Neural network model for Kp prediction based on solar wind data and ground-based magnetic observations

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A b s t r a c t: Several neural network (NN) models for the prediction of the Kp index have been proposed recently. Usually only solar wind data are used as inputs. In this paper an attempt is made to consider ground-based observations of geomagnetic variations as input to the NN model. The horizontal component H variations of the geomagnetic field from the Hurbanovo Geomagnetic Observatory were used for this purpose. The modeled geomagnetic activity level within the stormy intervals obtained by means of the modified NN model was compared with previous results to judge how the additional input information on a current state of the magnetosphere improves the accuracy of modeling. The results reveal that the November 2004 superstorm with a more complicated development is replicated better when the information on H component variations is taken into account.

Key words: neural network, Kp index, magnetic storm, solar wind

1. Introduction

The geomagnetic activity level does directly reflect the occurrence of disturbances observed on the Earth's surface as magnetic storms. They are

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caused by interaction processes between the variable solar wind and the Earth's magnetosphere. The geomagnetic activity level, enhanced during magnetic storms and intense substorms, is dynamically controlled by the impinging solar plasma.

Valach and Prigancová (2006) proposed the NN model (thereafter NN1 model) for the prediction of the Kp enhanced level (due to generated magnetic storms) on the basis of one-hour averages of IMF B_z (the north-south component of the interplanetary magnetic field), N (solar wind density), V (solar wind velocity) measured at libration point L1. A number of intervals with some 1997–1998 storms and the 7–11 November 2004 superstorm were considered. Four of them were used for the training and validation of the NNs. The final test was performed using further three storms. The earlier results for the NN1 model include the comparison of the modeled Kp with the results obtained on the basis of the three-hour averages for the same input parameters. In this reference model, the same structure of the training patterns and the same number of hidden neurons were used as in the so-called hybrid model *(Boberg et al., 2000)* with their expert network specialized in the Kp prediction during periods of magnetic storms. This expert network was also shortly described in *(Valach and Prigancová, 2006).* As follows from their comparison, the one-hour input data may yield better results. However, the Kp prediction for the interval including the November 2004 superstorm appeared to be less reliable, both for the NN1, as well as for the reference models.

In this paper we try to improve the NN1 model taking into consideration not only the solar wind data B_z, N, and V, but also information about the ring current effect, the signatures of which can be followed in the ground-based measurements. For this purpose the data on horizontal component variations of the geomagnetic field from the Hurbanovo Geomagnetic Observatory (47.88° N, 18.20° E) are employed as an additional input parameter to the modified NN model (thereafter NN2 model).

2. Data and method

The changing geomagnetic activity level within the intervals of seven magnetic storms on 14–18 May 1997, 1–7 May 1998, 26–29 August 1998, 24–27 September 1998, 18–22 October 1998, and 7–11 November 2004 used for Kp prediction in *(Valach and Prigancová, 2006)* are considered in this paper. As previously, for the description of geomagnetic activity, we used Kp index as reported by Adolf-Schmidt Observatory for Geomagnetism, Niemegk, Germany. In the earlier NN1 model solar wind data measured by WIND and ACE satellite at libration point L1 were taken via CDAWeb Data Service to generate one-hour averages of the IMF B_z component, proton number density N, and solar wind velocity V. In Fig. 1 their development is shown for the November 2004 superstorm.

In the modified NN2 model we employed the horizontal component H variations (1–minute data) as mentioned above on the basis of hourly means. The H variations were computed as ΔH deviations according to

$$\Delta H = H - H_0, \tag{1}$$

where H is an observed value and H_0 is a characteristic quiet value for a given hour (and for an appropriate portion of a day). The H_0 value is calculated as an average using ten quietest days in a given month (moreover, the correction for secular variation is done). In such a way the data were prepared for the final test, too. As seen in Fig. 1 the ΔH profile is in a good consistence with the development of the Sym-H storm variation and hence can be used as a measure of the ring current development. Meanwhile, Sym-H as a high-time resolution version of the well-known Dst index describing the ring current dynamics is available at the World Data Center for Geomagnetism (Kyoto).

To obtain the NN2 model, we needed, as earlier, one set of patterns for training the neural networks (NNs) and one storm at least for validation. In addition, an independent set of patterns for the final test of the NN2 model is required. As before *(Valach and Prigancová, 2006)*, we took the storms of May, June and September 1998 as the training patterns, the storm of May 1997 was used for the validation. The final test was performed using the storms of August and October 1998, and November 2004.

According to the approach applied in *(Valach and Prigancová, 2006)* we used three-layer feedforward NNs *(Kundu, 1996)* with one output node (for the predicted Kp value). The number of input nodes is 3τ, where τ is the history of input parameters. The outputs of the NNs were calculated using the formula

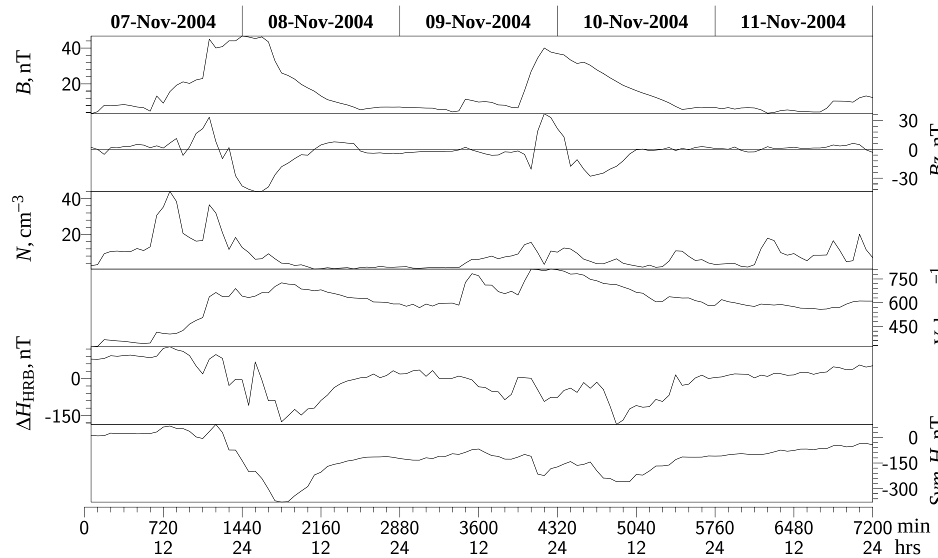

Fig. 1. Space weather conditions (hourly means) in the Sun-Earth system (ACE data): the IMF — total field B and B_z component, proton number density N, and solar wind velocity V. The profile of ΔH obtained on the basis of magnetic ground-based measurements from the Hurbanovo Geomagnetic Observatory during 7–11 November 2004, when 2 intense magnetic storms occurred is also shown along with the corresponding Sym-H storm variation (original 1–minute data).

$$y = \mathrm{f}\left(\sum_{i=1}^{\Omega} W_i \mathrm{f}\left(\sum_{j=1}^{3\tau} w_{ij}x_j + w_{i0}\right) + W_0\right), \tag{2}$$

where Ω is the number of hidden nodes, x_j are inputs to the NN ($j = 1, 2, ..., 3\tau$), w_{ij} and W_i ($i = 0, 1, ..., \Omega$) are weights determined from the training process. The backward-propagation algorithm (Gurney 1996, Kundu 1996) was used for training. In (2) f denotes the activation function for individual nodes $\mathrm{f}(z) = (1 + e^{-z})^{-1}$.

The estimation of the optimal Ω and τ values is based on the training processes for NNs within reasonable ranges of Ω and τ values. The consideration of pairs with $\Omega \leq 8$ and $\tau \leq 3$ proved to be sufficient. Always five NNs with randomly initialized weights were used to obtain the averaged values and thus to quantify the validation test by means of a root mean square error (RMSE) and correlation coefficient (CC) values for each pair (Ω, τ). The results of the validation test are shown in Tables 1 and 2. The RMSE values calculated for individual pairs (Ω, τ) are presented as averages and medians of RMSE in Table 1. In a similar way CC values (averages and medians of CC) are displayed in Table 2.

Only the pairs of (Ω, τ) with the most proper statistical characteristics were used for the further process of modeling. In other words, in Tables 1 and 2 we selected the individual pairs of (Ω, τ), for which the NNs were most successful. It is worth noting that to obtain the NN2 model, the pairs (Ω, τ) considered are not the same as in the NN1 model.

As the next step, altogether 34 new NNs were trained to obtain the NN2 model. The distribution of NNs with regard to (Ω, τ) is shown in Table 3. The number of NNs considered for individual pairs of (Ω, τ) is chosen according to the results of the validation test: the better RMSE and CC values, the more NNs were considered. The proper number of the hidden nodes was estimated to be less than six. The time history of input parameters is taken within the range from one to three hours. The modelled Kp index is a result of averaging of Kp values from individual NNs.

3. Results and discussion

The NN1 model was tested using three magnetic storms, namely: 26–29 August 1998, 18–22 October 1998, and 7–11 November 2004. The quality of performance for this model was controlled considering the RMSE and CC statistical measures. The calculated RMSE values for individual magnetic storms mentioned are 1.23, 1.00, and 1.95, respectively. Those of CC are 0.83, 0.72, and 0.67, respectively. The comparison of these values shows that the prediction for the November 2004 storm is less reliable. A quite complicated development is characteristic for this unusually intense storm due to their drivers *(Yermolaev et al., 2005; Valach and Prigancová, 2006*). The maxima in the Kp profile related to the two-step distinctive enhancement of the ring current effect are apart of approximately three days. This time interval is not enough for the magnetosphere to recover. Moreover, the second maximum of the geomagnetic activity level is comparable to the first one and occurred on the background of the still disturbed conditions

Table 1. Results of the validation test: the averages and medians of the RMSE calculated for subsets of NNs, consisting of five NNs initially trained (altogether 24 subsets of NNs were considered).

Averages of RMSE				Medians of RMSE			
Ω	$\tau = 1$	$\tau = 2$	$\tau = 3$	Ω	$\tau = 1$	$\tau = 2$	$\tau = 3$
0	1.14	1.16	1.13	0	1.14	1.16	1.13
2	0.97	1.25	1.51	2	0.96	1.18	1.39
3	1.33	1.37	1.38	3	1.29	1.34	1.39
4	1.18	1.21	2.16	4	1.15	1.19	2.00
5	1.15	1.60	2.10	5	1.16	1.68	2.48
6	1.33	1.85	2.70	6	1.30	1.79	2.64
7	1.52	1.89	2.42	7	1.44	1.84	2.25
8	2.14	2.15	2.99	8	1.88	2.56	2.76

Table 2. Results of the validation test: the averages and medians of the CC calculated for subsets of NNs, consisting of five NNs initially trained (altogether 24 subsets of NNs were considered).

Averages of CC				Medians of CC			
Ω	$\tau = 1$	$\tau = 2$	$\tau = 3$	Ω	$\tau = 1$	$\tau = 2$	$\tau = 3$
0	0.83	0.83	0.85	0	0.83	0.83	0.85
2	0.85	0.79	0.62	2	0.86	0.77	0.72
3	0.69	0.65	0.78	3	0.66	0.80	0.79
4	0.75	0.77	0.56	4	0.76	0.79	0.62
5	0.81	0.60	0.30	5	0.82	0.65	0.12
6	0.56	0.62	0.44	6	0.64	0.72	0.45
7	0.64	0.51	0.45	7	0.73	0.46	0.60
8	0.41	0.63	0.38	8	0.38	0.65	0.37

Table 3. Distribution of altogether 34 new NNs trained for the modified NN2 model using pairs (Ω, τ) chosen according to the validation test results.

Ω	$\tau = 1$	$\tau = 2$	$\tau = 3$
0	4	3	4
2	6	3	2
3	2	2	2
4	2	2	—
5	2	—	—

Table 4. Quality of performance for the NN1 model fed with solar wind data only *(Valach and Prigancová 2006)*.

Measure	26–29 Aug 1998	18–22 Oct 1998	7–11 Nov 2004
RMSE	1.23	1.00	1.95
CC	0.83	0.72	0.67

Table 5. Quality of performance for the NN2 model fed with both the solar wind and ΔH data.

Measure	26–29 Aug 1998	18–22 Oct 1998	7–11 Nov 2004
RMSE	1.25	1.01	1.83
CC	0.80	0.70	0.71

Table 6. Comparison of the performances of NN1 and NN2 models for the first and second portions of the 7–11 November 2004 superstorm.

Measure (RMSE and/or CC)	First portion of the storm	Second portion of the storm
RMSE in case of NN1 model	1.64	2.29
RMSE in case of NN2 model	1.69	1.99
CC in case of NN1 model	0.82	0.46
CC in case of NN2 model	0.78	0.59

in the magnetosphere. Since there was no complete recovery, yet it appears to be reasonable to take into account the current state of the disturbed magnetosphere, when predicting the Kp level.

The modified NN2 model described above is used to predict (*post factum*) the Kp values for the time intervals, when three magnetic storms on 26–29 August and 18–22 October 1998, and 7–11 November 2004 occurred. To compare the accuracy of prediction of Kp within the intervals of these stormy conditions, the statistical characteristics calculated (RMSE and CC) are compared for both NN1 and NN2 models and can be followed in Tables 4 and 5. The quality of performance for the NN1 and NN2 is generally comparable in case of two storms (26–29 August 1998 and 18–22 October 1998). That can be seen in modeled profiles obtained by means of the NN1 and

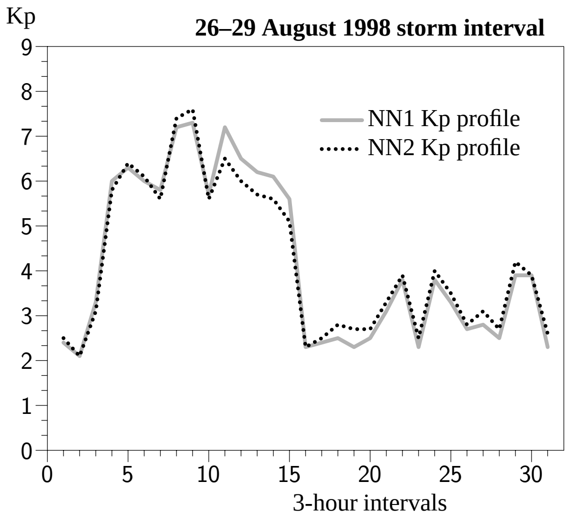

Fig. 2. Comparison of modeled Kp profiles for the 26–29 August 1998 storm: in case of the NN1 model based on solar wind data only (shaded line) and in case of the NN2 model based on both solar wind data and ground-based observations of the geomagnetic field (dotted line). The comparison of the observed K_p profile was discussed in *Valach and Prigancová (2006)*.

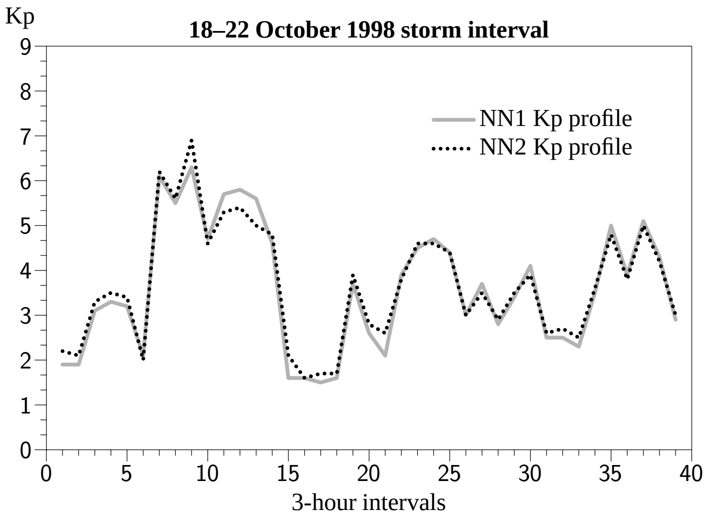

Fig. 3. As Fig. 1, but for the 18–22 October 1998 storm.

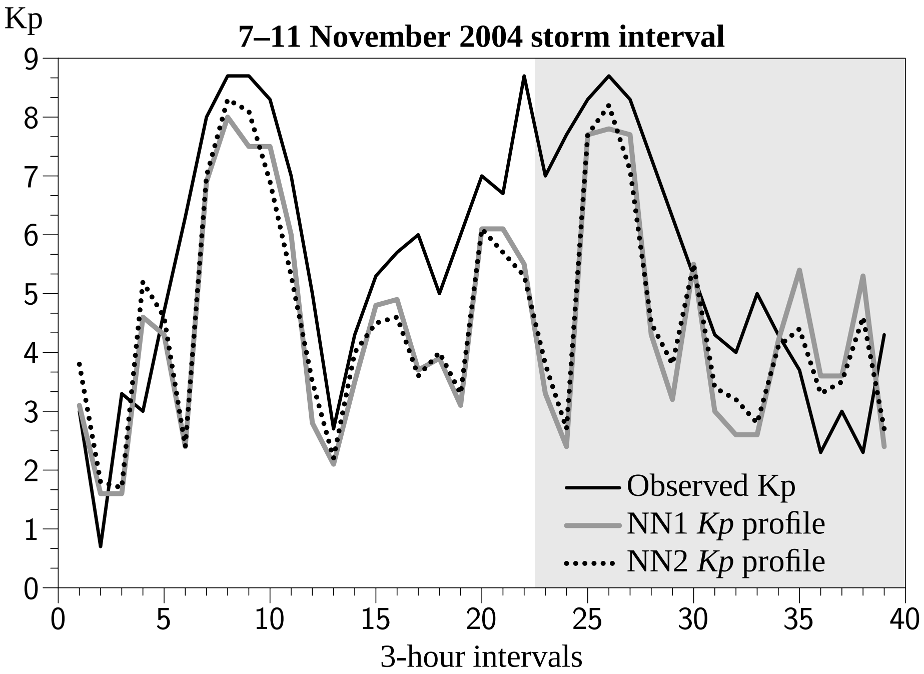

Fig. 4. Comparison of Kp profiles for the 7–11 November 2004 superstorm: observed values (solid lines) and model values in case of the NN1 model based on solar wind data only (shaded line) and in case of the NN2 model based on both solar wind data and ground-based observations of the geomagnetic field (dotted line).

NN2 for this stormy interval (Fig. 2 and 3). It seems to be confirmed that the Kp profiles during magnetic storms and intense substorms are dynamically controlled by the solar wind *(Gleisner and Lundstedt, 1999)* and that the NN model fed with only solar wind data *(Boberg et al., 2000; Valach and Prigancová, 2006)* is sufficient for the prediction of the Kp index.

On the other hand, the November 2004 superstorm is predicted better using the new NN2 model. Since this storm is of a quite complicated development that was considered as 2 successive stormy portions. Actually, it is of interest to divide the November 2004 storm into two portions as shown in Fig. 4. A separating line is chosen at the moment at which predictions by the NN2 model become better than those by the NN1 model. The first portion of the storm is predicted to some extent better when only the solar wind data are considered. In fact, both the RMSE and CC values are better in case of the NN1 model. But the second portion of the storm is predicted more adequately when also an additional information from ground-based observations of the geomagnetic field is considered. The performance of the NN1 and NN2 is compared for the first and second portions of the storm in Table 6. As seen, the reliability of prediction of the first portion of the storm is comparable, although both RMSE and CC values in the case of the NN2 are slightly poorer, which gives evidence of some noisy effect of the added input parameter (ΔH) in this case. However, the NN2 output for the second portion of the storm reveals the predicted Kp level to be more adequate than the NN1 output. Actually, as seen in Table 6, the RMSE and CC values are more accurate in case of NN2 model. That can be followed in Fig. 4, too. In the shaded portion of the storm the influence of not only the external forcing, but also of the disturbed conditions in the magnetosphere (still far from recovery) is replicated in a better way. In other words, in the case of the still disturbed magnetosphere, the additional ΔH input quantifying the current state of the magnetosphere is useful.

4. Conclusion

The analysis of a number of time intervals, when magnetic storms occurred, was carried out in order to assess the quality of prediction of the geomagnetic activity level (expressed by the Kp index) by means of the Neural Network model. The modified NN2 model based on both the solar wind data and ground-based observations of the geomagnetic field is compared with the previous NN1 model based on the solar wind data only. In the case of storms with a regular development the ΔH data, as input of the NN2 model, appear to be rather unnecessary, and even to supply an additional noise to the NNs input parameters. The significance of additional information is apparent when a storm occurs on the background of the disturbed magnetosphere. The information on the current state of the magnetosphere expressed by the horizontal component variations ΔH of the observed geomagnetic field at a given point, improves the quality of performance and a more adequate Kp prediction is obtained by means of the modified NN2 model.

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