UDC 721

Prof. **Shvorov S.A.** NUBPU)
Ph.D. **Zhyrov G.B.** (MIKNU)
Ph.D. **Shtepa V.M.** (NUBPU)
Chyrchenko D.V. (HNADU)
Ph.D. **Zhelnovan G.M.** (HNADU)

NEURAL NETWORK PREDICTING SOLAR (COSMIC) RADIATION IN SPECIAL SPACE SYSTEMS

Analyzed the negative impact of corpuscular radiation on solar panels satellites and other electronic components. Established feasibility of predicting such a perturbation. Design and implementation of information-measuring system (IMS) intensity of solar radiation, corpuscular radiation as a prototype in space - one energy source. Proposed to use neural networks for forecasting time series of solar radiation, but because of noisy information signal associated with a substantial list of possible influence of natural factors (decrease in the intensity of sunlight on the sensor IMS) adequate prediction was not received. Analyzes prerequisites using Hilbert-Huang transform for clearing signal intensity solar radiation of noise created an appropriate filter and confirmed the effectiveness of this approach. Retrieved qualitative prediction of the filtered signal using a multilayer perceptron.

The satellite, solar radiation, noisy, prediction, neural network, perceptron.

The relevance and background of research. Experience of exploitation solar panels on satellites showed that existing in the near-Earth space radiation corpuscular streams have a strong destructive effect on solar cells and other electronic components (A Vasil'yev A Landsman) - taking them down and reducing the period of the regular operation systems.

As you know, corpuscular radiation consists of:

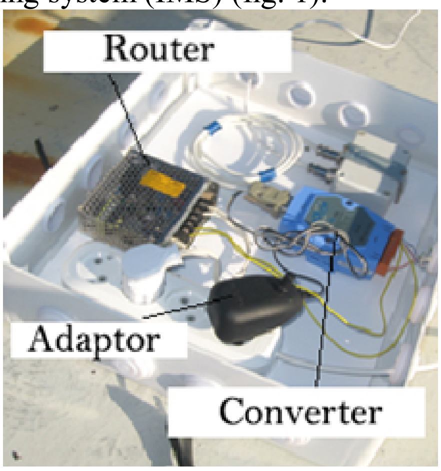
- Cosmic rays have a galactic origin, containing mainly protons and light nuclei (with low intensity and therefore not dangerous for solar panels);

- Cosmic rays, which appear as a result of solar flares. Continuing radiation from a few hours to days and consists mainly of protons. Observed 2-3 years after the maximum 11-year cycle of solar activity;

- Particles trapped by Earth's magnetic field. They represent the greatest danger for solar cells because they operate continuously.

Depending on the height of the satellite orbit, the factors affecting differently. Accordingly, the methods of protection will be different. It is clear that the ability to predict its value only increase the degree of protection.

To develop methods of forecasting and study character of natural disturbances in the form of solar radiation, as some prototype corpuscular radiation in space, built and installed information-measuring system (IMS) (fig. 1).



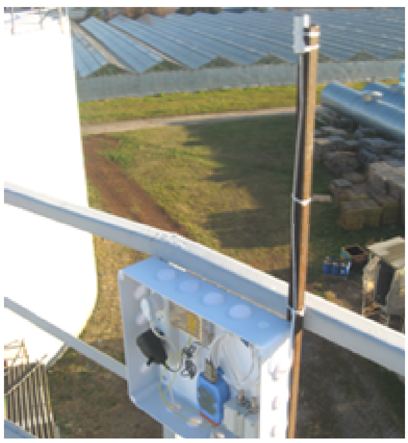


Fig. 1. Information-measuring system intensity of solar radiation

As a predictive mathematical tools in the research process for the prediction of the temperature time series applied neural networks (NN) [1]. However, the necessary efficiency prediction regarding solar radiation has not been received (Fig. 2). Best results demonstrated NN radial basis function with five inputs and two hidden layers: teaching error – 0,009317 W/m^2, control error – 0,008983 W/m^2, test error – 0,008991 W/m^2.

The above explains the noisy information signal associated with a substantial list of possible influence of natural factors (decrease in the intensity of sunlight on the sensor IMS) [2]: latitude and longitude location; distance from the Sun to the Earth, the height of clouds; cloud type; absolute humidity; the horizontal and vertical components of wind velocity; size and concentration of aerosol; condensation nuclei; cloud condensation nuclei and cloud droplets size; die size; water content; height of upper and lower boundaries of clouds; cloud radiative capacity; aquatic supply of clouds; rainfall intensity and so on.

That is why further research, with the ability to implement predictive power, deemed necessary application of mathematical filters.

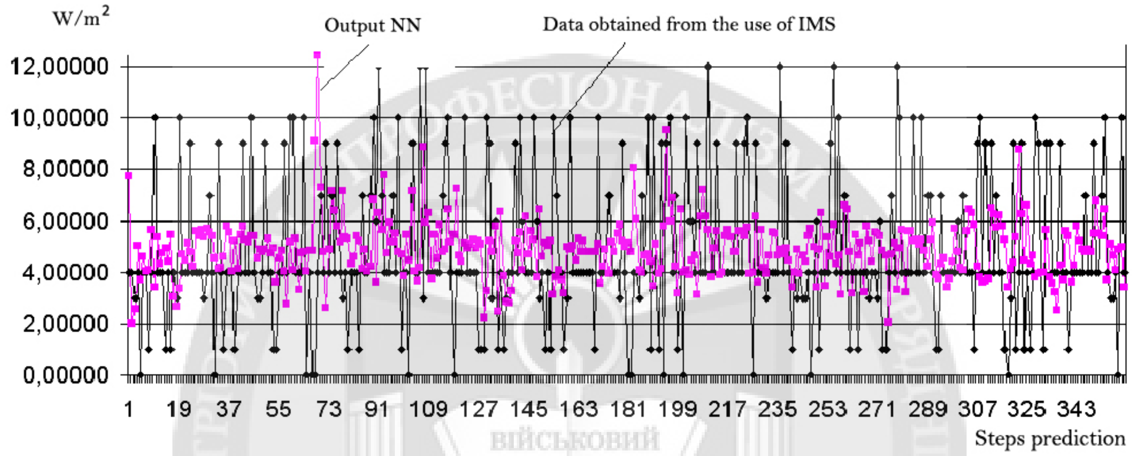


Fig. 2. Comparing the output NN (RBF) and experimental data (time interval - 30 minutes, discrete - 5 seconds)

Traditional methods of data analysis, designed generally for linear and stationary signals and systems [3]. At the same time it is obvious that the time series of solar radiation is nonlinear and non-stationary (see Fig. 2) [2]. So, a prerequisite for adequate data presentation will focus on the possibility of forming an adaptive basis, which functionally depend on the semantic component of the signal, and will not be pre-selected and the same as in the classical approach.

So requirements are met by Hilbert_Huang transform (HHT), which is defined as a method of time-frequency analysis based on empirical Mode decomposition (EMD) nonlinear and non-stationary processes and Hilbert spectral analysis (HSA) [4-6].

Purpose of research – to develop a method of neural network prediction of intensity solar radiation as a negative factor, which derives from the system of electronic components for special purpose.

Materials and methods of research. Generally EMD method is based on the assumption that any data set contains various modes of oscillatory processes [3]. Each of these vibrational modes can be represented by a function of the inner fashion (IMF) with the restrictions: the number of extrema and number of zero crossings of the function must be equal or differ by no more than one unit, at any point average of the envelope function curves defining local extremes, should be 0.

That is IMF are vibrational modes that instead of constant amplitude and frequency can have variable amplitude and frequency as a function of time.

The essence of EMD is consistent (iteration) to establish the functions of empirical mod $c_j(t)$ and the residual $r_j(t) = r_{j-1}(t) - c_j(t)$, where $j = 1, 2, 3, \ldots, n$ with $r_0 = y(t)$. Decomposition to represent the signal in a sum of modal functions and terminal residue [7]:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t), \quad (1)$$

where n – number of empirical events, which is set in the calculations.

Studies [4-6] have demonstrated that appropriate adaptive basis although not determined analytically, but meets the requirements of the traditional bases: completeness, convergence, orthogonality and uniqueness (controversial statement).

Thus the EMD algorithm has a clear iterative calculation, which creates preconditions for its implementation in intelligent control systems [4, 5]:

1) identification of local extrema signal and grouping them into arrays of coordinates and vectors corresponding amplitude values;

2) calculating the upper and lower envelope of the signal $y(k)$ for the selected maxima and minima;

3) calculation of average function values $m_1(k)$ and of the first approximation to the first function fashion IMF:

$$\mathrm{h}_1(k) = \mathrm{y}(k) - \mathrm{m}_1(k), \quad (2)$$

4) repetition of steps 1-3, taking the place of $y(k)$ function $h_1(k)$, and of the second approximation to the first function fashion IMF - function $h_2(k)$:

$$\mathrm{h}_2(k) = h_1(k) - \mathrm{m}_2(k). \quad (3)$$

Similarly calculated and the following approximation to the first function fashion IMF. The criterion for stopping iteration, for example, can be normalized square difference between two successive operations of approximation:

$$\delta = \frac{\sum_k (\mathrm{h}_{i-1}(k) - \mathrm{h}_i(k))^2}{\sum_k (\mathrm{h}_i(k))^2}. \quad (4)$$

The last values $h_i(k)$ terations taken by the high-frequency feature fashion $c_1(k) = h_i(k)$ family IMF, which is part of the output signal. This allows you to remove $c_1(k)$ from the signal and keep it more low-frequency components:

$$r_1(k) = y(k) - c_1(k), \quad (5)$$

The function $r_1(k)$ as a new data processed by the finding of a similar second IMF Mode function method – $c_2(k)$:

$$\mathrm{r}_2(k) = \mathrm{r}_1(k) - \mathrm{c}_2(k). \quad (6)$$

Thus, the signal decomposition is achieved in n - mods empirical approximation of the amount of residue $r_n(k)$ (1).

Stop signal decomposition must to happen at the maximum "straightening" balancethat is turning it into a trend signal by an interval of task. In practice, the process can be closed on the following criteria: balance $r_n(k)$ стає becomes a monotonic function without extremes, remains $r_n(k)$ are minor in importance or power compared to the signal; achieved preset relative mean square error reconstruction of the signal (4) without remainder $r_n(k)$.

In the case of treating the time series of solar radiation intensity for separating noise use the method [5], which is based on forming the frequency domain function $H(\omega)$low-pass filter with a cutoff frequency upper limit by the beginning of high noise, the multiplication of the signal for $H(\omega)$,translating the results of filtering in the time domain and use it as the initial (starting) function $m_1(k)$ in (2).

The method is characterized in that allows you to specify the transition area between the borders of the transmission and the suppression of frequency components of the signal, which increases the stability of EMD, adjustable width which can to some extent control the redistribution of functions between harmonics selection IMF. The above mentioned represents a flexible and sustainable method in respect of management expertise in interactive mode, a mathematical analysis tool noisiness of information signals.

Use the research time period of 6 hours (data received IMS) that technologically justified in terms of the width of the time window for further prediction and software V. Davydov and A. Davydov [9], making him a number of object-oriented change.

To eliminate errors transformation on a finite interval of processed data set studied time period extended to the end sections of 1% (43 points) also made its alignment in relation to the arithmetic mean value – 133,807 W/m^2 (Fig. 3).

To set the framework for cutting and counting filtered signal divergence angle of the input signal. This maximum angle to the first window and gradually decreases with increasing shear box calculations of the signal. But this reduction is uneven and in the limits of the information slows down due to the resistance dropout statistical noise and weak dependence of filters limits their width and transition zones. Slowing down can be fixed by changing the original local minimum angle differences. Thus, we had set a limit cutting - 65 cu (Fig. 4), the upper limit of complete suppression of high-frequency components for all filters - the same.

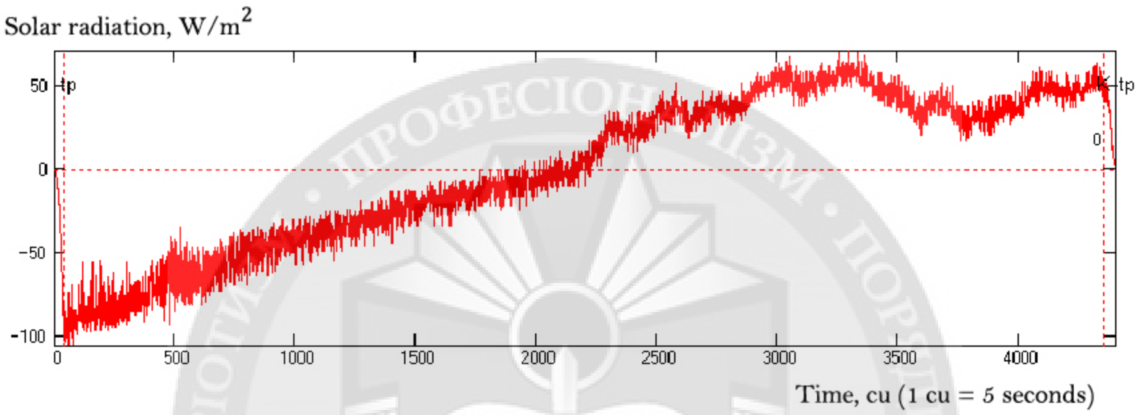


Fig. 3. Normalized and extended time series of solar radiation

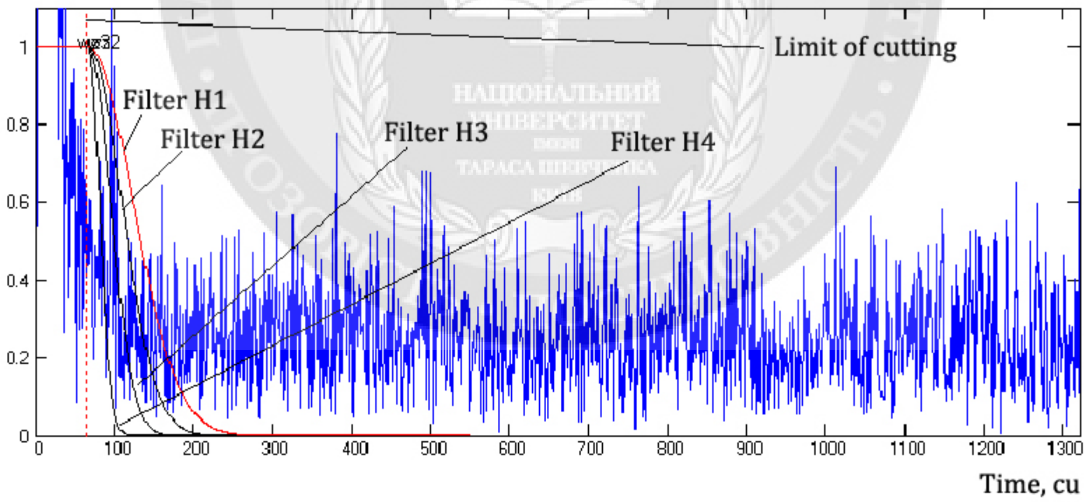


Fig. 4. Module spectrum of the time series of solar radiation with the appropriate filter settings

Also accepted that cleaning the noise of the time series of solar radiation will require four-dropout noise, that is to form IMF-1 = IMF-1a + IMF-1b + IMF-1c + + IMF-1d (fig. 5).

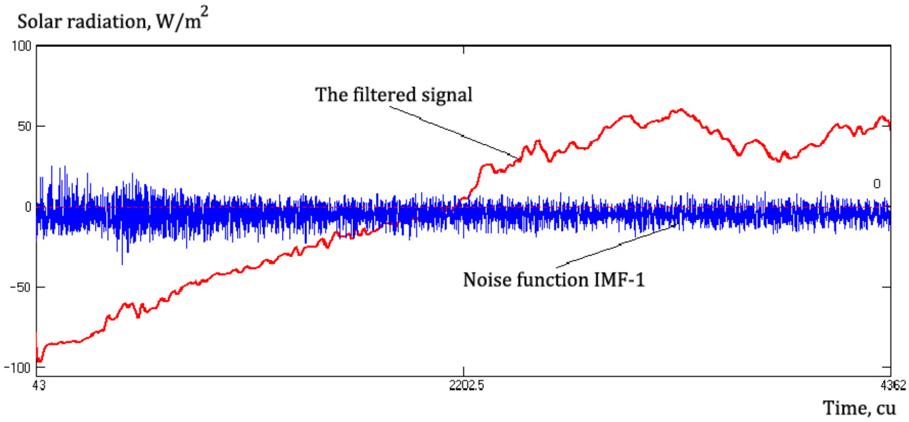


Fig. 5. The results of filtering the time series of solar radiation

Normalizing the filtered signal visually analyzed results of Hilbert_Huang transform and set the number of detected noise components in the input signal - 23.762% (fig. 6).

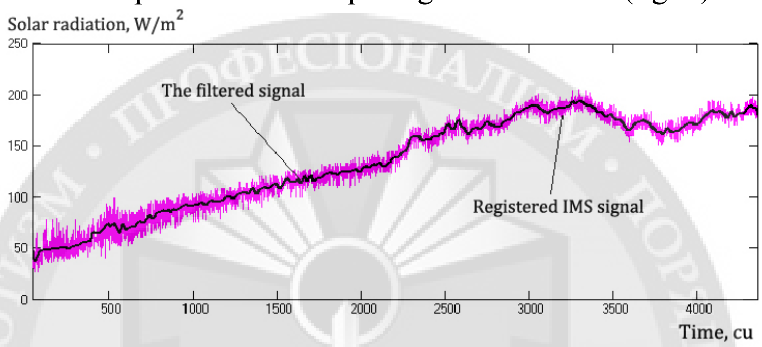


Fig. 6. Blending the input signal and the filtered time series of solar radiation

Having taught neuron network (fig. 7) filtered signal received appropriate quality prediction of solar radiation: RMS error - 8,1-9,3% (fig. 8).

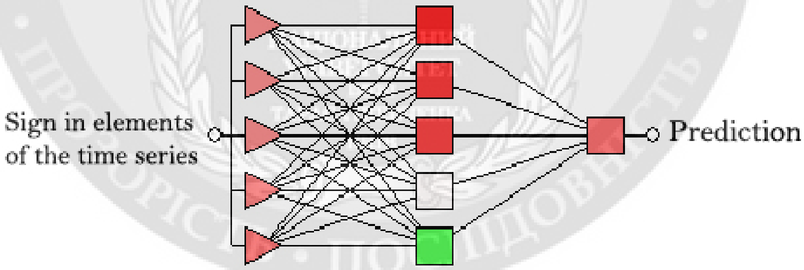


Fig. 7. A multilayer perceptron with five neurons in the hidden layer

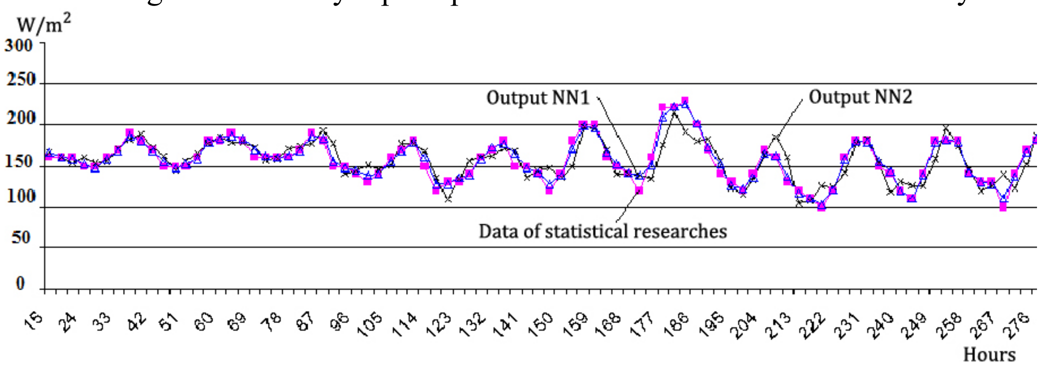


Fig. 8. Prediction of the filtered signal intensity of solar radiation by multilayer perceptrons (applied various optimization algorithms)

Conclusions. Based on the practical use of the developed technique neural network forecasting intensity of solar radiation is necessary to note the following:

mathematical filter based on Hilbert-Huang transform should be used to analyze the time series of solar radiation;

cleared by the results of the EMD signal characterized technologically sufficient resolution;

obtained from the Hilbert-Huang transform filtered signals can be used to construct appropriate neural network predictive models in special space systems.

REFERENCES:

1. Лисенко В.П. Ймовірнісна (Байєсівська) нейронна мережа класифікації температурних образів / В.П. Лисенко, В.М. Штепа, А.О. Дудник // Вісник аграрної науки. – К.: НААН. – 2011. – № 4. – С. 53-56.

2. Кондратьев К.Я., Атмосферный аэрозоль / К.Я. Кондратьев, Н.И. Москаленко, Д.И.Поздняков. – М.: Гидрометеоиздат, 1965. – 692 с.

3. Отнес Р. Прикладной анализ временных рядов / Р. Отнес, Л. Эноксон. – М.: Мир, 1982. – 428 с.

4. Huang N.E. Shen Z., Long S. R., Wu M. C., Shih H.H., Zheng Q., Yen N.C., Tung C.C., and Liu H.H. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of R. Soc. London, Ser. A, 454, pp. 903-995, 1998.

5. The Hilbert-Huang transform and its applications / editors, Norden E. Huang, Samuel S.P. Shen. - World Scientific Publishing Co. Pte. Ltd. 5 Toh Tuck Link, Singapore 596224.

6. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis / Huang N. E., Shen Z., Long S. R., Wu M. L. [and others]. – Proc. R. Soc. London, 1998. – Vol. 454. – P. 903-995.

Рецензент: д.т.н., проф. Сбітнєв А.І., провідний науковий співробітник науково-дослідного центру Військового інституту Київського національного університету імені Тараса Шевченка

д.т.н., проф. Шворов С.А., к.т.н., с.н.с. Жиров Г.Б.,
к.т.н., доц. Штепа В.М., Чирченко Д.В., к.т.н. Желнован Г.М.

НЕЙРОМЕРЕЖЕВЕ ПРОГНОЗУВАННЯ СОНЯЧНОЇ (КОСМІЧНОЇ) РАДІАЦІЇ У СПЕЦІАЛЬНИХ КОСМІЧНИХ СИСТЕМАХ

Проаналізовано негативний вплив корпускулярної радіації на сонячні батареї штучних супутників Землі та їх інші електронні компоненти. Встановлено доцільність прогнозування такого збурення. Розроблено та впроваджено інформаційно-вимірювальну систему (ІВС) інтенсивності сонячної радіації, як прототипу корпускулярної радіації у космосі – одні енергетичні джерела. Запропоновано застосовувати нейронні мережі для прогнозування часового ряду сонячної радіації, однак через зашумленістю інформаційного сигналу, пов'язану із можливим впливом значного переліку природних чинників (зменшенням інтенсивності дії сонячних променів на сенсор ІВС) адекватного предикту не було отримано. Проаналізовано передумови використання перетворення Гільберта-Хуанга для очищення сигналу інтенсивності сонячної радіації від шумів, створено відповідний фільтр та підтверджено ефективність такого підходу. Отримано якісний прогноз відфільтрованого сигналу із використанням багатошарового персептрона.

Ключові слова: супутник, сонячна радіація, зашумленість, прогнозування, нейронна мережа, персептрон.

д.т.н., проф. Шворов С.А., к.т.н., с.н.с. Жиров Г.Б.,
к.т.н., доц. Штепа В.М., Чирченко Д.В., к.т.н. Желнован Г.М.

НЕЙРОСЕТЕВОЕ ПРОГНОЗИРОВАНИЕ СОЛНЕЧНОЙ (КОСМИЧЕСКОЙ) РАДИАЦИИ В СПЕЦИАЛЬНЫХ КОСМИЧЕСКИХ СИСТЕМАХ

Проанализировано отрицательное влияние корпускулярной радиации на солнечные батареи искусственных спутников Земли и их другие электронные компоненты. Установлена целесообразность прогнозирования такого возмущения. Разработано и введена іинформационно-

измерительная система (ИИС) интенсивности солнечной радиации, как прототипа корпускулярной радиации в космосе - одни энергетические источники. Предложено применять нейронные сети для прогнозирования временного ряда солнечной радиации, однако из-за зашумленности информационного сигнала, связанную с возможным влиянием значительного перечня естественных факторов (уменьшением интенсивности действия солнечных лучей на сенсор ИИС) адекватного предикта не было получено. Проанализированы предпосылки использования преобразования Гильберта-Хуанга для очищения сигнала интенсивности солнечной радиации от шумов, создан соответствующий фильтр и подтверждена эффективность такого подхода. Получен качественный прогноз отфильтрованного сигнала с использованием многослойного персептрона.

Ключевые слова: спутник, солнечная радиация, зашумленность, прогнозирование, нейронная сеть, персептрон.