THE APPROACH OF FUZZY NEURAL NETWORKS FOR GEOMAGNETIC STORMS PREDICTIONS

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ABSTRACT

We summarize our first experience with the FNN approach used for the geomagnetic storm predictions.

INTRODUCTION

Most of the schemes of Dst predictions are based on Artificial Neural Networks (starting from Ludstedt and Wintoft, 1994). Here we consider neuro-fuzzy system (Nauck, Kruse, 1997) for that purpose.

SCHEME AND RESULTS

In the first step we used a pair of parameter sets, namely n.v and σ_{B_z} (product of solar wind density and its bulk speed, and variance of the north-south component of IMF magnetic field). Figure 1 is illustrating schematically the space of measured parameters and Figure 2 is providing an example of FNN. The results of this method are given in Tables 1 and 2.

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$$B_1 =< min_1, max_1 >=< 174, 55030 >$$
$$B_2 =< min_2, max_2 >=< 0.01, 15.68 >$$

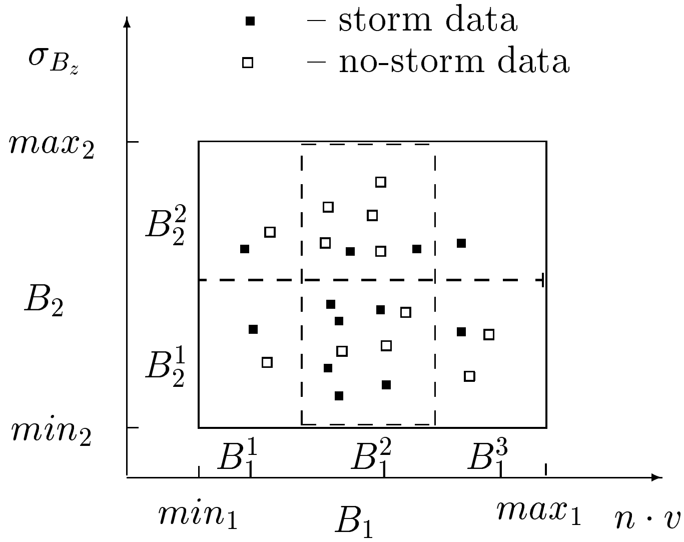

Figure 1: The space of measured data $n \cdot v$ and σ_{B_z} and its division into fuzzy subsets.

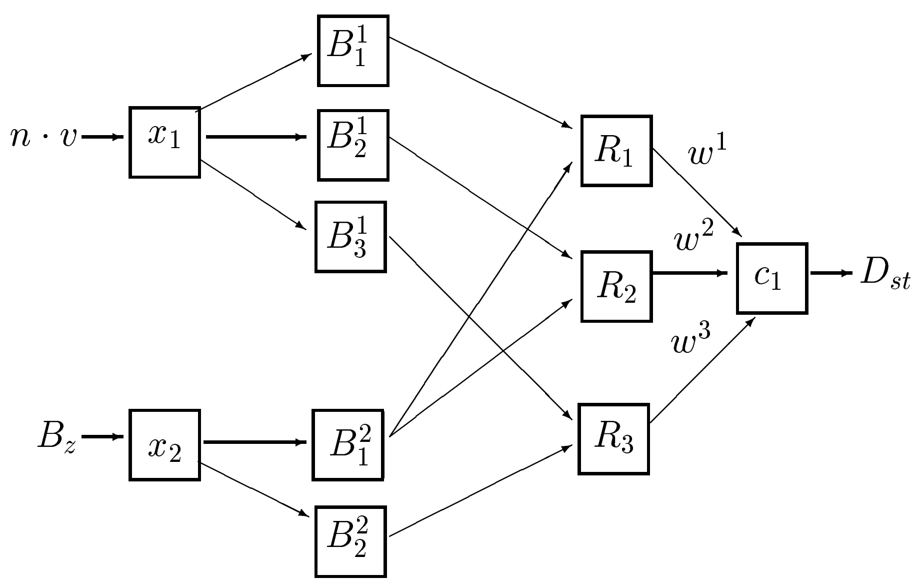

Figure 2: An example of a fuzzy neural network.

Table 1. The results computed by neuro–fuzzy classifier with parameters $n \cdot v, \sigma_{B_z}$ after the learning process. The values E_2 are better than the values in Table 2, but the values $1 - E_1$ are worse.

			Sample A ($B = 32$)			Sample B ($B = 94$)			Sample C ($B = 126$)		
α	β	R	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2
0.3	20	74	17	53.12	0.91	33	35.11	1.56	50	39.68	1.18
0.35	20	75	16	50.00	0.97	29	30.85	1.86	45	35.71	1.34
0.25	20	100	16	50.00	1.08	26	27.66	2.20	42	33.33	1.55

Table 2. The results computed by neuro-fuzzy classifier with parameters $n \cdot v, \sigma_{B_z}$ without the learning process. The values E_2 are worse than the values in Table 1, but the values $1 - E_1$ are better.

			Sample A ($B = 32$)			Sample B ($B = 94$)			Sample C ($B = 126$)		
α	β	R	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2
0.3	20	74	19	59.38	1.57	36	38.30	2.44	55	43.65	1.93
0.35	20	75	19	59.38	1.78	39	41.49	2.95	58	46.03	2.27
0.25	20	100	17	53.12	2.19	39	41.49	4.40	56	44.44	3.11

Table 3. The results computed by neuro–fuzzy classifier with parameters $n \cdot v, B_z$ after the learning process. The values E_2 are better than the values in Table 4, but the values $1 - E_1$ are worse.

			Sample A ($B = 37$)			Sample B ($B = 52$)			Sample C ($B = 89$)		
α	β	R	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2
0.30	20	136	18	48.65	0.99	14	26.92	1.68	32	35.96	1.22
0.45	20	116	15	40.54	0.64	12	23.08	1.62	27	30.34	0.97
0.25	20	145	19	51.35	0.98	12	23.08	1.58	31	34.83	1.18

Table 4. The results computed by neuro–fuzzy classifier with parameters $n \cdot v, B_z$ without the learning process. The values E_2 are worse than the values in Table 3, but the values $1 - E_1$ are better.

			Sample A ($B = 37$)			Sample B ($B = 52$)			Sample C ($B = 89$)		
α	β	R	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2	S	$1 - E_1$	E_2
0.30	20	136	29	78.38	2.78	27	51.92	3.94	56	62.92	3.18
0.45	20	116	24	64.86	2.28	23	44.23	3.47	47	52.81	2.68
0.25	20	145	29	78.38	2.41	28	53.85	3.69	57	64.04	2.85

In the second step the pair of parameter sets was constructed from $n \cdot v$ and B_z and Tables 3 and 4 are summarizing the results. The first experience is showing that the applied learning process in both cases is decreasing E2 (false predictions), however 1-E1 (correct predictions) is decreasing too. The same effect is seen for both pairs of parameter sets. Comparison of 1-E1 for the two steps (Tables 2 and 4) is illustrating the importance of the north-south component of IMF for the prediction and occurrence of geomagnetic storms with higher probability for $B_z < 0$ (better results for the second pair including B_z). It should be noted that recently more than two sets of input data are used.

There are many gaps in the solar wind and IMF data since many of these data sets are constructed from IMP measurements, the satellite being not on the whole orbit outside the magnetosphere. Recently an effort in checking the relevance of cosmic ray (CR) measurement, based on the ground observations with relatively small portion of the data gaps is progressing. CR particles are scattered by IMF inhomogeneities and thus it is expected that changes in their variability (temporal variability at a single station is related to anisotropy of particle flux in interplanetary medium) would reflect the redistribution of IMF inhomogeneities. CR are exposed to the redistributed IMF driven occasionally from the solar surface well before a "single inhomogeneity" reaches the Earth's orbit and direct interaction with the magnetosphere occurs. Strong enhancements of CR anisotropy were observed before and during January 1997 CME/magnetic cloud (Bieber and Evenson, 1998). This is consistent with the statistical study of crosscorrelations between Dst and CR variability deduced from a single neutron monitor measurements (Kudela et al, 1998 and references therein). We are currently trying to find a proper measure of CR anisotropy useful for implementing into the scheme of FNN. For this purpose and especially for the eventual use of real time CR data in the forecasting schemes the web sites (for instance that by V.Yanke, E. Eroshenko, A. Belov and colleagues in IZMIRAN, Russia) are very important.

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