Method of analysis of cosmic ray data based on neural networks of LVQ

O V Mandrikova¹, V V Geppener² and B S Mandrikova²

¹Institute of Cosmophysical Research and Radio Wave Propagation FEB RAS, Mirnaya str., 7, Paratunka, Kamchatki kray, Russia, 684034
²Saint Petersburg Electrotechnical University "LETI", Professora Popova str., 5, St. Petersburg, Russia, 197022

e-mail: oksam1@mail.ru, 55bs5@mail.ru

Abstract. An automated method for analysis of cosmic ray data and for detection of sporadic effects is described. The method is based on the application of multi-scale wavelet decompositions and neural networks of vector quantization. Using the method as the base, cosmic ray dynamics was investigated during increased solar activity and magnetic storms. Sporadic effects preceding and accompanying magnetic storms were detected. The method showed its efficiency for data real time analysis and detection of sporadic effects including those of low amplitude. The results are important in the tasks of space weather forecast.

1. Introduction
Investigation of cosmic ray data is of interest in the problems of solar-terrestrial physics and applied researches related to space weather. Change of the conditions on the Sun, in the solar wind, in the Earth magnetosphere and ionosphere affects significantly the operation and reliability of on board and ground technological systems and threatens human health and life. At present, the task of fast and accurate forecast of space weather has not been solved. [1, 2]. In order to make real time forecast of space weather, it is very important to create automated methods for analysis of recorded cosmic ray data and to detect sporadic effects timely. The sporadic effects are the Forbush-effects and large proton enhancements or Ground Level Enhancements (GLE-events). For the first time, Forbush-effects were noted by S. Forbush [3]. They are anomalous changes (increases and decreases) of cosmic ray intensity which are usually associated with strong magnetic storms. Ground Level Enhancements of solar cosmic rays (GLE) are serious threats to human health and life [4].

Space and ground data of the neutron monitor global network are used to investigate cosmic ray dynamics [11]. The recorded variations of cosmic rays are a complicated nonlinear dependence. On the Earth surface, cosmic ray intensity depends on air temperature, pressure, observation site latitude and geomagnetic field state, on electromagnetic state in the Solar system and physical conditions in the Galaxy [5]. The variation amplitude of initial cosmic rays depends on particle energy and interplanetary magnetic field strength [6]. Classical analysis methods of neutron monitor data (spectral methods [7, 8], smoothing methods [6, 9] are not effective enough. Current methods, for example, station circuit method [10], makes it possible to determine the main characteristics of cosmic ray
variations with acceptable accuracy. However, these methods require labor-intensive computation and they have not been automated.

Taking into account the incomplete knowledge on the processes in the near-space and, as a sequence, on the recorded data inner structure, the neural network apparatus has been proposed to be applied in the analysis of neutron monitor data. It is known that neural networks are capable of approximating complicated nonlinear dependences of data without complete a priori knowledge on inner relations and dependences [12-18]. The advantage of this apparatus is the possibility of numerical realization [19,20], that is important in the tasks of real time data analysis. At present, neural networks are intensively used in different applied fields for the tasks of analysis of complicated structure data including geophysics [17,18]. The approach considered in the paper is based on the application of neural networks of vector quantization [21]. It was proposed in the paper [22] for the first time. The paper suggests and grounds the technique to increase the method efficiency based on data pre-processing by multi-scale wavelet decomposition method [23]. We construct neural networks and estimate their operation in real time analysis regime. The results confirmed the possibility of application of the developed methods in the problems of detection of different-scale sporadic effects including those of low amplitude.

2. Description of the method

2.1. Multi-scale wavelet decomposition of a function

Having discrete values of a function \( f_j \) (i.e. function values on a grid with resolution \( 2^{-j} \)), as a sample space we consider the sub-space

\[
V_j = \text{clo}_{\mathbb{L}^2(R)} \{ \varphi(2^j t - n) \}, n \in \mathbb{Z}.
\]

\( \mathbb{L}^2(R) \) is the Leber space, the scaling function \( \varphi \) produces sub-spaces \( V_j \) by its shifts and stretching [36].

Mapping \( f_j \) into spaces \( V_{j-1} \) and \( W_{j-1} \), we obtain [26, 27]:

\[
V_j = V_{j-1} \oplus W_{j-1},
\]

(1)

(\( \text{the symbol } \oplus \text{ in (1) denotes orthogonal sum} \)). The basis of space \( W_j \) is a wavelet set 

\[
\Psi_{j,n} = 2^{j/2} \Psi(2^j t - n), n \in \mathbb{Z}.
\]

Based on the mapping (1), the function \( f_j \) has the representation

\[
f_j(t) = f_{j-1}(t) + g_{j-1}(t) = \sum \phi_{j-1,n}(t) + \sum d_{j-1,n} \psi_{j-1,n}(t),
\]

(2)

Each component in (2) is determined uniquely by coefficient sequences \( \{ c_{j,n} \} \) and \( \{ d_{j,n} \} \) of the function \( f_j \). The calculation procedure (2) is applicable to any resolution (scale) \( j \) [25, 26]. If the procedure is used for the function \( f_{jm} \) times, we obtain its representation in the form

\[
f_j(t) = g_{j,m}(t) + g_{j-2}(t) + \ldots + g_{j-m}(t) + f_{j,n}(t) = \sum_{k=j-1}^{j-m} d_{k,m} \psi_{k,m}(t) + \sum c_{j,n} \varphi_{j,n}(t),
\]

(3)

In ratio (3), components \( g_{j,m} \) are detailing (high-frequency) components, component \( f_{j,n} \) is a smoothing component. In wavelet transform, decomposition (3) is called orthogonal multi-scale wavelet decomposition to the level \( m \) [25, 26]. Fig.1 shows the results of multi-scale wavelet decomposition of neutron monitor (NM) data to the levels \( m=1,2,3 \). Analysis of the results in Fig. 1 show the presence of high-level noise in the recorded data and the possibility to apply the procedure of multi-scale wavelet decomposition to reduce it. Fig. 2 illustrates the amplitude-frequency characteristics (AFCh) of a wavelet function and a scaling function at 1- st and 2-nd levels of wavelet decomposition.
3. Selection of wavelet function

2.2. Criteria for selection of wavelet function families

In the paper to obtain numerically stable decompositions, we considered the classes of orthogonal wavelet functions. When selecting orthogonal wavelet functions, the following criteria, suggested in the paper [25], were used:

1. Large number of wavelet function zero times. The number of zero times $s$ of wavelet function $\Psi$, i.e.

$$\int_{-\infty}^{\infty} t^k \Psi(t) \, dt = 0, \quad k = 0, s - 1$$

characterizes its capability to detect the feature of the kind $\alpha \leq s$, where $\alpha$ is the degree of function smoothness.

2. Small carrier of a wavelet function. Wavelet transform provides artificial «jumps» at the edges of function $f$, the so called tip effects [24]. Neighborhood dimensions on scale $j$, containing a tip effect is determined by the formula

$$h_j = 2^{j} \cdot q$$

where $q$ is the carrier used for basic function. Thus, the less the carrier $q$ is, the less error we have at function edges.

3. High order of wavelet function smoothness. Similar to the number of zero times, wavelet function smoothness characterizes its capability to determine features of the kind $\alpha \leq s$.

When selecting a wavelet function, we come to the choice between the number of zero times and carrier dimensions. It is known [24] that the number of zero times and wavelet function smoothness are associated, however, the character of this relation may be different. For example, for the wavelet
function of Daubechies family [26] the following property is typical: wavelet function smoothness increases with the number of zero times. In the majority of practical problems, it is necessary that a smoothed component \( f_{j-m} \) (ratio (3)) allows one to obtain best approximation of a function and to identify separate local features of the function by small-scale components \( g_{j-i} \). In this case, it is important that not only the wavelet function \( \Psi \) but the scaling function \( \phi \) as well have zero times. In the class of orthogonal functions the Daubechies and the Koiflet wavelet families satisfy the criteria 1–3 the most:

- the Daubechies family is the only family of orthogonal wavelet functions which have minimum carrier when the number of zero times is defined [29].
- Koiflet family is the only family from orthogonal wavelet functions which have the carrier of the least dimension when the number of zero times in the scaling function \( \phi \) is sufficient [26].

It is known [26] that if \( f \in C^r \) (\( C^r \) is the space of continuously differentiated functions by \( r \) times) in the neighborhood of \( 2^{-m}n \) with \( r \leq p \), then

\[
2^{-m/2} \langle f, \varphi_{-m,n} \rangle = f(2^{-m}n) + O(2^{-m(r+1)})
\]

Approximation order increases with \( p \) increase, the resultant Koiflet has the carrier \( 3p-1 \). Fig. 3 shows the results of multi-scale wavelet decomposition by NM data applying Daubechies and Koiflet functions. Analysis of the results in Fig. 3 shows good approximating properties of Koiflet function that confirms property (6).

**Figure 3.** Black color shows NM data on July 12, 2016 (Kingston site); yellow – application of Duabechies 3 function, decomposition level \( m=5 \), red – Koiflet 3 function, decomposition level \( m=5 \).

### 2.2.2. Selection of the «best» basic wavelet function

In order to construct an approximating basis, we applied the minimax approach [38], according to which signal \( F \) was estimated by transformation of noised data \( f \) by solution operator \( D \). The overall estimate is

\[
\widetilde{F} = Df.
\]

Estimate error \( \tilde{r} \) is

\[
\tilde{r} (D, F) = E \left\| F - Df \right\|^r,
\]

where \( E \) is the mathematical expectation, \( \left\| \right\| \) is the norm. The minimum risk is the lower boundary calculated by all operators \( D \) [38]:

\[
r (\Theta) = \inf \sup \left\{ r (D, F) \right\}.
\]

Considering transformations of the kind (3) as \( D \) and following the results of the paper [39], estimate of \( \tilde{F} \) in the basis \( \beta^+ \) can be obtained by threshold function

\[
\tilde{F}^+ = \sum_n P_{\gamma} \left\langle f, \beta^+_n \right\rangle \beta^+_n,
\]

where \( P_{\gamma} \) is the threshold function. It is obvious that the best basis \( \beta^+ \) is such which minimizes the error.
The algorithm for selection of the «best» basic wavelet function can be based on the following operations:

1. For each basis $\beta^\lambda, \lambda \in \Lambda$, perform the function $f$ to the level $m$ (ratio (3)):
   \[ f_j(t) = \sum_{k=1}^{m} \sum_{n} d_{k,n}^\lambda \psi_{k,n}^\lambda + \sum_{n} c_{j,m,n}^\lambda \varphi_{j,m,n}^\lambda(t). \]

2. Applying the threshold functions $T_j$ (ratio (7)), we obtain the estimates
   \[ \tilde{F}_m^\lambda = \sum_{k=1}^{m} \sum_{n} T_j(d_{k,n}^\lambda) \psi_{k,n}^\lambda + \sum_{n} c_{j,m,n}^\lambda \varphi_{j,m,n}^\lambda, \]

3. We estimate the value
   \[ Q_m^\lambda = \sum_{n \in I_m^\lambda} |c_{j,m,n}^\lambda|^2 + \sum_{k=1}^{m} \sum_{n \in I_m^\lambda} |d_{k,n}^\lambda|^2, \]
   where the set of indexes $i' : n \in I_j, \ if \ |(y, \psi_{j,m,n}^\lambda)| \geq T_j$, and, according to (8), determine the «best» basis $\beta_m^\alpha$:
   \[ Q_m^\alpha = \max_{\lambda \in \Lambda} E \{ Q_m^\lambda \}. \]

The algorithm can be executed for different levels of application, including a full tree of sentences, which will allow creating the best approximative function $f$ in the class of considered orthogonal wavelet functions.

3. Classification of neutron monitor data based on neural network of vector quantization LVQ

3.1. Data pre-processing based on multi-scale wavelet transform:

- assuming that the initial time series $f_j$ belongs to the space with resolution $j=0$, based on multi-scale wavelet decomposition $f_0$ to level $m$ (ratio (3)), we obtain a smoothed component of the time series in the form
  \[ f_{-m}(t) = \sum_{n} c_{-m,n} \varphi_{-m,n}(t); \]
- to recover the initial resolution of the function, we perform the operation of wavelet reconstruction [23, 24]:
  \[ f_{-m}(t) = \sum_{n} c_{-m,n} \varphi_{-m,n}(t), \]
  (superscript (-m) corresponds to the function resolution before the wavelet reconstruction operation);
- in order to exclude the tip effect, we eliminate the first and the last $2^m * q$ of counts (neighborhood dimension containing tip effect at the decomposition level $m$ is determined by formula (5)) from the reconstructed set.

3.2. Architecture and operation principle of neural network LVQ

Neural network LVQ consists of 2 layers. The architecture used in the work is illustrated in Fig. 4 [27]. The first layer is the Kohonen layer (competitive layer [27,28], Fig. 4), the second one is the linear layer and it is formed at the stage of neural network training. The compliance between neuron numbers of the 1-st layer (clusters) $k$ and corresponding classes $l$ is determined [29]

\[ F_j = \sum_{i} w_{ij} y_{s_i}, \]

where $w_{ij}$ are the weight coefficients of neuron $l$ of the network second layer, associated with neuron $k$ of the network first layer, $y_{s_i}$ is the output value of neuron $k$ of the network first layer.

Clusterization of output vectors into the defined number of classes is carried out by the metric

\[ d_k = d(X, W_k) = \left\| X - W_k \right\| - \sqrt{\sum_{i=1}^{j} (x_i - w_{s_i})^2} \]

(9)

where $X$ is the input vector; $W_k$ is the vector of neuron $k$ weights of the first competitive layer, $I$ is the input vector dimension.

During the neural network (NN) operation in the first layer, winning neuron $p$ is determined based on the estimation of the distance $d_k$ (ratio (9)) $p$. For the neuron

\[ D = d_{\text{min}}(X, W_k) = \min_{i} \left\| X - W_i \right\|, \]
Output value of the winning neuron \( p \) is set to be equal to 1: \( y_p = 1 \), and that of other neurons is zero: \( y_k = 0, k \neq p \). The winning neuron determines the input vector membership to \( X \) class associated with this neuron (cluster).

NN output vector has the dimension equal to the number of classes \( L \) (\( L = 3 \) during the operation, classes are described below). In case of correctly trained network, one element of the output vector equals 1, the others are zero. Thus, NN allows us to solve the problem of input vector membership to one of a priori known classes.

3.3. Determination of neural network classes and the scheme for solution of data classification problem

In the paper we determined the following classes according to the investigation task [21,22]:

1. «Calm» class – absence of sporadic effects. «Calm» class is characterized by: (1) absence of active spots and flares on the Sun (flare activity is zero); (2) absence of solar wind flux from the visible side along the line with the Earth; (3) absence of magnetic storms and disturbances in the magnetosphere (geomagnetic activity index \( K \) (\( K \)-index) is \( \leq 2 \)).

2. «Weakly-disturbed» class – presence of sporadic effects of low amplitude. «Weakly-disturbed» is characterized by: (1) occurrences of insignificant flares on the Sun directed to the Earth; (2) weak disturbances in the magnetosphere (\( K \)-index is 3, 4).

3. «Disturbed» class – presence of sporadic effects of high amplitude. «Disturbed» class is characterized by: (1) penetration of high-speed fluxes of solar wind and/or a shock wave related to it to the Earth vicinity; (2) magnetic storm occurrence and strong disturbances in the magnetosphere (\( K \)-index is \( \geq 5 \)).

According to the suggested approach, solution of the problem of data classification can be represented in the form of a scheme illustrated in Fig. 5.
4. Results of method application

Minute data of neutron monitors of Kingston, Moscow and Irkutsk [30] sites were used in the experiments. Strong and moderate storms were analyzed for the period 2015–2018. The neural network was built separately for each station. When constructing a training sampling, the selection of data for each of the introduced class (Sections 1-3) was based on the analysis of geomagnetic activity values; A, K and Dst indexes were used [31]. The «calm» class was formed from the data for the time intervals during which the A-index was <7, K-index was <3, Dst-index was within ±4. The «weakly-disturbed» class was formed from the data for the time intervals during which A-index was <18, K-index was <5, Dst-index was within ±8. The «disturbed» class included the time intervals during which A-index was >18, K-index was >5, Dst-index was more than ±8. Twenty vectors were used to train neural networks: 10 vectors the geomagnetic indexes of which corresponded to the «calm» class; 6 vectors corresponded to the «weakly-disturbed» class; 4 vectors corresponded to the «disturbed» class. To test the network, 37 vectors were used (data were not used during network training): 15 vectors the geomagnetic indexes of which corresponded to the «calm» class; 15 vectors corresponded to the «weakly-disturbed» class; 7 vectors corresponded to the «disturbed» class. Data multi-scale wavelet decompositions were carried out applying the Daubechies and Koiflet wavelet functions the selection of which was described in Section 2. Function $f$ was decomposed to the decomposition level $m = 1, 2, 3$. The results with the least error were obtained applying the Daubechies wavelet functions of order 3 and Koiflet wavelet functions of order 3 (the algorithm described in Section 2.2.2 was used). The constructed neural networks and the results of their processing are the following:

1. LVQ1 is the dimension of input vector $N = 2880$ (corresponds to two days). NM initial data were applied to the input. The success of recognition of the «calm» class was 100%, that of the «weakly-disturbed» class was 60% (6 vectors were attributed to the «calm» class) and that of the «disturbed» class was 72% (2 vectors were attributed to the «weakly-disturbed» class by the network).

2. LVQ1_db3_1 is the dimension of the input vector, corresponds to two days, approximating components $f_{i}(t)$ (ratio (2)) obtained by Daubechies basis of order 3 were applied to the input. The success of recognition of the «calm» class was 60% (4 vectors were attributed to the «weakly-disturbed» class), that of the «weakly-disturbed» class was 53% (4 vectors were attributed to the «calm» class and 3 vectors to the «disturbed» class) and that of the «disturbed» class was 72% (2 vectors were attributed to the «weakly-disturbed» class by the network).

3. LVQ2 is the dimension of the input vector $N=4320$ (corresponds to three days), NM initial data were applied to the input. The success of recognition of the «calm» class was 100%, that of the «weakly-disturbed» class was 80% (3 vectors were attributed to the «calm» class) and that of the «disturbed» class was 93% (1 vector was attributed to the «weakly-disturbed» class by the NN).

4. LVQ2_db3_1 is the dimension of the input vector, corresponds to three days, approximating components $f_{i}(t)$ (ratio (2)) obtained by Daubechies basis of order 3 were applied to the input. The success of recognition of the «calm» class was 100%, that of the «weakly-disturbed» class was 87% (2 vectors were attributed to the «calm» class), and that of the «disturbed» class was 93% (1 vector was attributed to the «weakly-disturbed» class by the network).

5. LVQ2_db3_2 is the dimension of the input vector, corresponds to three days, approximating components $f_{i}(t)$ (ratio (3)) obtained by Daubechies basis of order 3 were applied to the input. The success of recognition of the «calm» class was 67% (5 vectors were attributed to the «weakly-disturbed» class by the network), that of the «weakly-disturbed» class was 47% (5 vectors were attributed to the «calm» class and 3 vectors to the «disturbed» class), and that of the «disturbed» class was 71% (1 vector was attributed to the «weakly-disturbed» class and 1 vector to the «calm» class).

6. LVQ1_coif3_1 is the dimension of the input vector, corresponds to two days, approximating components $f_{i}(t)$ (ratio (2)) obtained by Koiflet basis of order 3 were applied to the input. The success of recognition of the «calm» class was 53% (7 vectors were attributed to the «weakly-
disturbed\textsuperscript{\textregistered} class by the network), that of the «weakly-disturbed» class was 53\% (5 vectors were attributed to the «calm» class and 2 vectors to the «disturbed» class), and that of the «disturbed» class was 43\% (4 vectors were attributed to the «weakly-disturbed» class).

7. LVQ\textsubscript{2,coif3,1} is the dimension of the input vector, corresponds to three days, approximating components \( f_{j}(t) \) (ratio (2)) obtained by Koiflet basis of order 3 were applied to the input. The success of recognition of the «calm» class was 100\%, that of the «weakly-disturbed» class was 93\% (1 vector was attributed to the «disturbed» class), and that of the «disturbed» class was 93\% (1 vector was attributed to the «weakly-disturbed» class).

8. LVQ\textsubscript{2,coif3,2} is the dimension of the input vector, corresponds to three days, approximating components \( f_{j}(t) \) (ratio (3)) obtained by Koiflet basis of order 3 were applied to the input. The success of recognition of the «calm» class was 60\% (6 vectors were attributed to the «weakly-disturbed» class by the network), that of the «weakly-disturbed» class was 47\% (4 vectors were attributed to the «calm» class and 3 vectors to the «disturbed» class), and that of the «disturbed» class was 57\% (2 vectors were attributed to the «weakly-disturbed» class and 1 vector to the «calm» class).

Table 1 shows the results of the NN operation. They confirm the efficiency of the neural network LVQ apparatus for the investigation tasks. The analysis also shows the effectiveness of application of data pre-processing procedure based on multi-scale wavelet decompositions to the 1-st level (ratio (3)). Results with the least accuracy were obtained by Koiflet order 3 wavelet function. The dimension of the input vector corresponds to three days (Table 1). At the 2-nd level of wavelet decomposition, the network error increases that indicates the loss of some useful information during this operation. Analysis of AFCh of wavelet function and the scaling function at the 1-st and the 2-nd levels of wavelet decomposition (Fig. 2) shows that for the initial minute data, the wavelet function at the 2-nd level of decomposition detects the periods of oscillations from 3 to 14 min, which contain useful information on cosmic ray dynamics based on the results of NN operation.

| NN input data | LVQ\textsubscript{1} | LVQ\textsubscript{2} |
|---------------|------------------|------------------|
|               | 1 class | 2 class | 3 class | 1 class | 2 class | 3 class |
| Initial data  | 100\%   | 60\%    | 72\%    | 100\%   | 80\%    | 93\%    |
| db3\_1        | 60\%    | 53\%    | 72\%    | 100\%   | 87\%    | 93\%    |
| db3\_2        | -       | -       | -       | 67\%    | 47\%    | 71\%    |
| coif3\_1      | 53\%    | 53\%    | 43\%    | 100\%   | 93\%    | 93\%    |
| coif3\_2      | -       | -       | -       | 60\%    | 53\%    | 57\%    |

The algorithm can be realized for different decomposition levels \( m \), including the complete decomposition tree that will allow us to construct the best approximation of function \( f \) in the class of orthogonal wavelet functions under consideration.

Fig. 6 shows the results of NM data processing for the periods of January 16-22, 2016 (Fig. 6) and March 15-20, 2015 (Fig. 7). A magnetic storm occurred on January 21. It was caused by high-velocity flux of the solar wind from the coronal whole (the times of beginning of magnetic storms are marked by vertical lines in Fig. 6). Space weather analysis for this period showed [34] that from the beginning of the day on January 15 till 20:55 UT on January 18, solar wind velocity gradually decreased from 450 to 300 km/s, the IMF southern component fluctuated within \( B_{z}=\pm 5 \) nT. On January 20-21 the solar wind velocity was \( v=320-420 \) km/s, the IMF southern component was \( B_{z}=\pm 12 \) nT. From the beginning till the end of the day on January 21, the solar wind velocity gradually increased to 550 km/s, IMF fluctuations increased to \( B_{z}=\pm 19 \) nT. Analysis of the wavelet spectrum in Fig. 6b shows that from January 19 to 20, cosmic ray variation amplitude increased in a wide frequency range that indicates the occurrences of sporadic effects during this period. Data processing was carried out on the basis of NN in real time data analysis regime (in a moving 3-hour time window). It shows occurrences of sporadic effects of low amplitude from 9:00 UT on January 17 to 15:00 UT on January 18 («weakly-disturbed» class) and from 15:00 UT on January 18 till 15:00 UT on January 22.
Comparison of the results of NN operation with space weather data and wavelet spectrum of NM data confirms the accuracy of network decision.

During the period under analysis, a strong magnetic storm with sudden commencement occurred on March 17, 2015 (Fig. 7). It was caused by coronal mass ejection. Analysis of space weather showed [34] that on March 15, the solar wind velocity fluctuated at the level of 400 km/s, IMF component changed within $B_z = \pm 9$ nT. At the beginning of the day on March 17, the IMF suddenly decreased to $B_z = -22$ nT, the solar wind velocity increased to 500 km/s. In the second half of the day on March 17, IMF decreased to $B_z = -28$ nT, the solar wind velocity increased to 670 km/s. At the end of the day on March 18, the solar wind velocity increased to 800 km/s. According to the results of NN operation (Fig. 7d), sporadic effects of low amplitude («weakly-disturbed» class) occurred in CR dynamics on March 15. The period of March 17 – 18 was attributed to the «disturbed» class by the network that indicates large sporadic effects. Comparison of the results of NN operation with space weather data and wavelet spectrum (Fig. 7b) confirms the accuracy of network decision. These results prove the efficiency of application of the suggested method for real time detection of sporadic effects including those of low amplitude.

Fig. 8 illustrates the results of application of the suggested method to NM data of Irkutsk and Moscow sites during the period of August 21-29, 2018. Based on space weather data [34], owing to the decreased effect of coronal whole, solar wind velocity decreased from 510 to 300 km/s from August 22 to 24, IMF southern component fluctuations were within $B_z=\pm 4$ nT-$B_z=\pm 6$ nT. Due to the arrival of inhomogeneous accelerated flux from coronal mass ejection (CME on August 20), the solar wind velocity increased to 450 km/s on August 25, IMF southern component fluctuations increased to $B_z=\pm 11$ nT. At the beginning of the day on August 26, the inhomogeneous accelerated flux from two coronal wholes arrived, solar wind velocity increased and reached its maximum of 666 km/s on August 27, IMF fluctuations increased to $B_z=\pm 17$ nT. Then up to the end of the period under analysis, the solar wind velocity was within $v=500-550$ km/s, the IMF southern component fluctuations were at the level of $B_z=\pm 4$ nT. According to the results of LVQ2_coif3_2 neural network operation (Fig. 8d and 9d) sporadic effects of low amplitude («weakly-disturbed» class) occurred in cosmic ray dynamics on August 24. The period of August 25-27 was attributed to the «disturbed» class by the network that
corresponds to the occurrences of large sporadic effects. Comparison of the results of neural network operation with space weather data and wavelet spectrum (Fig. 8.b, 9.b) confirms the accuracy of network decision. We should note that in spite of the difference in geographical latitudes of Irkutsk NM (104 degrees 16.8396 minutes) and Moscow NM (37 degrees 37.22358 minutes), the neural network classified the magnetic storm at the same point of time.

**Figure 8.** a) neutron monitor data (Irkutsk) for August 21-29, 2018, b) wavelet spectrum of neutron monitor data, c) k-index data, b) results of LVQ2_coif3_2 neural network operation.

**Figure 9.** a) neutron monitor data (Moscow) for August 21-29, 2018, b) wavelet spectrum of neutron monitor data, c) k-index data, b) results of LVQ2_coif3_2 neural network operation.

**Figure 10.** a) neutron monitor data (Irkutsk) for March 12-20, 2018, b) wavelet spectrum of neutron monitor data, c) k-index data, b) results of LVQ2_coif3_2 neuron network operation.

**Figure 11.** a) neutron monitor data (Moscow) for March 12-20, 2018, b) wavelet spectrum of neutron monitor data, c) k-index data, b) results of LVQ2_coif3_2 neuron network operation.
Fig. 10, 11 illustrates the results of NM data processing for Irkutsk and Moscow sites for the period of March 12-20, 2018. Analysis of geomagnetic activity index data (Kp-index [34], Fig. 10 c,11 c) shows the presence of strong and long geomagnetic disturbances during the period under analysis. Owing to the arrival of an accelerated flux from the coronal whole at 11.00 UT on March 14, the solar wind velocity gradually increased to 533 km/s on March 14 and 15, IMF southern component fluctuations increased to Bz=±11 nT on March 14 (Fig. 10, 11). On March 16 and 17, the solar wind velocity was within v=410-530 km/s, IMF component was Bz=±6-±9 nT. From the beginning of the day on March 18 and to the end of the day on March 19, the solar wind velocity increased to 624 km/s and IMF fluctuations reached Bz=±10 nT owing to the arrival of an accelerated flux from the second part of the coronal whole.

According to the results of LVQ2_coif3_2 neural network operation (Fig. 10 d,11 d), small-scale sporadic effects («weakly-disturbed» class) occurred in cosmic ray dynamics before the magnetic storm (March 12-13 at Irkutsk site and on March 12 at Moscow site). The period of March 14-20 was attributed to the «disturbed» class by the network that corresponds to large sporadic effects and confirms the accuracy of their decision.

5. Conclusions
The method suggested in the paper to analyze neutron monitor data showed the efficiency of its application in the tasks of investigation of cosmic ray dynamics and detection of sporadic effects. The effectiveness of application of multi-scale wavelet decompositions at the stage of pre-processing of the data, applied to the neuron network input, was experimentally confirmed. An algorithm to determine the «best» approximating basis in orthogonal wavelet class was suggested. The results confirmed good approximating properties of Koiflet 3 wavelet function. On the examples of strong magnetic storms in 2015-2018, based on the measurements of different sites, the possibility of application of the method in the problems of real time analysis of neutron monitor data and detection of different-scale sporadic effects, including those of low amplitude, was shown. Estimates of the constructed neuron network operation showed their high performance. The LVQ2_coif3_2 network solution error was less than 5%.

In the future the authors plan to continue the investigation in this direction applying a wider spectrum of sites recording cosmic ray data and increasing statistical material.

6. References
[1] Dorman LI 1966 Variations of cosmic rays and study of the cosmos (Ohio: Foreign Technology Division) p 855
[2] Storini M 1990 Galactic cosmic-ray modulation and solar-terrestrial relationships Il Nuovo Cimento C 13(1) 103-124 DOI: 10.1007/BF02515780
[3] Forbush S E 1938 On cosmic ray effects associated with magnetic storms Eos, Trans Am Geophys Union 19(1) 193-193 DOI: 10.1029/TR019i001p00193-1
[4] Eroshenko E A, Belov A V, Kryakunova O N, Kurt V G and Yanke V G 2009 The alert signal of GLE of cosmic rays Proceedings of the 31st ICRC
[5] Ni S-L, Han Z-Y 2017 Interplanetary coronal mass ejection induced forbush decrease event:a simulation study with one-dimensional stochastic differential method Acta Physica Sinica 66 1-8 DOI: 10.7498/aps.66.139601
[6] Mishev A, Usoskin I 2016 Application of a full chain analysis using neutron monitor data for space weather studies
[7] Vipindas V, Gopinath S and Girish TE 2016 Periodicity analysis of galactic cosmic rays using Fourier, Hilbert, and higher-order spectral methods Astrophys and Space Sci 361 135 DOI: 10.1007/s10509-016-2719-y
[8] Livada M, Mavromichalaki H and Plainaki C 2018 Galactic cosmic ray spectral index: the case of Forbush decreases of March 2012 Astrophys and Space Sci 363 8 DOI: 10.1007/s10509-017-3230-9
[10] Belov A V, Bieber J W, Eroshenko E A, Evenson P, Pyle R and Yanke V G 2003 Cosmic ray anisotropy before and during the passage of major solar wind disturbances Adv. Space Res. 31(4) 919-924

[11] Belov A V, Abunina M A and Abunin A A 2017 Cosmic-ray vector anisotropy and local characteristics of the interplanetary medium Geomagn Aeron 57 389-397 DOI: 10.1134/S0016793217040028

[12] Grigoryev V G, Starodubtsev S A 2015 Global survey method in real time and space weather forecasting Bull Russ Acad Sci Phys 79 649-653 DOI: 10.3103/S1062873815050226

[13] Dorman L I 2004 Experimental Basis of Cosmic Ray Research Cosmic Rays in the Earth's Atmosphere and Underground 201-286 DOI: 10.1007/978-1-4020-2113-8_4

[14] Real time data base for the measurements of high-resolution Neutron Monitor URL: www.nmdb.eu (01.12.2018)

[15] Ageev A D 2002 Neuromathematics: Textbook for Universities (Moscow: IPRZhR) p 448

[16] Khaykin S 2006 Neural networks: full-time course (Moscow: Vil'yams) p 1104

[17] Spitsyn V G, BolotovaYu A, Phan N H and Bui T T T 2016 Using a Haar wavelet transform, principal component analysis and neural networks for OCR in the presence of impulse noise ComputerOptics 40(2) 249-257 DOI: 10.18287/2412-6179-2016-40-2-249-257

[18] Izotov P Y, Kazanskiy N L, Golovashkin D L and Sukhanov S V 2011 CUDA-Enable Implementation of a Neural Network Algorithm for Handwritten Digit Recognition Optical Memory and Neural Networks (Information Optics) 20(2) 98-106 DOI: 10.3103/ S1060992X11020032

[19] Mandrikova O V, Zhizhikina E A 2015 Automated technique to estimate geomagnetic field state Computer Optics 39(3) 420-428 DOI: 10.18287/0134-2452-2015-39-3-420-428

[20] Rudoy G I 2011 Selection of activation function during neuron network forecasting Machine learning and data analysis 1(1) 16-39

[21] Baldin N P 2011 Investigation of forecasting convergence by neural networks with feed-back Machine learning and data analysis 1(1) 61-76

[22] Golovko V A 2001 Neural networks: training, organization and application (Moscow: IPRZhR)

[23] Mandrikova O V, Zalyaev T L 2014 Modeling of cosmic ray variations and detection of anomalies based on the combination of wavelet transform with neural networks Machine learning and data analysis 1(9) 1154-1167

[24] Mandrikova O V, Zalyaev T L, Mandrikova B S and Kupriyanov M S 2018 Analysis of cosmic ray dynamics based on neural networks International Conference on Soft Computing and Measurement XXI

[25] Mandrikova O V, Zalyaev T L and Mandrikova B S 2018 Analysis of the dynamics of cosmic rays on the basis of neural networks Journal of Physics: Conference Series 1096 0121137 DOI:10.1088/1742-6596/1096/1/012137

[26] Chui C K 1992 An introduction in wavelets (Academic Press, New York) p 264

[27] Mallat S 1999 A wavelet tour of signal processing (London: Academic Press) p 620

[28] Mandrikova O V, Polozov Yu A 2014 Approximation and analysis of ionospheric parameters based on the combination of wavelet transform with collective neural networks Information technologies 7 61-65

[29] Daubechies I 1992 Ten Lectures on wavelets CBMS–NSF Lecture Notes (SIAM, Philadelphia)

[30] Kohonen T 2001 Self-organizing maps (Berlin; Heidelberg; New York; Barcelona; Hong Kong; London; Milan; Paris; Singapore; Tokyo: Springer) p 501

[31] Bertin E, Bischof H, Bertolino P 1996 Voronoi pyramids controlled by Hopfield neural networks Comput. VisionImage Understand 63(3) 462-475

[32] Hammer B, Villmann T 2002 Generalized relevance learning vector quantization Neural Networks 15 1059-1068

[33] Archive of neutron monitor data IZMIRAN Kingston site URL: http://cr0.izmiran.ru/kgsn/main.htm (01.12.2018)

[34] Zaytsev V V, Kruglov A A 2009 Radiophysics and Quantum Electronics 52 355

12
[35] Dobeshi I 2001 *Ten lectures on wavelets* (Izhevsk: NITs “Regulyarnaya i khaoticheskaya dinamika”) p 463

[36] Archive of geomagnetic activity Dst-index data URL: http://wdc.kugi.kyoto-u.ac.jp/dstdir/ (01.12.2018)

[37] Forecast of space weather according to the data of Federov Institute of Applied Geophysics URL: http://ipg.geospace.ru (01.12.2018)

[38] Donoho D 1994 Asymptotic Minimax Risk for Sup-norm Loss: Solution via Optimal Recovery *Probab. Theory Relat. Fields.* 99 145170

[39] Mallat S G 1998 *A wavelet tour of signal processing* (N. Y.: Academic Press)