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USING THE WAVELET DECOMPOSITION METHOD FOR MONITORING OF AMPLITUDE-MANIPULATED SIGNALS OF RAILWAY AUTOMATION

1. Introduction

In railway signaling systems, some parameters required for monitoring and controlling train movements are transmitted using amplitude shift keying (ASK) signals. This is due to the fact that the historical first electrical signaling systems were implemented on the basis of electromechanical transducers, in which the realization of more complex types of modulation encounters some limitations on the functionality of electromechanical devices [1].

Therefore the ASK signals are more often used in railway automated systems due to their simpler generation by contact transmitters, but such signals have a low level immunity.

Electrified railways are spatially distributed powerful sources of electromagnetic interference in a wide range of frequencies that can cause disturbances in railway signalling systems [2-6]. One of the main sources of electromagnetic interference at electrified railways is the rolling stock and the traction system as a whole. Rolling stock is a non-linear power load that generates electrical disturbances in the traction network, covering a wide frequency range with significant variations in amplitude, and these disturbances penetrate into railway signalling lines through conductive or inductive paths and can lead to maloperation of signalling systems.

Information on the state of the tracks, signal lights, railway switches, etc. is transmitted to the control room, and the control commands are sent in the opposite direction to the track signalling devices. The safety of train traffic is directly dependent on the accuracy of the transmission of information and control signals [1].

Ensuring of the timely detection of signal disturbances in transmission lines is possible by organizing the monitoring of electromagnetic interference in them.

Fast Fourier transform (FFT) is one of the most widely used methods for detecting and identifying frequency distortions of a signal. But distorted current is non-stationary and FFT-based methods are not suitable for its analyzing.

For spectral analysis of non-stationary signals Dennis Gabor [7] proposed the Short-Time Fourier Transform (STFT) that applies FFT to signal divided into segments of certain length (by sliding windows), where the signal could be admitted as stationary one.

STFT is widely used for spectral analysis of traction current, but this method has some limitations, and one of them is associated with trade-off between the FFT window length and the frequency band width caused by the use of a fixed-length window. This restriction becomes important when the signal has transient components localized in time. Therefore, the STFT is more useful for analyzing quasi-stationary signals.

In recent decades, wavelet theory has become a powerful signal processing tool, widely used for non-stationary signal analysis in many practical applications [8, 12]. Wavelet transform (WT) allows simultaneously analyze signal features in both time and frequency domains, but in contrary to STFT, the wavelet analysis uses a varied time window, the length of which depends on the frequency being analyzed. This property of WT makes it very ef-

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fective for revealing the features of continuous non-stationary signals [11,13,14].

The use of wavelet decomposition for decoding continuous automatic locomotive signaling codes was first described in [11]. The possibilities of power quality analysis using WT have been explored in many papers [13, 14].

But automatic on-line detection and localization of disturbances with values exceeding certain allowable levels by direct using WT for analyzing code signals in transmission lines requires large computer resources. Wavelet decomposition of the signal showed high efficiency for detecting and localizing features in continuous signals.

2. The purpose of the work

The purpose of the work is to investigate the efficiency of using the signal decomposition method by wavelet transform to reveal distortions for continuous ASK railway signals.

This paper is organized as follows. Section 2 gives brief overview on wavelet transform and multi-resolution analysis, section 3 describes results of signals simulation and their decomposition by WT, and section 4 concludes the work.

3. Wavelet Transform and Multi-Resolution Analysis

The wavelet theory was first put forward by Morla in 1984 [8]. Wavelets are mathematical functions that decompose data into different frequency components, but unlike the short time Fourier transform (STFT), each component is analyzed with a resolution matched to its scale. WT is suitable for analyzing physical situations where the signal contains discontinuities and sharp spikes. The commonly used wavelet algorithms are continuous wavelet transform (CWT), discrete wavelet transform (DWT), and discrete wavelet packet transform (DWPT).

Generally, the continuous wavelet transform of a finite energy signal $f(t)$, defined in $L^2(R)$ space, can be written as

$$CWT_{\Psi} f(a,b) = \langle f(t), \Psi_{a,b}(t) \rangle = \\ = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t) \Psi\left(\frac{t-b}{a}\right) dt$$

where b and a are the so-called translation (or time location) factor and the scaling (or dilation) factor, respectively, $|a|^{-1/2}$ is used for energy normalization across the different scales, $\Psi_{ab}(t)$ is a function obtained by dilations and translations of a so-called "mother wavelet" $\Psi(t)$. The CWT is characterized as redundant transform over representation of a signal in a form of a two-dimensional array.

In DWT the mother wavelet dilate and translate discretely by selecting $a = a_0^m$, and $b = nb_0 a_0^m$, where a_0 and b_0 are fixed values with $a_0 > 1$, $b_0 > 0$, $m, n \in Z$, and Z is the set of positive integers. Then the corresponding discrete wavelet transform is given by

$$DWT_{\Psi} f(m,n) = \langle f(t), \Psi_{m,n}(t) \rangle = \\ = a_0^{-\frac{m}{2}} \int_{-\infty}^{\infty} f(t) \Psi\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) dt$$

DWT provides a decomposition of a signal into sub bands with a bandwidth that increases linearly with frequency. In the case of dyadic transform ($a_0 = 2$, and $b_0 = 1$), each spectral band is approximately one octave wide. In this form, DWT can be viewed as a special kind of spectral analyzer.

The algorithm of multi-resolution signal decomposition introduced by Mallat [10] consists of a series decompositions of the signal (with length $2n$) into two components: detail coefficients D_j, which capture the high frequency low-scale information in the original signal and approximation coefficients A_j, which capture the low frequency high-scale information, both components with a reduced size of $2n-j$, where j is the decomposition level. Then the detail coefficients D_j remain unchanged while the approximation coefficients A_j are decomposed into new the detail and approximation coefficients. This process repeats until the decomposition level reaches. DWT can decompose the signal into different scales by utilizing the orthogonal wavelet basis as

$$f(t)=\sum_k A_m(k)\varphi(t-k)+$$
$$+\sum_k\sum_j D_j 2^{-j/2}\Psi\left(2^{-j}t-k\right),\ j=1,2...m,$$

where, $\varphi(t)$ is the scaling function, A_m represents the last scale approximate coefficient.

The frequency range of each sub-band can be presented as

$$\begin{cases} D_j:\left[2^{-j}f_{\max},\, 2^{-j+1}f_{\max}\right] \\ A_j:\left[0,\, 2^{-j}f_{\max}\right] \end{cases},$$

where, $f_{\max}$ represents the frequency of the highest component.

The wavelet packet transform (WPT) can be viewed as a generalization of the classical wavelet transform, which provides a multi-resolution and time–frequency analysis for non-stationary signal. A low and high pass filter is repeatedly applied to the function, followed by decimation by 2, to produce complete sub-band tree decomposition to some desired depth. Because WPT not only decomposes the approximations of the signal but also details, it holds the important information located in higher frequency components than WT in certain applications.

Thus, with the use of WPT, a better frequency resolution can be obtained for the decomposed signal. DWPT recursive decomposition can be expressed as:

$$\begin{cases} d_{0,0}(t)=f(t), \\ d_{i,2j-1}(t)=\sqrt{2}\sum_k h(k)\,d_{i-1,j}(2t-k), \\ d_{i,2j}(t)=\sqrt{2}\sum_k g(k)\,d_{i-1,j}(2t-k), \end{cases}$$

where $h(k)$ and $g(k)$ are high-pass and low-pass filter respectively, and $d_{i,j}$ is the reconstruction coefficients of wavelet packet decomposition (WPD) at the i-th level for the j-th node.

4. Simulation and analysis

The short-duration variation disturbances with durations of several tens of the signal periods are considered in this work,. Such disturbances can be generated by electrical equipment of the rolling stock, and they can cause failures in the railway signaling systems. The disturbances are described in detail in literature on power quality and include sags, swells, interference with signal carrier frequency or/and another frequencies, sharp peaks [13-21], and etc. Simulated signals (Fig. 1) were generated using MatLab as a pure ASK signal with a carrier frequency of 420 Hz and a modulation frequency of 8 Hz, as well as five variants of the original signal with disturbances in the form of a distorted signal shape, a signals with swells in pause, with sags (dips) at pulse durations, with 50 Hz interference, and with sharp pulses. The numbers, locations in time, amplitude values and durations of disturbances were randomly varying during generation of them. The average values of the disturbances were about to the signal amplitude. The signal segments of ten periods were decomposed using a five-level wavelet packet transform (WPT) with $fk18$ wavelet.

Histograms of relative energy (REn) of investigated signals, taken in logarithmic units with inverse sign (as $-\log 2(REn)$ are shown for the first 32 nodes in fig. 2.

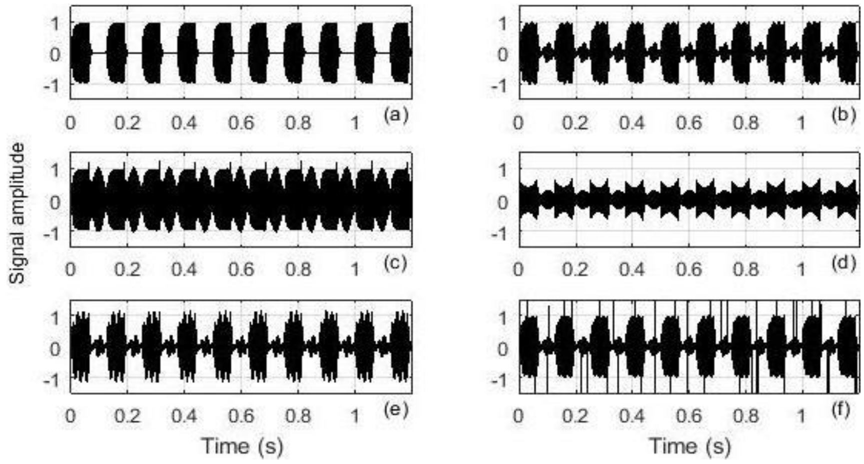

Fig. 1. Simulated signals in a form of original ASK signal (a), the signal with distorted envelope (b), with swells (c), with sags (d), with 50 Hz interference (e), with sharp pulses (f).

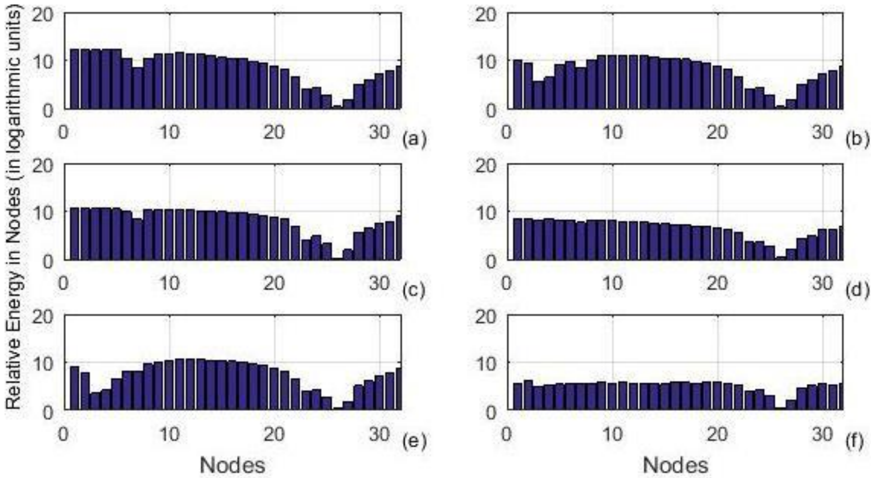

Fig. 2. Histograms of relative energy for the first 32 nodes of the original ASK signal (a), the signal with distorted envelope (b), with swells (c), with sags (d), with 50 Hz interference (e), with sharp pulses (f).

The time dependences of the WPT coefficients for first four decomposition nodes (4.0)..(4.3) are presented in fig. 3.

For all investigated signals, variations of the distortions or interference values lead, not only to changes in distribution of partial energies at the nodes, but also to the appearance of strong differences in the form of oscillations of the WPT coefficients (fig. 3).

WT coefficients correspondent to carrier frequency 420 Hz, 8 Hz, and side frequencies 420±8 Hz are contained in respective nodes for all investigated signals.

The variations in WPT coefficients in low-frequency nodes (4.0)..(4.3) reflect changes in the waveform due to pulse distortion, sags, swells, etc.

Disturbances of the signal in the form of its distorted shape, swells, sags, and interference 50 Hz lead to an increase of WT coefficients values at low-frequencies nodes by more than twenty times, from values of about 5·10–3 to values greater than 1·10–2, and even to 1·10–1 for the signals with sharp pulses (fig. 3).

The dips in WT coefficients of original signal in (4.2) node that corresponded pauses for ASK signal are smoothed out and therefore weakly pronounced for WT decompositions of the signals with swells. For signals with sags and 50 Hz interference the shapes and values of the WT coefficients in (4.1) node are strongly changed compared to original signal.

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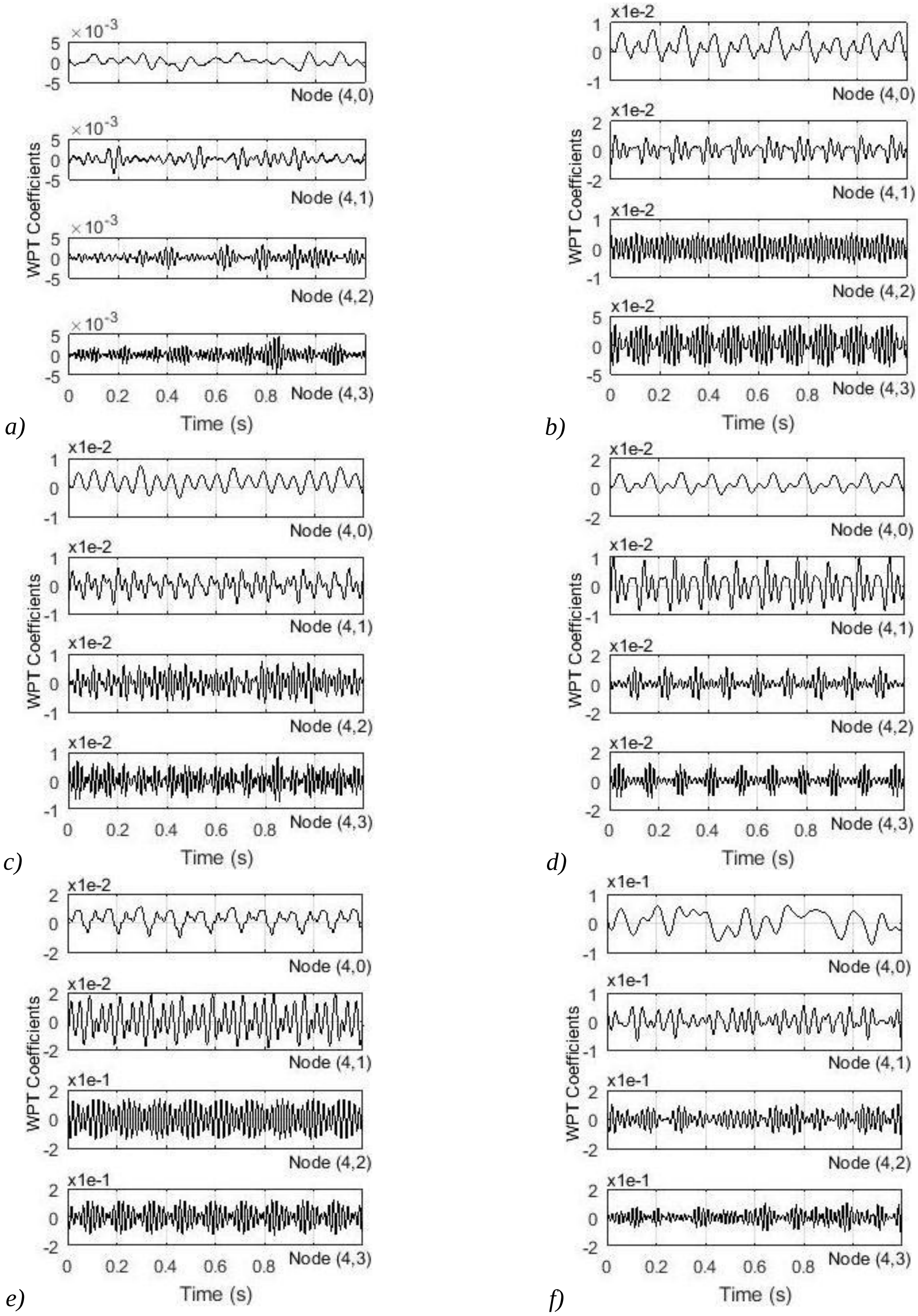

Fig. 3. WPT coefficients for original ASK signal (a), the signal with distorted envelope (b), with swells (c), with sags (d), with 50 Hz interference (e), with sharp pulses (f)

The feature corresponded to the higher frequencies components of disturbances (such as interference or sharp pulses) lead to variations of WPT coefficients in higher nodes (they aren't shown in fig. 3). These results confirm the effectiveness of the use of the wavelet decomposition method to reveal distortions in continuous ASK railway signals.

Conclusion

ASK signals are more often used in railway automated systems due to their simpler generation by contact transmitters, but such signals have a low level of immunity and interference in them can lead to incorrect operation of railway signaling systems. The efficiency of using the signal decomposition method by wavelet transform to reveal distortions for continuous ASK railway signals have been investigated in the work.

Simulated signals were generated as a pure ASK signals with a carrier frequency of 420 Hz and a modulation frequency of 8 Hz, as well as five variants of the original signal with disturbances in the form of signals with distorted signal shape, signals with swells, signals with sags, signals with 50 Hz interferences, and signals with sharp pulses .

The signal segments of ten periods were decomposed using a five-level wavelet packet transform (WPT) with $fk18$ wavelet.

For all investigated signals, the distortions or interferences in them lead, not only to changes in distribution of partial energies at the nodes, but also to the appearance of strong differences in the form of oscillations of the WPT coefficients.

The variations in WPT coefficients in low-frequency nodes reflect changes in the waveform due to pulse distortion, sags, swells, etc.

The obtained results confirm the efficiency of using the wavelet decomposition method in order to detect distortions in the ASK continuous railway signals.

References

1. Микропроцессорная централизация / Вд. В. Сапожников и др. М.: ГОУ, 2008. – 398 с.
2. Mariscotti, A. Distribution of the traction return current in AC and DC electric railway systems // IEEE Transactions on power delivery, 2003. – Vol. 18. – No. 4. – P.1422-1432.
3. Gavrilyuk, V. The modelling of electromagnetic influence of traction electrosupply system on track circuits / V. Gavrilyuk, A. Zavgorodnij // Transport Systems Telematics. IV Intern. Conf., Katowice-Ustron. P. 2004. – P. 18-19.
4. Cella, R. Measurement of AT electric railway system currents at power-supply frequency and validation of a multiconductor transmission-line model / R. Cella, G. Giangaspero, A. Mariscotti, and oth. // IEEE Transactions on Power Delivery, 2006. – Vol. 21. – No. 3. – P. 1721–1726.
5. Havryliuk, V. Modelling of the return traction current harmonics distribution in rails for AC electric railway system // 2018 International Symposium on Electromagnetic Compatibility (EMC EUROPE). – IEEE, 2018. – P. 251-254.
6. Havryliuk, V. I. Norms and methods of rolling stock test on electromagnetic compatibility with signalling and communication systems // Electromagnetic compatibility and safety on rail transport, 2016. – No. 12. – P. 48-57.
7. Gabor, D. Theory of communication. Part 1: the analysis of information // Journal of the institution of electrical engineers. – Part III: Radio and communication engineering. 1946. – Vol. 93. – No. 26. – P. 429–441.
8. Grossmann, A. Decomposition of hardy functions into square integrable wavelets of constant shape / A. Grossmann, J. Morlet // SIAM Journal on Mathematical Analysis. – 1984. – Vol. 15. – No. 4. – P. 723-736.
9. Mallat, S. G. A wavelet tour of signal processing representation. San Diego. Academic Press, Elsevier, 1999.– 629 p.
10. Mallat, S. G. A theory for multiresolution signal decomposition: the wavelet representation // IEEE Transaction on Pattern Analysis and Machine Intelligence. – 1989. – Vol. 11. – Iss. 7. – P. 674–693.
11. Hololobova, O. O. Application of Fourier transform and wavelet decomposition for decoding the continuous automatic locomotive signaling code / O. O. Hololobova, V. I. Havryliuk // Наука та прогрес транспорту. Вісник Дніпропетровського на-

ціонального університету залізничного транспорту, 2017. - № 1 (67) С. 7-17

12. Havryliuk, V. Fault diagnosis for electromagnetic relay using discrete wavelet transform and wavelet packet entropy // Zeszyty Naukowe Wyzszej szkoly technicznej w Katowicach, 2017. – No. 9. – P. 31-40.
13. Sinha, P. Classification of Power Quality Events Using Wavelet Analysis and Probabilistic Neural Network / P. Sinha, S. Debath, S. K. Goswami //IAES International Journal of Artificial Intelligence (IJ-AI). – 2016. – V. 5. – No. 1. – P. 1-12.
14. Latran, M. B. A novel wavelet transform based voltage sag/swell detection algorithm / M. B. Latran, A. Teke. // Int. J. Electr. Power Energy Syst., 2015. – V. 71. – P. 131–139.
15. Meliopoulos, A. P. S. An alternative method for transient analysis via wavelets / A. P. S. Meliopoulos, C. H. Lee // IEEE Transactions on Power Delivery. – 2000. – V. 15. – No. 1. – P. 114-121.
16. Chien-Hsing, Lee. A Literature Survey of Wavelets in Power Engineering Applications / Chien-Hsing Lee, Yaw-Juen Wang, Wen-Liang Huang // Proc. Natl. Sci. Counc. ROC(A), 2000. – Vol. 24. – No. 4. – P. 249-258.
17. Borghetti, A. Continuous-wavelet transform for fault location in distribution power networks: Definition of mother wavelets inferred from fault originated transients // IEEE Transactions on Power Systems. – 2008. – Vol. 23. – No. 2. – P. 380-388.
18. Saini, M. K. Classification of power quality events–a review / M. K. Saini, R. Kapoor // International Journal of Electrical Power & Energy Systems. – 2012. – Vol. 43. – No. 1. – P. 11-19.
19. Saribulut, L. Fundamentals and literature review of Fourier transform in power quality issues / L. Saribulut, T. Ahmet, M. Tümay // Journal of Electrical and Electronics Engineering Research. – 2013. – Vol. 5. – No. 1. – P. 9-22.
20. Goh, H. H. Power quality diagnosis in distribution network using wavelet transform // American Journal of Applied Sciences. – 2014. – Vol. 11. – No. 2. – P. 291-300.
21. Lopez-Ramirez M. et al. EMD-based feature extraction for power quality disturbance classification using moments // Energies. – 2016. – Vol. 9. – No. 7. – P. 565.

Ключові слова: електромагнітні завади,залізнична сигналізація, вейвлет перетворення, вейвлет розкладання сигналу.

Ключевые слова: электромагнитные помехи, железнодорожная сигнализация, вейвлет преобразование, вейвлет разложение сигнала.

Keywords: electromagnetic disturbances, railway signalization, wavelet transform, wavelet decomposition.

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