Analysis of cosmic rays variations on the basis of neural networks

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Abstract. The work is devoted to the study of the dynamics of variations in cosmic rays and the identification of periods of sporadic effects. The data of the world network of neutron monitors have been studied, and signs of sporadic effects have been identified. Various architectures of neural networks were used and the quality of their work was assessed. The effectiveness of the application of vector quantization neural networks for the task of classification of cosmic ray data is shown. A method for improving the quality of the regression neural network operation based on the application of fast wavelet decompositions is proposed.

1. Introduction

The work is aimed at studying the variations of galactic cosmic rays (GCR) according to the ground-based observations (neutron monitors). The study of GCR variations is important for fundamental research in the field of solar-terrestrial physics, as well as for applied research in space weather prediction problems[1, 2]. Anomalous effects (ground level enhancements in cosmic-ray intensity (GLE events), magnetic storms, ionospheric disturbances) that occur in near-Earth space have a negative impact on modern technical means and human health. At present, the task of effective prediction and timely detection of anomalies in the near-Earth space is not solved, which determines the relevance of the study.

The GCR flux in the interplanetary space is affected by the atmosphere of the Earth, the Earth's magnetic field and the heterogeneous magnetic field structure of the Sun and the solar wind. Due to the influence of these factors, the recorded GCR data has a complex structure, and includes recurrent and sporadic components. Recurrent components include 22-year, 11-year, 27-day and diurnal variations [3, 4]. Sporadic changes, which are the subject of this study, include Forbush decreases and GLE-events [5–8]. Forbush decreases are changes in the intensity of GCR, which occur as a result of their interaction with the inhomogeneities of the magnetic field in the solar wind.

The complex structure of the GCR data, the high noise level (instrument errors and noise of an obscure nature) (see Figures 1 and 2) and incomplete a priori knowledge of the processes in the near-Earth space make it difficult to construct effective methods of its processing and analysis. This leads to the necessity of using a mathematical apparatus capable of approximating complex nonlinear dependencies and adapting to a set of initial data without complete a priori knowledge. It is known that the apparatus of artificial neural networks is successfully used to solve such problems[9–12]. This
mathematical apparatus was taken as a basis for constructing a technique for processing and analyzing of the GCR data.

For the research we used data of the neutron monitors of Kingston and Apatite stations (www.nmdb.eu). The choice of data was determined by the small number of omissions and the presence of representative statistics, which is a necessary condition for the possibility of using neural networks. In the work we considered various architectures of neural networks and estimated their effectiveness in relation to the task of sporadic effects detection. It is shown that the use of vector quantization neural networks makes it possible to estimate the intensity of the GCR flux and to identify the periods of the onset of anomalous changes associated with the appearance of sporadic effects. Regression neural networks were used to construct the approximation of the cosmic ray dynamics. We also propose a method to increase the efficiency of their work on the basis of fast wavelet decompositions (MRA)[13, 14].

2. Description of the proposed methods

2.1. Classification of data from neutron monitors based on neural networks of vector quantization

2.1.1. Architecture and learning algorithm for the neural network

By vector quantization is meant the process of transformation a certain vector \( X \) from the set \( A \in \mathbb{R}^N \) into a vector \( W \) from the set \( B \in \mathbb{R}^N \), where \( M < N \)[15, 16]. Vector quantization is carried out by the method of "nearest neighbor" (Voronoi-classifier [17]) - a vector which is at the minimum Euclidean distance from the input is chosen (see relation (1)). The result of the operation of the neural network is the determination of the belonging of the input vector to the certain class. We used the Learning Vector Quantization (LVQ) architecture of the neural network, the main advantage of which, in comparison with the traditional Kohonen network [18], is controlled learning (training with the teacher). The structure of the LVQ neural network is shown in Fig.1. The dimension of the input vector of the neural network (NN) was determined taking into account the duration of sporadic effects occurring in the GCR, and is equal to 2,880 samples, which corresponds to two days (minute data).

![LVQ neural network structure](image)

Training of LVQ neural network is performed according to the following algorithm:

1. The neuron-winner is determined by estimating the Euclidean distance:

\[
\|x - w_c\|^2 = \min_j \|x - w_j\|^2 ,
\]

where \( x \) is the vector of inputs; \( w_c \) is a vector of weights; \( w_j \) is the vector of weights of the competing layer neuron \( j \).

2. The weights of the winning neuron are changed according to the rule:

\[
w_c(k + 1) = \begin{cases} w_c(k) + \alpha_c(k) * [x(k) - w_c(k)] & \text{if } j = c \\ w_c(k) - \alpha_c(k) * [x(k) - w_c(k)] & \text{if } j \neq c \end{cases}
\]

where \( w_c(k + 1) \) – the succeeding weight value; \( w_c(k) \) – previous weight value; \( x(k) \) – input value, \( \alpha_c(k) \) – training parameter.
Training parameter \( \alpha_c (k) \) in (2), (3) is calculated by:

\[
\alpha_c (k) = \frac{\alpha_c (k-1)}{1 + \alpha_c (k-1) \cdot s(k)}
\]

where \( \alpha_c (k) \) – succeeding training parameter value; \( \alpha_c (k-1) \) – training parameter value; \( s(k) \) is calculated by the formula:

\[
s(k) = \begin{cases} +1, & \text{if } w \text{ and } x \text{ belong to the same class} \\ -1, & \text{otherwise} \end{cases}
\]

1. If the vectors \( x \) and \( w_c \) belong to the same class, option (2) is used, otherwise option (3) is used.

2.1.2. Definition of neural network classes

In accordance with the task, the following 3 classes of the neural network are defined in the work:

1. "Quiet" class - no sporadic effects. "Quiet" class is characterized by: (1) - the absence of active spots and flares on the Sun (flare activity zero); (2) absence of the solar wind stream on the line with the Earth from the visible side; (3) - the absence of magnetic storms and perturbations in the magnetosphere (the geomagnetic activity index K has values \( \leq 2 \)).

2. "Slightly disturbed" class - the presence of sporadic effects of small amplitude. The "slightly disturbed" class is characterized by: (1) the emergence of minor flares on the Sun directed to the Earth; (2) - the presence of weak perturbations in the magnetosphere (the geomagnetic activity index K has the values 3 or 4).

3. "Disturbed" class - the presence of sporadic effects of large amplitude. The "disturbed" class is characterized by: (1) arrival of disturbed high-speed solar wind streams and associated shock waves into the vicinity of the Earth; (2) - the appearance of a magnetic storm and the presence of strong perturbations in the magnetosphere (the geomagnetic activity index K (K-index) has values \( \geq 5 \)).

2.1.3. Construction of the training sample of neural network

To train the neural network, we used 20 vectors: 10 vectors corresponded to the "quiet" class, 6 vectors to the "slightly disturbed" class and 4 vectors to the "disturbed" class.

The choice of data for each introduced class was based on the analysis of geomagnetic activity indices - A, K, Dst - geomagnetic activity indices were used. The "quiet" class contains time intervals during which the A-index had values \( \leq 7 \), the K-index had values of \( < 3 \), the Dst-index was within \( \pm 4 \). The "slightly disturbed" class contains time intervals for which the A-index was \( < 18 \), the K-index was \( < 5 \), the Dst-index was within \( \pm 8 \). The "disturbed" class contains time intervals for which the A-index was \( > 18 \), the K-index was \( > 5 \), the Dst-index is beyond \( \pm 8 \). Figure 2 as an example shows the wavelet spectrum of GCR data for September 2015. Analysis of the wavelet spectrum shows that during the period of increased geomagnetic activity on September 8-9, the amplitude of the GCR variations significantly increases (characterizes the appearance of a sporadic effect in the GCR), and during the calm geomagnetic situation on September 24-25, the range of CR variations is substantially narrowed (see Fig. 2). This result confirms the possibility of using the values of geomagnetic activity indices (characterize the degree of geomagnetic field perturbation) as a sign of the presence of sporadic effects in the GCR.

![Figure 2. Wavelet-spectrum of the GCR data for September 2015.](image)

2.1.4. The results of the neural network

At the testing stage of the neural network construction, we used data not used at the stage of its training.
On the input of the trained NN were given: (1) - ten vectors, the geomagnetic indices of which corresponded to the class "quiet". The success of this experiment was 100%; (2) - ten vectors, the geomagnetic indices of which corresponded to the "slightly disturbed" class. The success of this experiment was 60%: the four vectors of the NN were classified as "quiet". (3) - five vectors whose geomagnetic indices corresponded to the "disturbed" class. The success of this experiment was 80%: one vector of the NA was assigned to the class of "slightly disturbed".

2.1.5. Analysis of the results

Figure 3 shows the wavelet spectrum of the GCR data for March 2015. This period contains the time interval of March 6-7, which the NN classified as "quiet." Since the geomagnetic situation in this period corresponded to the "slightly disturbed" class (March 6, the value of the A-index is 11, the maximum value of the K-index is 4, March 7, the value of the A-index is 15, the maximum value of the K-index is 4) this result was considered as an error (see test results, § 2.1.4.). Analysis of space weather (https://www.spaceweatherlive.com/ru/arhiv/2015/03/06/rsga) during this period showed that on March 6-7 velocity of the solar wind gradually increased to 600 km/sec. The vertical component of the interplanetary magnetic field (IMF) fluctuated within $B_z = \pm 8$ nT. Integral solar activity in the period preceding the analyzed (March 3-5) was low, and flare activity was moderate.

The analysis of the wavelet spectrum in Fig. 3 shows that during the period March 6-7 the amplitude of GCR variations was small, which corresponds to the absence of sporadic effects in this period. In this case, the decision of the NN is correct.

Figure 4 shows the wavelet spectrum of the GCR data for April 2015. This period contains the time interval of April 14-15, which the NN classified as "slightly disturbed". Since the geomagnetic situation in this period corresponded to the "disturbed" class (the value of the A-index is 22, the maximum value of the K-index is 5), in assessment of the NN operation, this result was taken as an error (see test results, § 2.1.4.). Analysis of space weather during this period (https://www.spaceweatherlive.com/ru/arhiv/2015/04/14) showed:

1. From the beginning to the middle of the day on April 14, the southern component of the interplanetary magnetic field (IMF) fluctuated near zero. In the afternoon of April 14, the value of the $B_z$ component dropped to $-10$ nT due to the arrival of an accelerated stream from the southern coronal hole, the solar wind speed slightly increased to 400 km/sec on April 14. Integral solar activity was low. The flare activity was moderate.

2. Due to the arrival of accelerated fluxes from coronal mass ejections (CME on April 12, 23.48 UT, April 13 at 01.33 UT) and from the first coronal hole, the speed of the solar wind increased from 300 to 650 km/sec by the middle of the day on April 15. On April 15 were recorded strong fluctuations of the southern component of the IMF ($B_z = \pm 12$ nT). Integral solar activity is moderate. Flash activity is low.

The analysis of the wavelet spectrum in Fig. 4 shows that in the period April 14-15 the variations in the GCR do not contain visible anomalous features, which corresponds to the absence of sporadic effects of large amplitude during this period. In this case, the decision of the NN to not assign the period to the class "indignant" was correct. The question of a more precise definition of belonging to a class ("quiet" or "slightly disturbed") requires an additional more detailed study.
Based on the results of analysis of the NN performance, it can be concluded that the dynamics of secondary CRs (recorded by ground stations) is not always reflected in the state of the magnetosphere. Considering the obtained results, we can assume that the use of vector quantization neural networks is promising. Also note that the great advantage of this approach is the ability to automatically determine the periods of sporadic effects in the GCR, which is important for the tasks of operational forecast of space weather.

2.2. Approximation and analysis of GCR data on the basis of regression neural networks

The authors used the architecture of directional multilayer neural networks [9]. The problem of statistical extrapolation was solved:

\[ y : f \rightarrow f^* \]

where \( f - \text{NN input}, \ f^* - \text{NN output} \). When the function values \( f \) from the interval \( (l - Q + 1, l) \) are applied to the input of the trained NN, the network calculates its predicted values on the time interval \( (l + 1, l + I) \), where \( l \) is the current discrete time instant; \( I \) is the length of the prediction interval. The NN error is defined as the difference between the desired \( f^* \) and the actual \( \hat{f}^* \) output values of the function:

\[ e(t) = \hat{f}^*(t) - f^*(t) \].

The internal structure of the NN was determined by an adaptive method [The training factors of the NN were: the achievement of errors of the threshold value (indicating the onset of overtraining), the achievement of a finite number of iterations, the achievement of a minimum gradient. The dimension of the input vector of NN corresponds to one day (1440 samples), which was determined taking into account the diurnal variation of the GCR. The structure of the constructed NN1 is shown in Fig. 5.

The data of the Kingston station (http://cr0.izmiran.ru/kgsn/main.htm) of 2015 were used for training of the NN1 for time intervals corresponding to "quiet" conditions (geomagnetic state was considered from ftp://ftp.swpc.noaa.gov/pub/lists/geomag/). For quiet conditions, a day was taken during which the 3-hour values of the index of geomagnetic activity (K-index) did not exceed the value of 2. Time intervals used as test data, were not used for the NN training. In Figure 6, as an example, a graph of the root-mean-square error of the trained neural network is presented. We note that the error rate of the NC errors in the quiet period does not exceed 1.5. Obviously, in the case of a change in the temporal course of the CR data, the errors in the NN will increase, which will indicate a sporadic effect and is of interest in this study.

Figure 7 shows the results of the operation of the NN, on the input of which we fed a time interval corresponding to the period of a moderate geomagnetic disturbance (the degree of perturbation of the geomagnetic field is characterized by the Dst index represented in Fig. 7). According to space weather data (http://ipg.geospace.ru/space-weather-review-13-01-2015.html): flash activity in the Sun's atmosphere is moderate on January 22 and 26, low in the rest of the time; On January 21, due to the accelerated flow from the coronal hole, the solar wind velocity increased to 550 \( km / sec \); the southern (negative) component of the interplanetary magnetic field (IMF) dropped to \( B_z = -15 \ nT \);
On January 27, under the influence of accelerated flow from the southern polar coronal hole, the solar wind velocity increased from 400 to 530 km/sec.

\[
\Phi_{\text{FIPM}}(\lambda(n)) = \frac{1}{1 + e^{-\alpha(n)}},
\]

\[q(r) = wr + \theta\]

**Figure 5.** The structure of the constructed feed forward neural network.

**Figure 6.** The standard deviation (STD) of the NN errors for July 2015.

**Figure 7.** Results of data processing for the period January 13 - 27, 2015: a) data from the neutron monitor, Kingston station; b) the standard deviation of the error HCl; c) Dst-index.

Analysis of the results in Figure 5 shows that during the period of enhanced geomagnetic activity, the errors of the NN increased (the STD of errors increased by 3-5 times, with relation to quiet state). The maximum of the NN error vector was about 00.00 UT on January 26, 2015, which corresponds to the beginning of the Dst-index decrease, and as a result, to the moment of increase in geomagnetic...
activity. The results of this experiment confirm the good approximating properties of the NN, and also show the possibility of use of NN for the problem of approximating of GCR dynamics and allocat on of the abnormal periods characterizing the occurrence of sporadic effects.

Figure 8 shows the operation of the NN during strong magnetic storm that occurred on March 17 of 2015 (geomagnetic activity index A rised to a value of 81; K-index to the value of 8). According to space weather review of March 18 [http://ipg.geospace.ru/space-weather-review-18-03-2015.html], solar wind velocity increased from 600 to 800 km / sec due to the arrival of the accelerated flow from the front edge of southern coronal hole at the end of day, the southward component of IMF Bz dropped to = -5 nT. In the next five days, the solar wind velocity varied within 500-750 km / s because of the accelerated flow from prolonged polar coronal holes. Analysis of GCR data shows that STD of NN error increased 8-15 times relatively slightly disturbed intervals in the interval between the storms from 17 to 20 March. The maximum of the error vector was about 18.00 UT on March 18, 2015. The analysis of this experiment also confirms the good approximating properties of NN and the possibility of their application to the research task.

![Figure 8. Results of data processing for the period March 14 - 20, 2015: a) data from the neutron monitor, Kingston station; b) the standard deviation of the error HC1; c) Dst-index.](image)

2.3. Approximation of the dynamics of GCR based on combining MRA and neural networks

The processing of GCR data was performed on the basis of the following operations:

1. On the basis of MRA [13], [14] a representation of the data was obtained in the form:

\[
f(t) = f_{a,(-5)}(t) + \sum_{j=-1}^{5} f_{d,j}(t)
\]

where \( f_{a,(-5)}(t) \) – approximating component, \( f_{d,j} \) – detailing components,

\( f_{a,(-5)}(t) = \sum_{n} c_{-5,n} \phi_{-5,n}(t) \), \( f_{d,j}(t) = \sum_{n} d_{j,n} \Psi_{j,n} \), \( \Psi_{j,n} = \{\Psi_{j,n}\}_{n\in\mathbb{Z}} \) – wavelet basis, \( \phi_{j,n} = \{\phi_{j,n}\}_{n\in\mathbb{Z}} \) – basis generated by a scaling function, \( j \) – scale.

The level of decomposition (see eq (1)) and the wavelet basis of the Coiflet family of order 3 were determined in the work by minimizing the extrapolation error based on the NN, the error estimates are given in [19].

2. On the basis of the feedforward multilayer NN for the component \( f_{a,(-5)}(t) \) (see eq. (5)) we constructed a map of the form (4):

\[
\gamma: f_{a,(-5)} \rightarrow \hat{f}_{a,(-5)},
\]

where \( f_{a,(-5)} \) – input of the NN, \( \hat{f}_{a,(-5)} \) – output of the NN3. The error of the NN3 at time \( t \) is defined as \( e(t) = f_{a,(-5)}(t) - \hat{f}_{a,(-5)}(t) \). The internal structure of NN was determined by the adaptive method.
described in [19]. The dimension of the input vector NN3 was determined on the basis of minimization of the extrapolation error (estimates are given in [20]) and is equal \( \gamma_0 = 6 \) six samples.

The constructed NN performs a mapping of the input data of the form:

\[
\bar{c}_{-5,n+1}^2 = \phi_3^2 \left( \sum_{i} \omega_{ki} \phi_1^2 \left( \sum_{l} \omega_{il} \phi_1^2 \left( \sum_{z=0}^{e_{-5,n-2}} \omega_{ln} \right) \right) \right)
\]  

where \( \omega_{ki}, \omega_{il}, \omega_{ln} \) – weights of the NN, \( \phi_1^2 = \phi_2^2 = \frac{1}{1+e^{-x}} - 1; \phi_3^2 = a \ast z + b; \gamma \) – the dimension of the input vector of the NN.

Training sets for the neural network were formed from data for periods of quiet environment with a total length of at least 15 days (21600 counts). Training of the NN was performed on the basis of the Levenberg-Marquardt algorithm [21].

The operation (6) allows to reproduce typical variations of the CR (approximates the typical level of CR variations). During the period of anomalous changes in dynamics of the CR, the absolute values of the errors of the trained NN increase, so the operation of their allocation can be based, for example, on checking the following condition:

\[
|\epsilon(t)| > T_s,
\]

where \( T_s \) – a threshold value that determines the presence of an anomaly. To estimate the threshold \( T_s \), we compared the error of the NN operation in periods containing sporadic effects, and in quiet periods.

The data conversion scheme obtained on the basis of operations (5) - (6) is shown in Fig. 9.

![Figure 9. GCR data conversion scheme.](image)

Figure 10 presents the results of the work of NN for the period from 13 to 27 January 2015. This period was considered above, and contained two moderate magnetic storms. The analysis of the results in Fig. 10 shows that in the quiet period the errors of the NS do not exceed the value \( T_s = 0.00094 \), which shows the high efficiency of the proposed method based on combining KMA and NS, which allows reducing the level of errors of the HC by more than 10 times. At the time of the onset of the first magnetic storm (approximately at 8:00 UT on January 21), NN errors increased significantly (more than 20 times relatively to the threshold \( T_s \) marked by the dotted line in Figure 10), and remained at this level for the next two days. As shown in [20], such dynamics of the error of the trained NN is typical for the presence of a long Forbush decrease in the GCR data. The second magnetic storm was recorded at about 6:00 am on January 26, and at the same time there was a significant increase in the errors of the NN. Analysis of the experiment and comparison with the results presented in Figure 7 show the high efficiency of the proposed method.

Figure 11 shows the results of the work of the NN in the period of a strong magnetic storm that occurred on March 17, 2015. Analysis of the results shows that at the time of the beginning of the magnetic storm, the NN errors exceeded the threshold by more than 10 times, which indicates the occurrence of a sporadic effect in CR variations. The errors of the NN remained at a high level until 01:00 UT on March 20, 2015, which allows to obtain information on the duration of the Forbush decrease at the analyzed station. The analysis of this experiment confirms the effectiveness of the proposed approach for the research problem.

3. Conclusions

The results of the application of neural networks of various architectures have shown the promise of using this apparatus for the analysis of data of galactic cosmic rays.

An analysis of the operation of the vector quantization neural network showed that the dynamics of secondary cosmic rays (recorded by ground stations) is not always reflected in the state of the magnetosphere. The advantage of the proposed approach is the possibility of automatically
identification of the periods of sporadic effects in cosmic rays, which is important for the tasks of operational forecast of space weather.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure10.png}
\caption{The results of data processing for the period January 13, 2015, January 26, 2015. a) data from the neutron monitor; b) the component $f_{a,(-5)}$ and its model; c) errors of NN3; d) Dst-index.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure11.png}
\caption{The results of data processing for the period March 14-20 of 2015. a) data from the neutron monitor; b) the component $f_{a,(-5)}$ and its model; c) errors of NN3; d) Dst-index.}
\end{figure}

The results of the regression neural network used to approximate the time course of the GCR data showed the effectiveness of the wavelet filtering operation in the data preprocessing phase (reducing the level of neural network errors by more than 10 times). The application of this neural network allows to estimate the moments of occurrence of sporadic effects and their duration with high accuracy (within the time range, equal to 60 min.). In the future, the authors plan to continue the research in this area with the involvement of a wider range of GCR data recording stations and an increase in statistical material.

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