Modeling and analysis of natural time series based on a combination of cognitive decision rules and KAN neural network

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Abstract

A method for modeling and analyzing natural time series based on a combination of cognitive decision rules with the Kolmogorov-Arnold neural network (KAN) is proposed. The problem of approximating the data time changes of the galactic cosmic ray flux variations is considered. Anomalous changes in the galactic cosmic ray flux indicate disturbances in the near-Earth space and are an important factor in space weather. The non-stationary structure of data of the cosmic ray flux variations, limited data samples, and a high proportion of incomplete a priori knowledge reduce the efficiency of existing data analysis methods, including the latest developments in machine learning and artificial intelligence. The cognitive rules developed by the authors are based on the synthesis of risk theory elements with adaptive threshold wavelet estimates. They allow suppressing interference (including correlated interference) and detecting an information signal at the rate of data receipt by the processing system. The obtained estimates showed that the combination of cognitive rules with the KAN neural network makes it possible to improve the qualitative characteristics of the KAN network. Application of the method allowed us to obtain an adequate model of the data time changes of cosmic ray variations (the MSE model values of the best network NN8_filt is 0.84633 and errors are white Gaussian noise), giving a forecast with a lead step of 10 counts. The example of the event on May 10, 2024 shows the prospects of using the developed method for the task of describing anomalous changes in the rate of cosmic ray arrival to the Earth based on the data from high-latitude neutron monitors. The efficiency and accuracy of the method were also confirmed by the estimates of the deviations in the L2 norm of the true (observed) values from the values obtained by the network (with the use of cognitive rules $E_{L2} = 2.0136$, without cognitive rules $E_{L2} = 3.8538$).

Keywords: natural data analysis methods, correlated noise, neural network, adaptive filtering, wavelet transform.

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Introduction

Development of the methods for modeling and analyzing natural time series is important for a wide range of theoretical studies, as well as practical problems related to the study of natural processes and phenomena. Examples of such studies are the study of the properties of living organisms, populations, communities, ecosystem monitoring, etc. Of particular importance are the studies aimed at creating methods and tools for detecting catastrophic natural phenomena, such as earthquakes, tsunamis, extreme geomagnetic storms, etc. Important quality criteria for such tools are efficiency and accuracy.

Taking into account the specifics of natural data (significant non-stationarity, presence of correlated interference, high proportion of lack of a priori information, limited data sets, etc.), to solve the problems in this field, scientists actively use and develop methods of machine learning, artificial intelligence and digital signal processing aimed at reducing the noise level and amplifying information signals [1 – 8]. For example, the work [4] presents a modified multicomponent model of the time series of ionospheric parameters based on the combination of wavelet transform and autoregressive integrated moving average models. Based on the proposed modified model [4], an algorithm for analyzing ionospheric parameters was developed. It makes it possible to detect ionospheric disturbances in near real-time mode. The authors of [5] proposed a method based on the use of convolutional neural networks and empirical decision rules to solve the problem of recognizing geomagnetic storms. The method [5] ensured an increase in the probability of correct recognition of geomagnetic storms up to 82.3 % by applying the data from the URAGAN muon hodoscope and neutron monitors. Chinese researchers [6] proposed a new KANs-Unet method for the problem of detecting anomalous areas in the images of the power spectra of ionospheric electric fields in space. It includes a convolutional module KAN-Conv based on the KAN neural network. The method [6] made it possible to increase the average value of the proportion of correctly classified pixels in images up to 0.998973. The paper [7] proposes a short-term wind power forecasting model based on a combination of an exponentially weighted moving average (EWMA) and a Kolmogorov-Arnold transformer network. The work [7] notes that application of EWMA allowed the authors to suppress noise and improve the quality of the transformer network. Application of the KAN network, using cubic B-splines, allowed the researchers to improve the capability of the constructed model to describe nonlinear relationships and improved the accuracy of the transformer model for wind energy [7].

The object of the study in this paper is the methods for analysis of the data of galactic cosmic ray flux variations, aimed at studying the characteristic properties and detecting anomalous changes in the rate of cosmic ray arrival to the Earth. Galactic cosmic rays are an important factor in space weather, which has significant impact on modern terrestrial and space infrastructure. This work continues the cycle of the studies [9, 10]. The experimental base is the data from the high-latitude network of ground stations of neutron monitors (NM), recording the cosmic ray flux intensity [www.nmdb.eu]. In the works [9, 10] it is shown that the time series of neutron monitor data contain a high level of correlated noise associated with solar processes. The natural noise effect leads to a significant decrease in the signal-to-noise ratio and reduces the accuracy in the solution to the problem of detecting anomalies in the data with the direct application of existing data analysis methods, including the latest developments in the field of artificial intelligence and machine learning. This is due to the overlap and coincidence of the characteristics of the information component of the neutron monitor data time series and noise. In [9, 10], cognitive rules for making decisions about the data state are proposed for detecting the information component of neutron monitor data and suppressing noise. The developed rules are based on the synthesis of elements of the theory of statistical decisions with wavelet transform. The rules are implemented numerically and allow us to obtain a solution close to the optimal one, in a certain statistical sense, at the rate of data arrival to the processing system. In [9, 10], it is shown that the use of cognitive rules together with the Autoencoder neural network increases the efficiency of solving the problem of detecting anomalies in neutron monitor data preceding the onset of geomagnetic storms.

This paper considers the problem of approximating the time variation of neutron monitor data during quiet and disturbed periods in the near-Earth space. The problem solution is based on the combination of the developed cognitive rules for making decisions with a neural network of the KAN architecture [11]. KAN neural networks are a good alternative to the multilayer perceptron. Important advantages of KAN networks, compared to the perceptron, are interpretability and the capability to train on small data samples [11]. The estimates obtained in the work showed the prospects of the proposed approach for the research task. Application of cognitive rules allowed us to improve the qualitative characteristics of the KAN network. Based on the method, an adequate model of the time course of data on cosmic ray flux variations was obtained, giving a forecast with a lead step of 10 samples (corresponding to the time interval of 50 minutes). Our earlier studies [12] using the combination of wavelet filtering operations with a multilayer perceptron made it possible to obtain a model for describing the data time changes of cosmic ray flux variations (data from ground-based neutron monitors were used) for only 1 sample. This result confirms the advantage of KAN over a multilayer perceptron. Using the example of the event on May 10, 2024, the paper also shows the prospects for using the developed method for the problem of detecting anomalous changes in the rate of cosmic ray arrival to Earth based on the data from high-latitude neutron monitors.

1. Description of the method

Taking into account the structure of the natural time series, let us present it as

$$f(t) = R(t) + A(t) + e(t) = S(t, \Theta) + \sum_n p_n \phi_n(t) + e(t) = I(t) + e(t), \tag{1}$$

where $R(t) = S(t, \Theta)$ describes the regular components of the time series, Θ is a parameter set $A(t) = \sum_n p_n \phi_n(t)$, contains anomalous features and has a nonparametric form, p_n are the coefficients, $\phi_n(t)$is the basis, $I(t) = R(t) + A(t)$ is an information component of a time series, $e(t)$ is the noise, t is the time.

1. *Application of cognitive rules to suppress noise and detect the information component* $I(t)$. According to the model (1) and considering a simple hypothesis Γ_0 against a simple alternative Γ_1, making a decision on the data state the at time t (noise s_0 / information signal s_1) gives a likelihood ratio [12]

$$\frac{w\big(f(t)|\Gamma_1\big)}{w\big(f(t)|\Gamma_0\big)} \geq T, \tag{2}$$

where $W(f(t)|\Gamma_0)$ and $W(f(t)|\Gamma_1)$ are the probability densities of distributions under the validity of the hypotheses Γ_0 and Γ_1, respectively, T is the threshold.

Following the results of [9], for the functions f with limited variation, the best solution, according to the likelihood ratio (2), is given by the representation in a two-parameter wavelet basis and the *cognitive rule 1* can be applied: *the data at the time* $t = n$ *have a state* s_1 *(hypothesis* Γ_1 *is true), if the amplitudes of the wavelet coefficients* $|c_{k,n}| = |\langle f, \Psi_{k,n}\rangle|$ *in the vicinity of the point* $t = n$ *do not satisfy the condition*

$$|\langle f, \Psi_{k,n}\rangle| \leq Qk^{q+0.5} = \Pi_k, (Q = const > 0, q \text{ is the Lipschitz exponent})$$

and the lowest risk is given by the adaptive threshold estimate

$$\hat{I}(t) = \sum_k \sum_n P_{T_{\alpha,k,n}}(c_{k,n}) \Psi_{k,n}(t)\,, P_{T_{\alpha,k,n}}(c_{k,n}) = \begin{cases} c_{k,n}, if |c_{k,n}| \geq T_{\alpha,k,n} \\ 0, if |c_{k,n}| < T_{\alpha,k,n} \end{cases}, \tag{3}$$

with the thresholds $T_{\alpha,k,n} = h_{\alpha} * \hat{\sigma}_{k,n}$.

The thresholds $T_{\alpha,k,n}$ in relation (3) are estimated in the vicinity of the points (k, n) according to the Neyman-Pearson criterion [13] from the condition $\int_A W(|c_{k,n}||\Gamma_0) d|c_{k,n}| = \alpha$, where α is the error of the first type.

As long as the efficiency of procedure (3) obviously depends on the chosen wavelet basis Ψ, according to the estimates in the work [14], the risk of estimating $\hat{I}(t)$ in the wavelet basis Ψ can be limited by the value

$$R_{\Psi}\left(\hat{I}(t), I(t)\right) = E\left\{\left\|\hat{I}(t) - I(t)\right\|^2\right\} = \sum_{k,n} min(|\langle I, \Psi_{k,n}\rangle|^2, \sigma_{k,n}^2) \le \sum_{k,n} \sigma_{k,n}^2, \quad (4)$$

where $\sigma_{k,n}^2$ is the noise variance.

Then, using (4) and estimating the errors for different wavelet bases, we can determine the wavelet basis that gives the least error

$$\Psi_{best}: R_{\Psi_{best}}\left(\hat{I}(t), I(t)\right) = \underset{\Psi \in D}{min} R_{\Psi}\left(\hat{I}(t), I(t)\right) = \underset{\Psi \in D}{min} \sum_{k,n} \left(\sigma_{k,n}^{\Psi}\right)^2, \quad (5)$$

where D is the dictionary of wavelet bases, $(\sigma_{k,n}^{\Psi})^2$ is the noise variance estimated in the basis Ψ.

Thus, we obtain cognitive rule 2: using the dictionary of bases $D = \lambda \epsilon \Lambda \Psi_{\lambda}$, for the function $f(t)$ we calculate $R_{\Psi_{\lambda}}(\hat{I}(t), I(t)) = \underset{\Psi_{\lambda} \in D}{min} \sum_{k,n} (\sigma_{k,n}^{\Psi_{\lambda}})^2$, and, according to the estimate (5), we determine the best wavelet basis Ψ_{best} that minimizes the error

$$\mathcal{R}_{\Psi_{best}}\left(\hat{I}(t), I(t)\right) = \min_{\Psi_{\lambda} \in D} \sum_{k,n} \left(\sigma_{k,n}^{\Psi_{\lambda}}\right)^2 . \quad (6)$$

Following the work [9, 10] and using fast wavelet packet decompositions, the adaptive threshold estimate (3) can be implemented based on *cognitive rule 3*: *in wavelet packets* $B_j^p = \{\Psi_j^p(2^j t - n)\}_{n \in N}$, *where* B_j^p *is the basis of spaces* $W_j^p : W_j^p = W_{j+1}^{2p} \oplus W_{j+1}^{2p+1}$, *the lowest risk is given by the adaptive threshold estimate (Figure 3):*

Step 1. The basis $B_{p,j} = \{\Psi_{j,n}^p\}_{n \in N}$ of space W_j^p is the basis of

$$B_{p,j} = \begin{cases} \Psi_{j,n}^p, if\ O\left(c_{j,n}^p\right) + O\left(c_{j+1,n}^{2p}\right) \ge O\left(c_{j+1,m}^{2p+1}\right), \\ \Psi_{j+1,n}^{2p} \cup \Psi_{j+1,n}^{2p+1}, if\ O\left(c_{j,n}^p\right) + O\left(c_{j+1,n}^{2p}\right) < O\left(c_{j+1,n}^{2p+1}\right), \end{cases} \quad (7)$$

where $O(c_{j+k,n}^{lp+k}) = \sum_{n \in I^{lP+1}} |c_{j+k,n}^{lp+1}|^2$, $c_{j,n}^p = \langle f(t_n), \Psi_{j,n}^p \rangle$, $|c_{j,n}^p| \ge T_{\alpha,j}^p$, $T_{\alpha,j}^p = t_{1-\frac{\alpha}{2}, N-1} \hat{\sigma}_{p,j}$ are thresholds.

Step 2. Error $B_{p,j}$ is $\epsilon_{B_{\lambda}} = \|f(t) - \tilde{f}_{B_{\lambda}}(t)\|^2$, where $\tilde{f}_{B_{\lambda}}(t) = \sum_{j,n} T_{\alpha,j}^p(\langle f, \Psi_{j,n}^p \rangle) \Psi_{j,n}^p(t)$.

Step 3. Best wavelet packet basis $R_{B_{best}} = min_{B_{\lambda}} \epsilon_{B_{\lambda}}$.

Note that the use of wavelet packets according to operation (7) allows us to analyze not only the low-frequency but also the high-frequency components of the time series, compared to the traditional smoothing operations, and obviously ensures the preservation of a greater proportion of useful information.

Application of cognitive rule 3 is shown in Fig. 1.

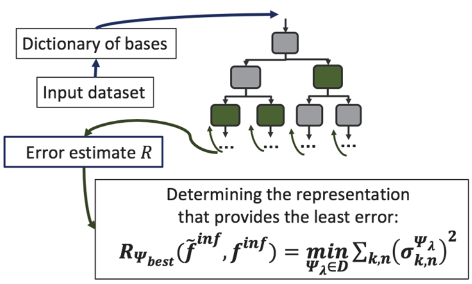

Fig. 1. Fragment of a wavelet packet tree and elements of the cognitive rule 3

Based on the cognitive rules 1 – 3, we obtain the following numerical algorithm for noise suppression and detection of the information signal:

Step 1. Calculation of the expansion coefficients into wavelet packets up to level m:

$$C = \left\{d_{j+1}^0, d_{j+1}^1, \dots, d_{j+m}^{(2^m - 2)}, d_{j+m}^{(2^m - 1)}\right\},$$

where $C -$ is a set of vectors of wavelet packet tree coefficients, $d_{j+1}^0 = \sum_n h_n \cdot f_{j,n}$, $d_{j+1}^1 = \sum_n g_n \cdot f_{j,n}$, … $d_{j+m}^{(2^m-2)} = \sum_n h_{n-2k} \cdot d_{j+m-1,n}^{(2^{(m-1)}-2)}$, $d_{j+m}^{(2^m-1)} = \sum_n g_{n-2k} \cdot d_{j+m-1,n}^{(2^{(m-1)}-2)}$, $h -$ are low-pass filters, $g -$ are high-pass filters, $f = \{f_i\} -$ is the natural time series, $i = 1 \dots N$.

Step 2. Calculation of the thresholds T for each node (j,p) at a given significance level α (operation (7)):

$$T = \left(T^0_{j+1,\alpha}, \dots, T^{(2^m-1)}_{j+m,\alpha}\right) = t_{1-\frac{\alpha}{2},N-1} * \hat{\Sigma},$$

where $\hat{\Sigma} = \left(\hat{\sigma}_{0,j+1}, \dots, \hat{\sigma}_{(2^m-1),j+m}\right), \hat{\sigma}_{p,j} = \sqrt{\frac{1}{N^*-1}\sum_{i=0}^{N^*-1}\left(d_j^p - \overline{d_j^p}\right)^2}$, $N -$ is the length of the coefficient d_j^p, $\overline{d_j^p} = \frac{1}{n}\sum_{i=0}^{n-1} d_{j,n}^p$, $n -$ is the number of samples in the node d_j^p.

Step 3. Determination of the information components of the time series and suppressing noise:

$$C^{inf} = \{d^0_{j+1}{}^{inf}, d^1_{j+1}{}^{inf}, \dots, d^{(2^m-2)}_{j+m}{}^{inf}, d^{(2^m-1)}_{j+m}{}^{inf}\},$$

where $d^p_{j,n}{}^{inf} = \begin{cases} d^p_{j,n}, if |d^p_{j,n}| \geq T^p_{j,\alpha} \\ 0, if |d^p_{j,n}| < T^p_{j,\alpha} \end{cases}$.

Step 4. Recursive restoration of time series original resolution:

$$\tilde{f}^{inf} = \sum_n h_n \cdot d^0_{j+1}{}^{inf} + d^1_{j+1} = \sum_n g_n \cdot d^1_{j+1}{}^{inf}.$$

Step 5. Determining the representation that provides the least error (operation (6)):

$$R_{\Psi_{best}}\left(\tilde{f}^{inf}(t), f^{inf}(t)\right) = \min_{\Psi_\lambda \in D} \sum_{k,n}\left(\sigma^{\Psi_\lambda}_{k,n}\right)^2,$$

where $D -$ is the dictionary of wavelet bases.

Figure 2 shows, as an example, the results of applying the described numerical Algorithm (Fig. 2*b*) to the neutron monitor data of the Oulu station (Fig. 2*a*). During the analyzed time interval (December 5 - 10, 2018), the data contain two Forbush effects (the moments of registration of Forbush effects are marked with red arrows) according to the source [spaceweather.izmiran.ru]. In Figure 2, the red dashed curves mark the calculated mean value of the data, as well as the confidence interval, which was calculated using the formula:

$$\Lambda = \bar{f} \pm z * (\sigma / \sqrt{n}),$$

where $\Lambda -$ is the confidence interval, $\bar{f} -$ is the sample mean (estimated taking into account the daily time course), $\sigma -$ is the standard deviation, $n -$ is the length of the time series. The time interval was calculated at a 99 % significance level, $z = 2{,}576$.

Figure 2 shows that the application of cognitive rules reduced the noise level and detected anomalous features (Forbush effects on December 7 and 8, 2018). Figure 2*a* shows that the noise exceeds the confidence interval for the entire analyzed period from December 5 to 10. After applying cognitive rules (Figure 2*b*), the confidence interval is exceeded on December 7 and 8, 2018, when Forbush effects in cosmic ray variations occurred. The effectiveness of the method is also confirmed by the estimates presented below in Tables 1 and 2.

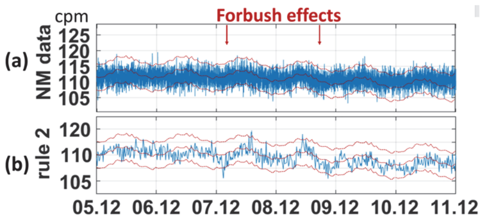

Fig. 2 Result of applying the Algorithm

2. Application of KAN network for time series approximation. The typical architecture of KAN network realizes the Kolmogorov-Arnold theorem (superposition theorem) [11]: a multivariate continuous function with bounded variation can be represented as a finite superposition of continuous one-dimensional functions:

$$Y(T) = Y(t_1, \dots, t_n) = \sum_{q=1}^{2n+1} \Theta_q\left(\sum_{p=1}^{n} \theta_{q,p}(t_p)\right). \quad (8)$$

The KAN neural network is trained on the basis of the error backpropagation algorithm. During the training process, the KAN network parameterizes equation (8). A layer of the KAN network with n_{in} inputs and n_{out} outputs is defined through a function matrix, which has the form

$$\Theta = \{\theta_{q,p}\}, p = 1,2, \dots, n_{in}, q = 1,2, \dots, n_{out}.$$

The typical architecture of the KAN network is a composition of two KAN layers, it is shown in Fig. 3. Each activation function $\theta_{q,p}(t)$ is, by analogy with a multilayer perceptron, the sum of a basis function $b(t) = t/(1+e^{-t})$ and a spline function $spline(t) = \sum_i c_i B_i(t)$ ($B_i(t)$ is B-splines, c_i are the training parameters):

$\theta_{q,p}(t) = \upsilon_q b(t) + \upsilon_p spline(t)$, υ_b, υ_s are the training parameters.

A deep KAN network is a composition of KAN layers

$Y = (\Theta_{L-1} \circ \Theta_{L-2} \circ \ldots \circ \Theta_1 \circ \Theta_0)T.$

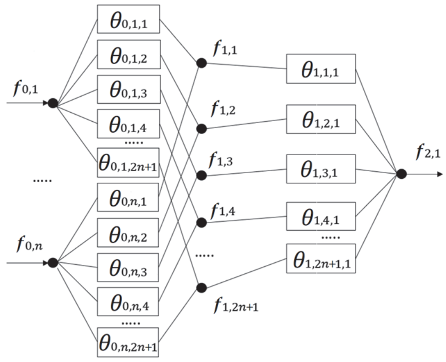

Fig. 3. Typical architecture of the KAN NN

The scheme for solving the problem based on a combination of the cognitive rules and the KAN network is presented in Fig. 4.

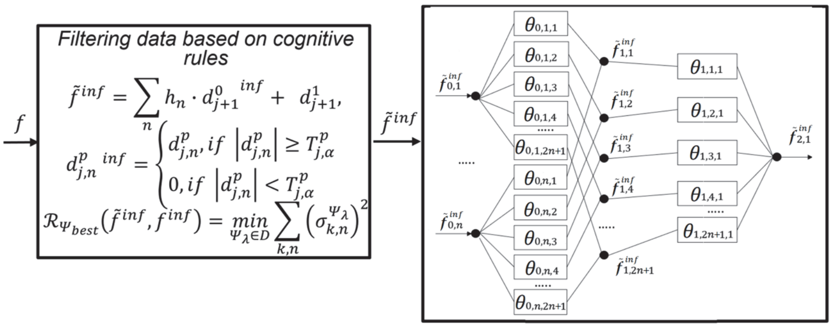

Fig. 4. Scheme for the problem solving

2. Data Processing Results

The experiments used the data from the neutron monitor global network of [nmdb.eu]. In order to optimize the procedure for training and testing neural networks, the experiments were conducted with 5-minute data from neutron monitors. To train the network, 5000 vectors with a dimension of 288 samples (daily vector) were used as input data and 5000 vectors with a dimension of 10 samples were used as output data, where each subsequent vector was supplied with a time lag of one sample. The training data were selected for the periods during which the state of near-Earth space (NES) was very calm (k-index<3, Dst-index<18). The neutron monitor data for 2018 (low solar activity) were used. The network architecture was built taking into account the minimization of true (observed) values deviation from the values obtained by the network, according to the L2 norm according to the formula:

$$E_{L2} = \sqrt{\sum_{i=1}^{n}\left(f_i - \tilde{f}_i\right)^2},$$

where n – is the total number of data points, f_i – is the true (observed) value for the i-th data point, $\tilde{f}_i$ – is the values obtained by the network for the i-th data point.

Table 1 presents the results of the estimates obtained both with the use of the cognitive rules (filtered data) and without rules (with the original data from neutron monitors). The results show that the best result was obtained using filtered data, with one internal layer of the dimension 144. Analysis of the results in Table 1 confirms the efficiency of the combination of the developed cognitive rules and the KAN neural network. Application of the cognitive rules allowed us to significantly reduce the errors of the constructed neural network model for all analyzed architectures.

Table 2 presents the results of assessing the adequacy of the constructed neural network model. The model adequacy was tested on test data (the data was not used to train neural networks).The results presented in Table 2 show that the application of the method allowed us to reduce the MSE values for the KAN neural network. With the use of cognitive rules, the MSE model values of the best network NN8_filt is 0.84633, without the use of rules, the smallest MSE model values of the NN8 network is 1.42754. The model's adequacy also was verified using the Ljung–Box Q-statistics and the Jarque–Bera test [13]. The Ljung–Box Q-statistic (Q_{stat}) confirmed the hypothesis on the joint equality of all the autocorrelations of the model residuals series up to the order m inclusive (column 4 and 5, Table 2). The Jarque-Bera test (J_B) showed that the model errors were normally distributed (columns 4 and 5, Tab. 2). Thus, according to Ljung–Box Q-statistics and the Jarque–Bera test the networks errors are the white Gaussian noise. The results of the tests confirmed the adequacy of the constructed neural network model.

Tab. 1. Estimates of the constructed neural networks

NN architecture, [input vector dimension, number of neurons in internal layers, number of neurons in output layer]	**With cognitive rules, E_{L2}**	**Without data filtering, E_{L2}**
[288, 2, 5, 10]	NN1_filt: 11.4794	NN1: 12.3260
[288, 3, 7, 10]	NN2_filt: 10.0962	NN2: 11.9539
[288, 4, 5, 10]	NN3_filt: 9.9976	NN3: 11.1474
[288, 20, 10]	NN4_filt: 7.1154	NN4: 10.0631
[288, 30, 10]	NN5_filt: 6.8383	NN5: 8.9775
[288, 70, 10]	NN6_filt: 4.7469	NN6: 7.8553
[288, 100, 10]	NN7_filt: 3.0483	NN7: 4.9635
[288, 144, 10]	**NN8_filt: 2.0136**	NN8: 3.8538

Tab. 2. Estimate of the neural networks adequacy

NN architecture, [input vector dimension, number of neurons in internal layers, number of neurons in output layer]	**With cognitive rules, MSE**	**Without data filtering, MSE**	**With cognitive rules, Ljung–Box Q-statistics, Jarque–Bera test**	**Without data filtering, Ljung–Box Q-statistics, Jarque–Bera test**
[288, 2, 5, 10]	NN1_filt: 1.96743	NN1: 2.29374	$JB = 3.37$; $Q_{stat} = 19.23$	$JB = 3.66$; $Q_{stat} = 25.84$
[288, 3, 7, 10]	NN2_filt: 1.72985	NN2: 1.99637	$JB = 3.63$; $Q_{stat} = 20.71$	$JB = 3.82$; $Q_{stat} = 23.24$
[288, 4, 5, 10]	NN3_filt: 1.57658	NN3:1.92234	$JB = 3.28$; $Q_{stat} = 19.68$	$JB = 3.65$; $Q_{stat} = 22.34$
[288, 20, 10]	NN4_filt: 1.43595	NN4: 1.90846	$JB = 3.27$; $Q_{stat} = 19.24$	$JB = 3.92$; $Q_{stat} = 22.60$
[288, 30, 10]	NN5_filt: 1.26478	NN5: 1.79557	$JB = 3.14$; $Q_{stat} = 16.23$	$JB = 2.98$; $Q_{stat} = 24.23$
[288, 70, 10]	NN6_filt: 1.22564	NN6: 1.66012	$JB = 2.24$; $Q_{stat} = 17.37$	$JB = 2.06$; $Q_{stat} = 21.38$
[288, 100, 10]	NN7_filt: 0.99455	NN7: 1.54001	$JB = 2.56$; $Q_{stat} = 17.91$	$JB = 2.31$; $Q_{stat} = 22.79$
[288, 144, 10]	**NN8_filt: 0.84633**	**NN8: 1.42754**	$JB = 2.39$; $Q_{stat} = 15.23$	$JB = 2.76$; $Q_{stat} = 20.64$

Examples of NM data approximation using neural networks of the NN8_filt and NN8 architectures are shown in Figure 5 and Figure 6 (detail). The NM data for the period of May 14, 2024, which do not contain anomalies (corresponding to the calm state of the NES), were used as test data. The results show that application of the cognitive decision rules made it possible to suppress noise and improve the approximating capabilities of the KAN network. This is confirmed by the calculations obtained in Table 1 (the deviations of the predicted values of the neural network from the actual ones according to the L2 norm) end Table 2 (MSE model values). It should also be noted that the network was trained on the data of 2018 (a period of low solar activity), and the testing result in Figure 5 and Figure 6 are presented using the data of 2024 (a period of high solar activity). The time course of neutron monitor data depends significantly on the level of solar activity. The results confirm the efficiency of the method for the research task.

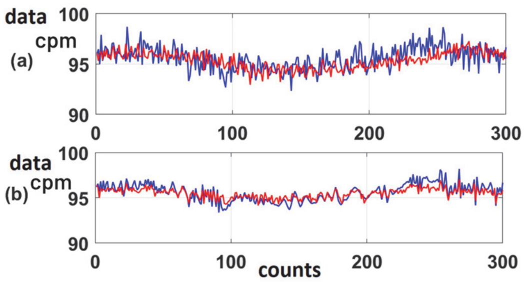

Fig. 5. Result of testing the constructed neural network model: (a) without data filtering; (b) using cognitive rules

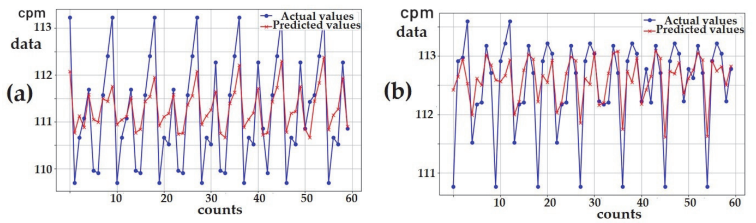

Fig. 6. Result of testing the constructed neural network model (detail): (a) without data filtering; (b) using cognitive rules

Figure 7 shows the results of NM data processing during the period containing the extreme geomagnetic storm of May 10, 2024 (the storm onset is marked with a vertical dotted line). The initial NM data are shown in blue, and the neural network result is shown in red. Analysis of the results shows satisfactory approximating properties of the neural network model during the disturbed period. However, during disturbances in near-Earth space, the network errors increased, indicating the need for further, more detailed studies.

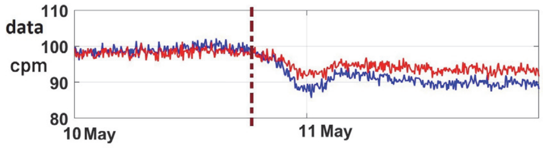

Fig. 7. Result of testing the constructed NN on NM data for May 9-10, 2024

Conclusions

The proposed method for modeling and analyzing natural time series has shown the promise of its application for approximating the time course of data on variations in the flux of galactic cosmic rays. Evaluations of the constructed neural network model have shown that the combination of the developed cognitive decision-making rules with the KAN neural network improves the quality characteristics of the KAN network. The use of cognitive rules made it possible to suppress noise in the data on variations in the flux of cosmic rays and detect the information component of the time series. The constructed neural network model provides a satisfactory forecast of data with a lead step of up to 10 samples (corresponding to a time interval of 50 minutes). This result indicates higher approximating properties of the obtained neural network model, compared to analogs in this area [12, 15 – 17].

Using the example of the extreme geomagnetic storm of May 10, 2024, the paper shows the promise of using the developed method to describe anomalous changes in the rate of arrival of cosmic rays to Earth. But the increase in network errors during disturbances in near-Earth space indicates the need for further, more detailed studies.

The developed method can be recommended for describing time series with a high level of interference, including correlated noise. The constructed neural network model can be used to study the dynamics of variations in the cosmic ray flux and to forecast space weather.

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