ACCOUNTING OF THE PROCESS OF MAGNETOSPHERIC LOADING BY THE KINETIC ENERGY OF THE SOLAR WIND IN THE PROBLEM OF CLASSIFICATION OF ISOLATED SUBSTORMS

© 2025 N.A. Barkhatov[a]*, S.E. Revunov[a], O.M. Barkhatova[b], V.G. Vorobjev[c], E.A. Revunova[b], O.I. Yagodkina[c]

[a]*Nizhny Novgorod State Pedagogical University (Minin University), Nizhny Novgorod, Russia*

[b]*Nizhny Novgorod State University of Architecture and Civil Engineering, Nizhny Novgorod, Russia*

[c]*Polar Geophysical Institute, Apatity, Russia*

**e-mail:* nbarkhatov@inbox.ru

Received May 27, 2024

Revised August 06, 2024

Accepted September 26, 2024

Abstract. The study classifies isolated magnetospheric substorms according to the temporal characteristics of substorm phases together with data on the solar wind and interplanetary magnetic field parameters. The classification results demonstrate causal relations of substorm activity with the characteristics of the solar wind flux flowing to the Earth's magnetosphere. Combinations of solar wind parameters are utilized to account for the process of solar wind kinetic energy loading into the polar magnetosphere. Neural network experiments have shown that the dynamic parameters of substorm activity contain information about the characteristics of plasma flows. This was expressed in the detection of classes of the studied patterns that correspond to the physical concepts of generation of high-latitude geomagnetic activity.

Keywords: *substorms, magnetosphere, classification, neural networks*

DOI: 10.31857/S00167940250202e4

1. INTRODUCTION

The study of the solar wind and forecasting of geomagnetic disturbances, based on data from patrol spacecraft located outside the magnetosphere, continues to be one of the tasks of modern heliogeophysics. There are a number of factors that contribute to the interest in these problems. It is known that the most significant restructuring of current systems in the magnetosphere and high-latitude ionosphere occurs during periods of magnetospheric substorms that follow the impact of magnetized solar wind flow on the Earth's magnetosphere [Gallardo-Lacourt et.al., 2012]. An indicator of such events, in particular, is the dynamics of the *AL index,* which characterizes the development phases of the substorm process. It is believed that the beginning of the active phase of a substorm is the explosive transition of accumulated potential energy of the distorted magnetic field of the polar magnetosphere into the kinetic energy of charged particles filling the ring current and plasma sheet of the magnetosphere and ionizing the high-latitude atmosphere [Henderson et.al., 1996]. The accumulation of energy in the magnetosphere, occurring during the preparatory phase of the substorm, is provided by the enhancement of the large-scale westward electric field of convection across the magnetotail [Nishimura et.al., 2010].

The task of classifying geomagnetic substorms, along with the development of fundamental scientific theories of their occurrence, is also of scientific interest as it contributes to a better understanding of the interaction between Earth's magnetosphere and the solar wind. In the work [Vorobyev et al., 2016], based on the results of visual analysis of geomagnetic field variations at high latitudes, a division of substorms into 5 types was proposed depending on the values of the *Bz component of the* IMF before and during the onset of the substorm development phase. The authors focus primarily on substorms whose development phase occurred during the southward orientation of the IMF (type 1) and substorms whose onset was associated with a northward turning of the *Bz component of the* IMF (type 3). In the study [Barkhatov et al., 2023], an automatic neural network classification of a similar set of isolated substorms into 5 classes was performed, taking into account features characterizing the peculiarities of generation of different substorm phases. Analysis of the obtained classes allowed formulating their features and drawing physical conclusions. However, when using only the durations of phases as classification features, their cause-and-effect relationships with solar wind and IMF parameters were considered indirectly.

In the present study, neural network classification is performed with direct consideration of solar wind parameters, and therefore, this approach should reflect their cause-effect physical relationship in the substorm process. At the same time, it is extremely difficult to consider the dynamics of a substorm and all its phases if only instantaneous values of the main parameters of the interplanetary magnetic field (IMF) and solar wind plasma (Bz , N , V) are taken into account, since the process of gradual accumulation of solar wind magnetic energy in the magnetosphere occurs under conditions of continuous inflow of kinetic energy of particles (NV^2) from the solar wind (N - density, and V - solar wind velocity). Previously, in [Barkhatov et al., 2017], to describe the process of substorm formation and predict its dynamics, it was proposed to use an integral parameter in the form of a cumulative sum $\sum NV^2$ along with other geoeffective parameters of the solar wind. However, this parameter can be used not only for forecasting but also for classification of magnetospheric substorms. Thus, in this work, the classification of isolated substorms is performed taking into account the duration of the initiation phase, development phase, and recovery phase of the substorm, the duration of the entire substorm, as well as the values of the Bz -component of the interplanetary magnetic field, the cumulative parameter $\sum NV^2$, amplitude values of the AL index and electric field E in the solar wind flow.

The purpose of this work is to demonstrate the results of solving the problem of neural network classification of isolated substorm events, taking into account the process of loading the kinetic energy of the solar wind into the polar magnetosphere.

2. DATA AND METHODS

The research material consisted of isolated substorms selected according to variations in minute values of the *AL* index for all winter seasons from 1995−2012. The primary selection of substorms was conducted visually based on daily variations of the *AL index.* An additional sign of substorm occurrence was the presence of corresponding variations in magnetic activity indices *SYM/H* (*D*) or *ASYM/H* (*D*) [Vorobyev et al., 2016]. We used 106 isolated substorm events of various intensities, the catalog of which is presented on the pages (http://pgia.ru/lang/en/data/). Data on magnetic activity indices and interplanetary medium parameters with 1-minute resolution were taken from the OMNI Web portal (https://cdaweb.gsfc.nasa.gov /).

Previously, in the work [Barkhatov et al., 2023], we performed a neural network classification of isolated substorms, taking into account features characterizing the generation peculiarities of various substorm phases. For this purpose, classification features were selected such as the duration of the initiation phase, development phase, recovery phase, and the duration of the entire substorm, as well as implicitly considering the behavior pattern of the *Bz* component of the

IMF. The latter feature refers to the southward turning of the Bz -component of the IMF, which determines the beginning of the substorm initiation phase. The Bz component itself was not included in the classification parameters. The considered features were accepted as input series for the created self-learning neural network models [Barkhatov et al., 2023]. The result of the classification neural networks was the formation of graphical images of the set of specified classification features, each containing information about the duration of phases of the considered substorms. The classification neural network experiments conducted in [Barkhatov et al., 2023] allowed dividing substorms into five classes. The physical characteristics of the identified classes, in all likelihood, are determined by the cause-effect relationships between the duration of substorm phases and solar wind parameters and IMF features.

Classification neural network experiments presented in this study were conducted using a neural network previously trained on four classification features of substorms [Barkhatov et al., 2023]: duration of the initiation phase ($P1$), development phase ($P2$), recovery phase ($P3$) of the substorm, and the duration of the entire substorm ($P4$). While maintaining the number of considered features, we now also involve a number of other parameters, namely, the Bz component of the IMF, the cumulative parameter $\sum NV^2$ (calculated for 2 hours before the substorm development begins), the amplitude of the AL_{max} index, and the electric field E_{max} of the solar wind. The applied neural network contains previously fixed optimal weight coefficients at its inputs and in its layers. The task of detecting substorm classes when using other features should, as before, meet the following criteria/limitations:

1. The number of neural network inputs (classification parameters) must always be equal to 4.
2. The number of classes into which the neural network attempts to divide the sample of available events is always equal to 5.
3. The use of the original classification parameters ($P1$, $P2$, $P3$, $P4$) allows obtaining a reference classification picture, with which the classification outcomes for other parameter sets should be compared.
4. The replacement of the original classification parameters ($P1$, $P2$, $P3$, $P4$) with classification features (Bz , $\sum NV^2$, AL , E) is organized sequentially, in order to determine the contribution of each new parameter.
5. The results of each classification experiment with a specific set of parameters are compared with the reference classification picture, and corresponding conclusions are drawn.

3. DISCUSSION

The results of each classification experiment performed with a specific set of parameters were compared with the reference classification pattern. For this purpose, the indexed substorm events assigned by the neural network to the same class in different experiments were accounted for. The results of such indexation with an assessment of classification quality (conformity of the new classification outcome to previous conclusions) are presented in Table 1 for the most illustrative experiments.

As can be seen from Table 1, for the specified combinations of classification parameters, more than 70% of substorm events were assigned by the neural network to classes previously identified in [Barkhatov et al., 2023], when only the durations of various substorm phases were used as features. It can be noted that in parameter combinations, the durations of the initiation phase (*P1*) and the development phase (*P2*) always appear. This indicates the importance of these classification features for determining the substorm type; essentially, they define the characteristics of event classes. At the same time, parameters responsible for the duration of the recovery phase (*P3*) or the entire substorm (*P4*) can be replaced by one of the new classification features.

Demonstration of the obtained results is performed using the data visualization algorithm developed in [Barkhatov et.al., 2020]. It allows representing existing cause-and-effect relationships with graphic images. Figures 1-5 demonstrate the data from experiment No. 6826, for which there is a maximum match between the classification experiment results when using the parameter set (*P1* , *P2* , *P3* , Bz_{max}) with the reference classification pattern (84 out of 106 events or 79%). Visual assessment can be performed using color coding of classes: class 1 – white in a black frame (substorms with prolonged development and recovery phases and with a shortened initiation phase), class 2 – dark gray in a black frame (substorms with a prolonged initiation phase), class 3 – white in a gray frame (substorms with equal phases), class 4 – black in a gray frame (substorms with a prolonged development phase), class 5 – light gray in a black frame (substorms with a short recovery phase). The number of the substorm event is indicated under each graphic image. Errors in determining classes based on the new dataset are detected when colors are mixed.

It can be noted that class 5 (Fig. 5) turned out to be the most mixed, which in the reference classification corresponded to substorm events with a short recovery phase. In other experiments, this particular class is the most problematic to identify. Attraction of new classification parameters of the solar wind or interplanetary magnetic field is not manifested here under the required classification conditions . This can be explained by the fact that these parameters do not physically participate in the recovery phase of the substorm process. The obtained classification results confirm the cause-and-effect relationship between high-latitude geomagnetic activity and the analyzed parameters of near-Earth space. A total of 5 classes were discovered. It was established that: class 1 involves prolonged development and recovery of the substorm with a shortened onset phase, which is observed mainly during the southern orientation of the IMF; classes 2 and 3 with a prolonged onset phase and equal development and recovery phases of the substorm are associated with a northward turn of the *Bz* component of the IMF, with the largest deviations observed in the *AL* index; class 4 is associated with a prolonged development phase and is characterized by high negative values of *Bz* ; class 5 contains substorms with a short recovery phase, for which the attraction of new classification parameters of the solar wind or interplanetary magnetic field is not manifested under the required classification conditions. The physical features of the discovered classification determine the cause-and-effect relationships between the duration of substorm phases and the parameters of the solar wind and IMF.

As experiments have shown, accounting for the kinetic energy of the solar wind through the cumulative parameter NV^2 is a key element for identifying the features of the impact of cosmic plasma flows on the high-latitude magnetosphere. Using an integral parameter in the form of a cumulative sum $\sum NV^2$ along with other geoeffective parameters of the solar wind allows more accurate modeling of these impacts and developing methods to protect against their negative consequences. This is important for ensuring the safety of space flights, protecting cellular networks and other communication systems, as well as maintaining the operability of spacecraft under conditions of increased solar activity.

4. CONCLUSION

A classification neural network study of the characteristics of isolated substorms, which were selected based on variations of 1-min values of the *AL index, was conducted.* Special criteria, described in detail in [Vorobyev et al., 2016], were used to select substorms. The automatic neural network classification was performed taking into account solar wind parameters, and therefore this approach reflects the causal physical connection existing in the substorm process between phenomena in the solar wind and the Earth's magnetosphere. Using different sets of parameters, it was demonstrated that the studied configurations of the *AL index* dynamics contain information about the characteristics of plasma flows. It is shown that in the combinations of classification parameters, the durations of the initiation phase and the development phase of substorms always appear. This indicates the importance of these classification features for determining the type of substorm when jointly considering solar wind parameters. Thus, the features of event classes and cause-effect relationships within groups of classification parameters are determined. The results of this study can be considered more objective compared to previous conclusions, since along with the parameters of substorms as consequences of the physical process, the parameters of the solar wind as causes of what is happening were also taken into account.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ACKNOWLEDGMENTS

The authors express their gratitude to the moderators of NASA's Space Physics Data Facility website for the opportunity to obtain data on solar wind parameters and the interplanetary magnetic field.

FUNDING

The work was carried out without financial support.

REFERENCES

– *Barkhatov N.A., Vorobyev V.G., Revunov S.E., Yagodkina O.I.* Manifestation of solar wind parameter dynamics in the formation of substorm activity // Geomagnetism and Aeronomy. Vol. 57. No. 3. P. 273–279. 2017.

– *Barkhatov N.A., S.E. Revunov, O.M. Barkhatova, E.A. Revunova, V.G. Vorobyev, Yagodkina O.I.* Classification of isolated substorms taking into account generation conditions and phase characteristics // Cosmic Research. 2024. (accepted for publication)

– *Vorobyev V.G., Yagodkina O.I., Zverev V.L.* Investigation of isolated substorms: conditions of generation and characteristics of different phases // Geomagnetism and Aeronomy. Vol. 56. No. 6. P. 721–732. 2016.

– *Vorobjev V.G., Yagodkina O.I., Antonova E.E., Zverev V.L.* Influence of solar wind plasma parameters on the intensity of isolated magnetospheric substorms // Geomagnetism and Aeronomy. Vol. 58. No. 3. P. 311−323. 2018.

– *Barkhatov N.A., Vorobjev V.G., Revunov S.E., Barkhatova O.M., Revunova E.A., Yagodkina O.I.* Neural network classification of substorm geomagnetic activity caused by solar wind magnetic clouds // Journal of Atmospheric and Solar–Terrestrial Physics. V. 205. № 105301. 2020. / https://doi.org/10.1016/j.jastp.2020.105301

– *Gallardo-Lacourt B., Nishimura Y., Lyons K.R., Donovan E.* External triggering of substorms identified using modern optical versus geosynchronous particle data // Ann. Geophysicae V. 30. P. 667–673. 2012. https://doi.org/10.5194/angeo-30-667-2012

– *Henderson M.G., Reeves G.D., Belian R.D., Murphree J.SD.* Observations of magnetospheric substorms occurring with no apparent solar wind/ IMF trigger // J. Geophys. Res. V. 101 № A5. P. 10773–10792. 1996 https://doi.org/10.1029/96JA00186

– *Nishimura Y., Lyons R. L., Zou S., Angelopoulos V.* Substorm triggering by new plasma intrusion: THEMIS all sky imager observations // J. Geophys. Res. V. 115. № A07222. 2010. https://doi.org/10.1029/2009JA015166

Table 1. Percentage of classification outcomes matching the reference classification

Experiment number out of total 7920	Parameter combination	Number of exact matches of classification outcomes with reference classification	Percentage of classification outcomes matching the reference classification
301	$P1 , P2 , P4 , \sum NV^2$	74	70
1422	$P1 , P2 , P3$, $\mathrm{Bz}_{\mathrm{To}}$	79	75
1604	$P1 , P2 , P3 , E_{\mathrm{To}}$	78	74
2499	$P1 , P2 , Bz_{\mathrm{max}} , P3$	77	73
5012	$P1 , P2 , P3 , E_{\mathrm{max}}$	82	77
3284	$P1 , P2 , P3 , AL_{\mathrm{max}}$	84	79
6826	$P1 , P2 , P3 , Bz_{\mathrm{max}}$	84	79

Figure Captions

Fig. 1 . New class 1 includes substorms with prolonged development and recovery phases and shortened onset phase

Fig. 2. New class 2 includes substorms with prolonged onset phase

Fig. 3 . New class 3 includes substorms with phases of equal duration

Fig. 4. New class 4 includes substorms with prolonged development phase

Fig. 5. New class 5 includes substorms with short recovery phase

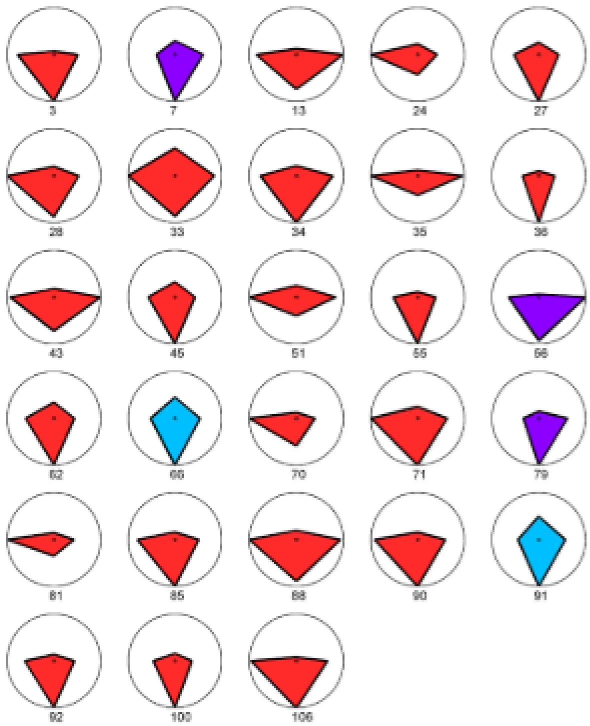
3
7
13
24
27
28
33
34
35
36
43
45
51
55
56
62
66
70
71
79
81
85
88
90
91
92
100
106

Fig. 1.

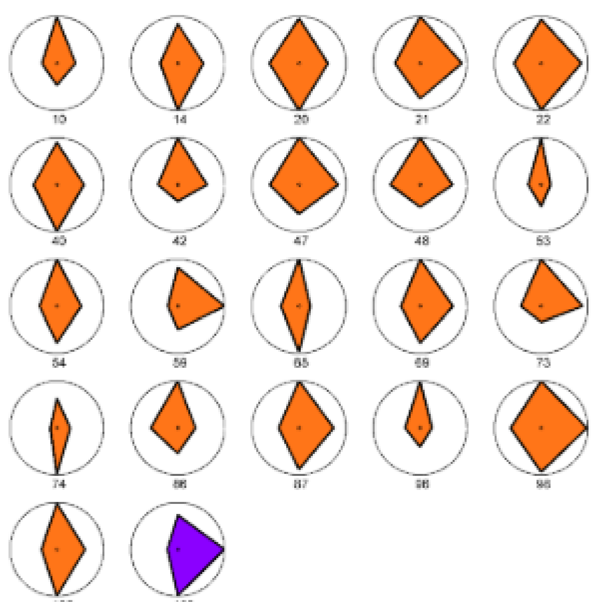
10
14
20
21
22
40
42
47
48
53
54
59
65
69
73
74
86
87
98
99
102
103

Fig. 2.

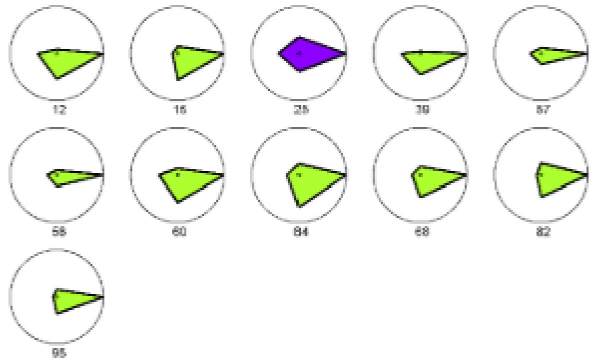
12
15
25
39
57
58
60
64
68
82
95

Fig. 3.

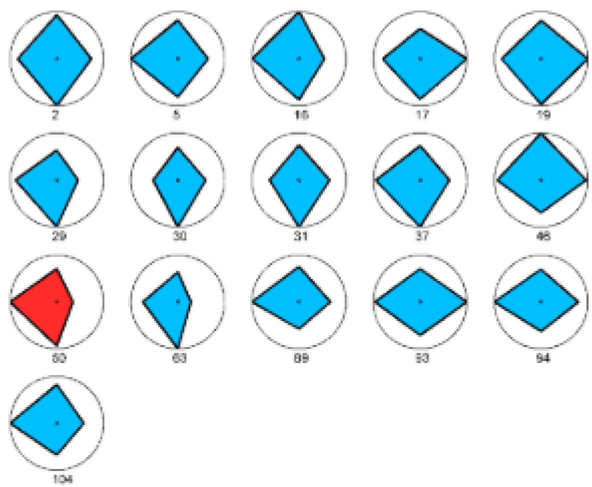
2
5
16
17
19
29
30
31
37
46
50
63
89
93
94
104

Fig. 4.

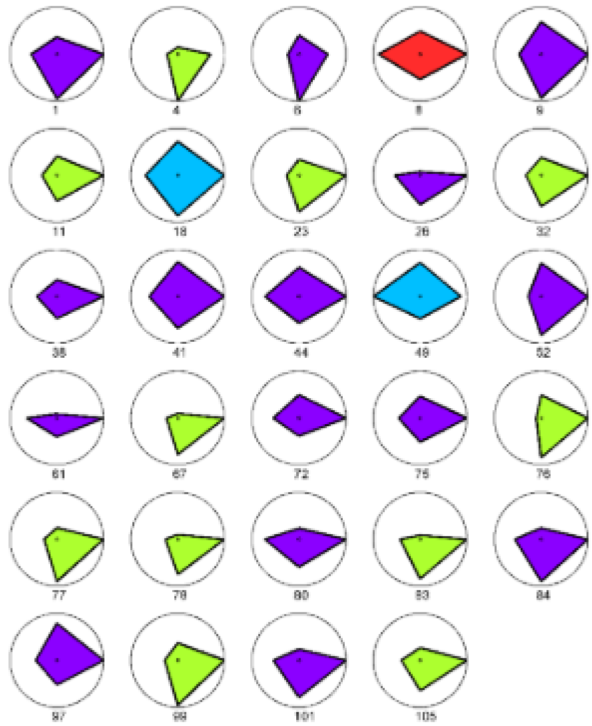
1
4
6
8
9
11
18
23
26
32
38
41
44
49
52
61
67
72
75
76
77
78
80
83
84
97
98
101
105

Fig. 5.