1 point, those being one-hour ahead (transit time in case of the solar wind velocity of  $\approx 400 \text{ km s}^{-1}$ ), are favorable for the  $Kp$  predictions.

As described below our NN model intends the utilization of either one-hour values closest to the corresponding three-hour intervals or those together with one and/or two preceding one-hour values. The model is likely to improve the accuracy of prediction. To confirm this assumption a comparison with the model based on three-hour averages is also considered.

## 2. Data and method

This study is focused on seven magnetic storm intervals, namely 14–18 May 1997, 1–7 May 1998, 25–26 June 1998, 26–29 August 1998, 24–27 September 1998, 18–22 October 1998, and 7–11 November 2004. Solar wind data for these intervals are based on measurements by ACE satellite at libration point L1 as presented at <ftp://ftp.ngdc.noaa.gov>. The one-hour averages of the IMF  $B_z$  component, of the proton number density  $n$ , and of the solar wind velocity  $V$  were calculated. The geomagnetic activity level was quantified using  $Kp$  indices prepared by Adolf-Schmidt Observatory for Geomagnetism, Niemegk, Germany.

To construct the NN model the sets of patterns for a training process and the another sets for a validation test are needed. In addition, independent sets of the patterns for a final test of the NN model are considered. The storm intervals on May 1998, June 1998, and September 1998 were used as the training patterns. The May 1997 storm was used for the validation. The final test was performed using the August 1998, October 1998, and November 2004 storms.

We used three-layer feed-forward neural networks with one output node (for the predicted  $Kp$  value) (*Kundu, 1996*). The number of input nodes is  $3\tau$ , where  $\tau$  is the length of input vectors (i.e., a history of input parameters).

The output of NN model can be expressed by the following expression:

$$y = f \left[ \sum_{i=1}^H W_i f \left( \sum_{j=1}^{3\tau} w_{ij} x_j + w_{i0} \right) + W_0 \right]. \quad (1)$$

Here  $H$  is the number of hidden nodes,  $x_j$  are the inputs to the NN ( $j = 1, 2, \dots, 3\tau$ ),  $w_{ij}$  and  $W_i$  are the so-called weights. These parameters were calculated within the training process realized with the backward-propagation algorithm (*Gurney, 1996; Kundu, 1996*). The symbol  $f$  in (1) denotes an activation function of the nodes. It was implemented that  $f(z) = [1 + \exp(-z)]^{-1}$  for each node.

In order to estimate reasonable values for  $H$  and  $\tau$  we trained networks with various pairs of  $H$  and  $\tau$ . Five NNs with randomly initialized weights for each pair  $H, \tau$  were considered. The results of the validation test are collected in Tabs 1 and 2 using averages and medians of root mean square

error (RMSE) and/or of correlation coefficient (CC) quantities to judge the most adequate option of  $H$  and  $\tau$  values.

Analysing the CC and RMSE we selected the pairs of  $(H, \tau)$  for which the simple NNs were most successful. As the next step, 34 new networks for these  $(H, \tau)$  were trained. As shown in Tab. 3, the final numbers of trained simple NNs for pairs of  $H$  and  $\tau$  chosen were accepted taking into account results of the validation test. The final model consisting of 34 independent NNs was used for  $Kp$  prediction. The results obtained are discussed below.

### 3. Results and discussion

The proposed NN model for real time prediction of the  $Kp$  index consists of 34 individually trained simple NNs. The NN model is fed with solar wind data  $B_z$ ,  $n$ , and  $V$ , measured at libration point L1, using one-hour averages. Inputs of individual NNs include either one-hour values closest to the corresponding three-hour intervals or those together with one-hour values taken ahead with the shift of 1 and/or 2 hours. Outputs calculated using individual NNs are then averaged to obtain the final predicted value of  $Kp$ . Within the final test of the NN model the prediction of  $Kp$  profiles during three storm intervals on 26–29 August 1998, 18–22 October 1998, and 7–11 November 2004 were performed. As seen in Figs 1–3 the predicted  $Kp$  profiles (shaded lines) fit observed  $Kp$  profiles (black lines) quite well. The accuracy of prediction is most transparent in case of twostorm intervals

Tab. 1. Validation test for different numbers of hidden nodes  $H$  and different lengths of input vectors  $\tau$ . The averages and medians of RMSE from five individually trained NNs are shown

Averages of RMSE					Medians of RMSE				
$H$	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$H$	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
0	1.15	1.16	1.17	1.16	0	1.15	1.16	1.17	1.16
2	0.99	1.04	0.96	1.24	2	1.02	1.03	0.88	1.24
3	0.91	1.39	1.18	1.57	3	0.98	1.31	1.25	1.60
4	1.03	1.32	1.38	1.27	4	0.95	1.34	1.36	1.21
5	1.01	1.30	1.79	1.52	5	0.97	1.25	1.86	1.44

Tab. 2. Validation test for different numbers of hidden nodes  $H$  and different lengths of input vectors  $\tau$ . The averages and medians of correlation coefficients from five individually trained NNs are shown

Averages of CC					Medians of CC				
$H$	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$H$	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
0	0.85	0.84	0.84	0.84	0	0.85	0.84	0.84	0.84
2	0.83	0.85	0.86	0.74	2	0.86	0.87	0.89	0.74
3	0.86	0.71	0.79	0.70	3	0.87	0.70	0.78	0.74
4	0.83	0.81	0.80	0.81	4	0.86	0.82	0.82	0.80
5	0.83	0.78	0.59	0.76	5	0.83	0.79	0.57	0.79

Tab. 3. Numbers of simple NNs trained for the final NN model. Altogether 34 NNs are considered for option of  $H$  and  $\tau$  values taking into account results of the validation test

$H$	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$
0	2	—	—	—
2	4	5	8	—
3	8	—	—	—
4	5	—	—	—
5	2	—	—	—

for 1998 (Figs 1 and 2). In case of the third storm interval the observed and modeled  $Kp$  profiles are consistent during 7 November 2004. Later on differences in the observed and modeled  $Kp$  values become apparent.

As a matter of fact, the November 2004 storm interval was unusually intense. Actually two storms occurred, namely on 7 and 9 November 2004. The geomagnetic activity levels for these 2 storms were comparable as follows from  $Kp$  values. During early November 2004 the Sun was most active. The large full halo CME observed on 6 November 2004 and resulted massive magnetic cloud of solar plasma caused the first storm. The high depression of the geomagnetic field was due to a strong ring current in the Earth's magnetosphere along with the other currents in the ionosphere magnetosphere system (Feldstein *et al.*, 2003). The Earth-directed CMEs followed further on and the second massive magnetic cloud along with the shock passage on late 9 November impacted the magnetosphere. As a result the second

storm, its intensity being comparable with the first one, was observed. The development of the second storm under most disturbed conditions in the magnetosphere, i.e. before its complete recovery, was attributed not only to the solar wind parameters, but also to the actual state of the magnetosphere. Due to the high activity level ( $Kp \gtrsim 3.5$ ) this is quite obvious. However, no parameters of the current magnetospheric state are included into the NN model. This fact appears to be the plausible reason of the relatively worse  $Kp$  prediction after 7 November 2004.

In order to quantify the performance of the NN model proposed, we calculated the CC and RMSE quantities for  $Kp$  prediction performed within three storm intervals comparing observed and modeled  $Kp$  values. As seen in Tab. 4, for each storm  $CC \sim 0.7\text{--}0.8$  and  $RMSE < 2$ . The averaged CC is 0.74 and averaged RMSE is 1.39. On the other side, if the model calculation are based on three-hour averages of solar wind parameters, the modeled values fit observed  $Kp$  worse. *Boberg et al. (2000)* found that for their expert network specialized to high  $Kp$  prediction the optimal characteristics are  $H = 10$  and  $\tau = 2$ . In addition we trained five NNs with these

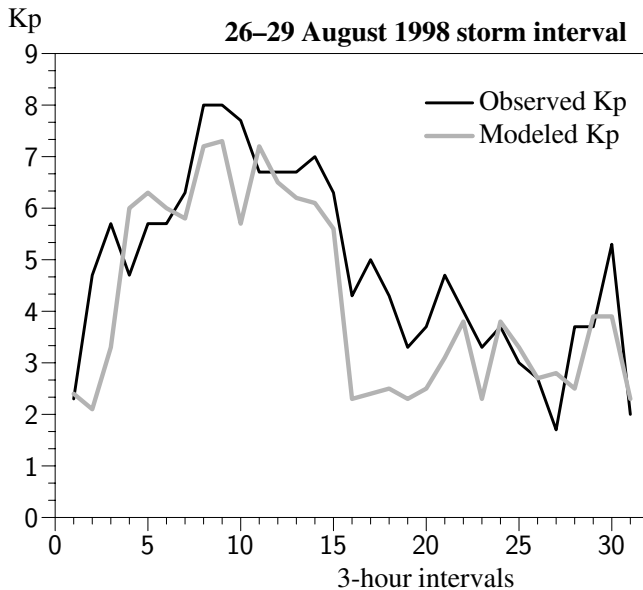


Fig. 1. Modelled  $Kp$  indices compared with the observed ones for the geomagnetic storm occurred on 26–29 August 1998.

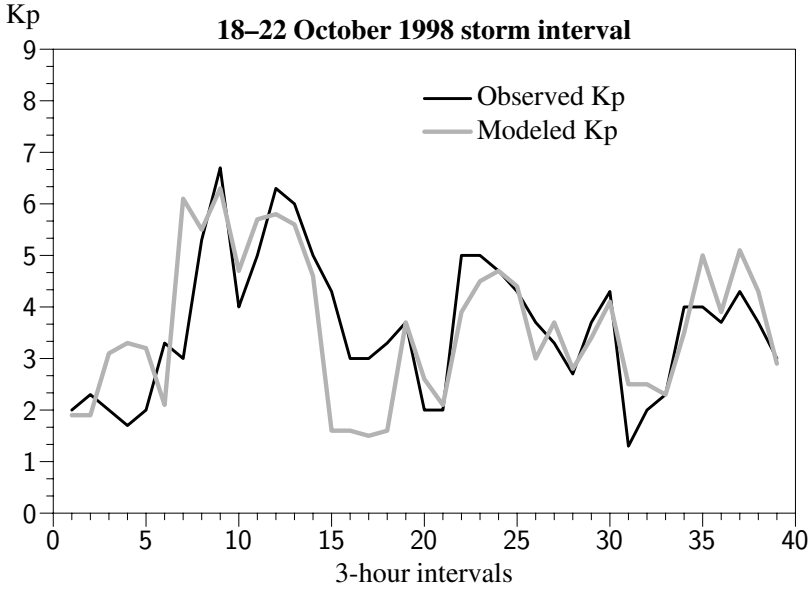


Fig. 2. Modelled  $Kp$  indices compared with the observed ones for the geomagnetic storm occurred on 18–22 October 1998.

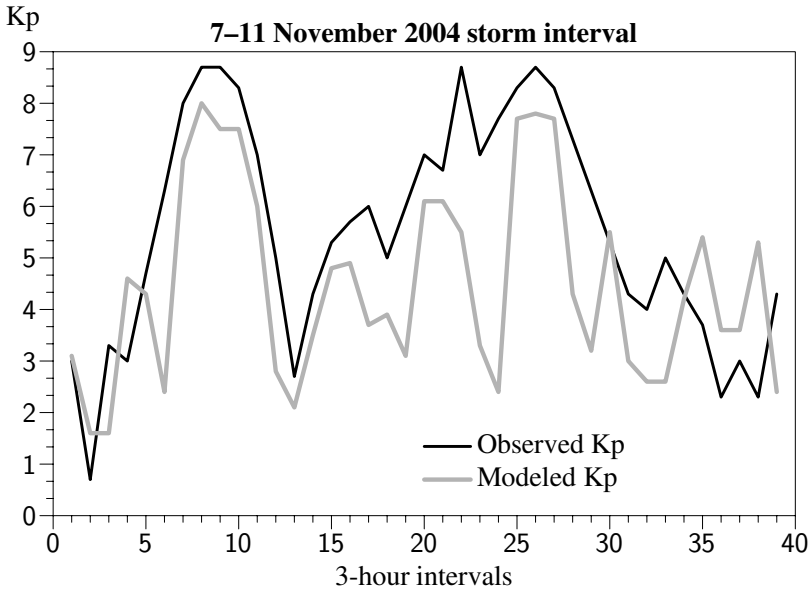


Fig. 3. Modelled  $Kp$  indices compared with the observed ones for the geomagnetic storm occurred on 7–11 November 2004.



Tab. 4. Quality of performance for the NN model based on the one-hour averages of the solar wind data

Measure	August 26–29, 1998	October 18–22, 1998	November 7–11, 2004	Average
RMSE	1.23	1.00	1.95	1.39
CC	0.83	0.72	0.67	0.74

Tab. 5. Typical quality of performance (medians of the correlation coefficients and RMSEs of the individual NNs) for the simple NNs based on the three-hour averages of the solar wind data

Measure	August 26–29, 1998	October 18–22, 1998	November 7–11, 2004	Average
RMSE	1.33	1.93	2.83	2.03
CC	0.73	0.56	0.36	0.55

characteristics. Both the training and validation storm events were used for this purpose. These five simple NNs yielded RMSE and CC values for three storm intervals as stored in Tab. 5. As seen, the averaged CC  $\sim 0.5$  and analysed RMSE  $\sim 2$ . The quantitative comparison (Tabs 4 and 5) gives evidence on the improvement of  $Kp$  prediction on the basis of one-hour averages of the solar wind parameters.

#### 4. Conclusion

The NN model based on the one-hour averages of solar wind parameters was proposed for  $Kp$  prediction. In our NN model altogether 34 networks are considered for pairs of  $H$  and  $\tau$  values as chosen taking into account results of the validation test. Within the final test of the NN model the prediction profiles during three storm intervals on 26–29 August 1998, 18–22 October 1998, and 7–11 November 2004 were performed and discussed. The averaged CC and RMSE indicate quite good coincidence of observed and modeled  $Kp$  values. The comparison with results of modeling based on three-hour averages gives evidence that in case of NN model based on

the one-hour averages the more accurate  $Kp$  predictions during the selected storm intervals are obtained.

**Acknowledgments.** The authors are grateful to VEGA, the Slovak Grant agency (grant No. 2/5121/25) for the support of this work.

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