DOI: 10.18372/2310-5461.67.18510
УДК 621.391.825

M. Gariachiy, Researcher
Ivan Kozhedub Kharkiv National Air Force University,
Kharkiv, Ukraine
https://orcid.org/0000-0001-5177-6958
e-mail: garyachiy054@gmail.com;

S. Shcherbinin, PhD in Engineering
Deputy Head of Air Force Research Center
of Ivan Kozhedub Kharkiv National Air Force University,
Kharkiv, Ukraine
https://orcid.org/0000-0003-0966-2476
e-mail: shcherbinin.sa@gmail.com

ANALYSIS OF METHODS FOR ENHANCING SPECTRAL EFFICIENCY IN INFORMATION SYSTEMS

Introduction

The evolution of data transmission systems has led to the widespread adoption of wireless access technologies, such as cellular networks, satellite communications, the Internet of Things (IoT), and others. These technologies enable heterogeneous users to be integrated into a unified electronic communication framework. In modern corporate networks, characterized by a high number of subscribers (end users) and large-scale data flows, the demand for information confidentiality has significantly increased.

In the early stages of electronic communication development, deterministic signals were predominantly used. These signals featured a simple structure, predictability, and ease of processing. However, with the advancement of communication technologies, signals with complex structures-particularly chaotic and stochastic signals-have gained prominence due to their ability to enhance both the efficiency and reliability of information transmission in accordance with modern requirements.

As a result, the use of stochastic signals in electronic communication systems has become increasingly necessary. These signals offer a higher level of information protection, making them suitable for secure transmission scenarios. However, they also tend to reduce transmission speed due to their inherent statistical nature.

One of the primary challenges in the field of information transmission is the development of optimal strategies for signal generation and processing that ensure high interference immunity, spectral efficiency, and data security.

The relevance of this problem lies in the increasing necessity for efficient utilization of the radio frequency spectrum, which is inherently limited and requires optimal solutions to guarantee the stable operation of electronic communication systems.

Moreover, in the context of modern cybersecurity threats, the issue of information protection has become increasingly critical. This has intensified interest in the study of chaotic and stochastic signals, which offer inherent advantages in terms of confidentiality and unpredictability.

Currently, widely adopted signal processing methods include the Fourier Transform, Wavelet Transform, Hilbert Transform, and various numerical techniques. However, these conventional approaches are often insufficient for achieving high spectral efficiency under complex interference conditions.

Therefore, there is a pressing need to develop innovative methods capable of more effectively analyzing signals, reducing spectral bandwidth, and maximizing the volume of transmitted useful information.

Analysis of recent research and publications

An analysis of the properties of both deterministic and non-deterministic signals reveals that each type used in information systems offers specific advantages and drawbacks. Deterministic signals-such as harmonic waveforms-are characterized by their simple and well-defined structure, which facilitates their analysis and integration into narrowband communication systems.

However, the main drawback of such signals lies in their relatively low spectral efficiency. They require significant bandwidth resources to transmit even small amounts of information. Although various modulation techniques such as Amplitude Modulation (AM) or Frequency Modulation (FM) can be applied to improve their characteristics, deterministic signals remain suboptimal for high-throughput transmission tasks. Their predictability, while advantageous in certain contexts, limits their efficiency in applications where maximum spectral utilization is critical [1–19].

Moreover, the simplicity of generating such signals does not provide sufficient robustness against interference, which significantly limits their applicability in modern communication systems that demand both high spectral efficiency and strong interference resilience [6–11, 20–21].

In contrast, chaotic and stochastic signals-owing to their inherent unpredictability and statistical properties-can provide a significantly higher level of information security. These characteristics greatly reduce the likelihood of interception or unauthorized access. However, the use of such signals typically results in spectrum broadening and increased energy consumption, which negatively impacts overall spectral efficiency. [8, 15, 16, 17, 21, 22].

Despite the widespread adoption of traditional signal processing techniques-such as the Fourier Transform, Wavelet Transform, and Hilbert Transform-these methods often fail to meet the increasingly stringent requirements for spectral efficiency in modern systems. Consequently, there is a growing need to explore more innovative, albeit less conventional, techniques aimed at enhancing signal analysis, minimizing spectral redundancy, and maximizing the volume of useful transmitted hus, the use of chaotic and stochastic signals, in combination with modern signal generation and processing techniques, offers a high level of information protection. However, achieving sufficient spectral efficiency requires the integration of these approaches with careful consideration of signal properties and the specific characteristics of the transmission system. This integration enables the development of electronic communication systems that simultaneously optimize spectrum utilization and ensure a high level of data security [4–7, 12, 13, 22–26].

The purpose of the article

The purpose of the article is to identify the physical properties of chaotic and stochastic signals that affect spectral efficiency in an information transmission system.

Presentation of the main material

A signal is a physical process whose characterristics carry information about a certain phenomenon or state of an object, or transmit control commands and notifications. If a signal is specifically created to transmit a message, then a certain parameter of it (for example, the amplitude of the signal, its frequency, etc.) changes according to the information that needs to be transmitted [6].

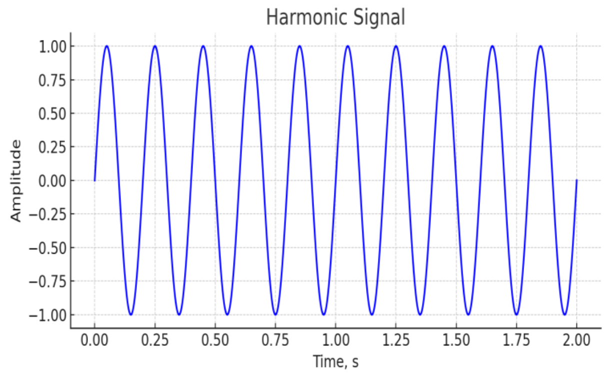

Fig. 1. Harmonic Signal in the Time Domain.
Source: developed by the authors

In radio engineering, signals are conventionally classified into simple (unmodulated) and complex (modulated) types. The primary form of a simple signal is the basic harmonic signal, which is characterized by constant amplitude and frequency, and is typically represented as a sinusoidal waveform (see Fig. 1) [3, 4].

In the general case, a simple harmonic signal can be described by the following expression (1):

$$x(t) = A\sin(\omega t + \varphi), \quad (1)$$

where A – amplitude of the signal; ω – frequency; φ – the initial phase [1, 2].

Based on the temporal variation of their parameters, signals are classified as either deterministic or non-deterministic.

Unlike simple harmonic signals, whose values are either known or can be precisely calculated at any given moment in time, the values of chaotic and stochastic signals are described by probabilistic characteristics. According to the works of Y. H. Sosulin, the mathematical model of random signals is represented by a random function of time as (2):

$$F(x,t_i) = P\{f(t_i) < x\}, \quad (2)$$

where $F(x,t_i)$ – the random function of time; P – the cumulative distribution function; $f(t_i)$ – the instantaneous value of the random signal; x – a signal parameter (a numerical value associated with the cumulative distribution function, characterizing a specific property of the random signal) [6, 10].

Unfortunately, the use of simple deterministic signals alone does not meet the modern requirements for information confidentiality in contemporary communication networks.

Stochastic signals, on the other hand, provide a higher level of information security due to their random nature. However, this comes at the cost of reduced transmission speed, which adversely affects the overall spectral efficiency of the information system.

A chaotic signal is a deterministic signal that exhibits the characteristics of a random process (see Fig. 2). It is defined by its extreme sensitivity to initial conditions, which results in unpredictable variations over time.

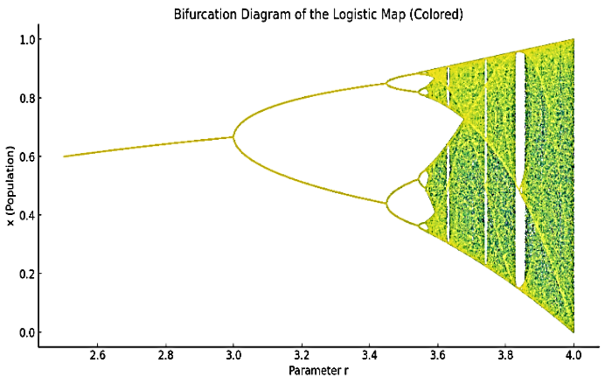

Fig. 2. Bifurcation diagram of the logistic map illustrating the system’s transition to chaotic behavior.
Source: developed by the authors

Chaos in the signal manifests as apparent disorder and a high sensitivity to even minimal changes in the system’s initial state. A common example of a chaotic signal is the logistic map (3), which demonstrates such behavior under specific parameter settings:

$$x_{t+1} = r \cdot x_t \cdot (1 - x_t)\,, \tag{3}$$

Where x_t – the value of the signal at time t; r – a variable signal parameter that governs its dynamics.

As shown in Fig. 2, for initial values of the parameter r the system remains in a stable state. However, as r increases, periodic oscillations begin to emerge. When $r > 3{,}57$ the system transitions into a chaotic regime [14]

The causes of a system transitioning into a chaotic state are:

1. Period doubling and the Feigenbaum constant:

All nonlinear systems similar to the logistic map exhibit a critical behavior at parameter values $r > 3{,}57$, where the periodicity of the system successively doubles ($2 \rightarrow 4 \rightarrow 8 \rightarrow 16 \rightarrow \ldots$) until chaos emerges. This phenomenon is known as period doubling and follows the Feigenbaum constant: $\delta \approx 4{,}669$ which is a universal constant characterizing the onset of chaos in all nonlinear dynamical systems [22].

2. Balance between nonlinearity and randomness.

When $r > 3{,}57$, the system becomes highly sensitive to initial conditions, such that each subsequent state appears unpredictable. This behavior is typical of chaotic systems, even though the governing equation remains entirely deterministic.

3. The value of r determines the energy or intensity of growth within the system. In physical systems, this parameter often corresponds to a growth rate coefficient or the strength of nonlinear interactions. As r increases, the system gradually loses stability and transitions into a chaotic state.

The key properties of chaotic signals that affect their spectral efficiency are:

1. Wideband nature: chaotic. signals exhibit a broad frequency spectrum due to their complex structure and the presence of multiple interacting modes. This wideband characteristic enables the transmission of larger amounts of data within the same frequency band compared to narrowband signals, such as harmonic or modulated sinusoids.

2. Nonlinearity. Chaotic systems often exhibit nonlinear dynamics, which can lead to the development of spectral components in unexpected frequency ranges. Such nonlinear interactions between signal components result in frequency mixing and the generation of new harmonics, significantly expanding the signal's spectrum. This behavior is fundamentally different from harmonic signals, whose spectrum consists only of the fundamental frequency and its harmonics.

3. Sensitivity to initial conditions: A small deviation in the initial state of a chaotic system can lead to significant changes in the spectral properties of the signal-a phenomenon commonly referred to as the “butterfly effect.” This sensitivity results in variations in the spectral distribution, transitions to chaotic oscillations, and the formation of an irregular signal spectrum.

4. Randomized dynamics. Chaotic signals often exhibit a random-like nature that leads to unpredictable variations in their spectral efficiency. This randomness implies that chaotic signals are aperiodic, with dynamically changing spectral characteristics. Their energy is unevenly distributed across a wide frequency range, making them unpredictable and noise-like in appearance.

Considering these properties, the spectrum of chaotic signals (Fig. 3) can be complex and challenging to analyze using traditional techniques such as the Fourier Transform. It is also important to note that chaotic behavior may manifest differently depending on the system or physical process that generates the signal [1, 5, 6, 11].

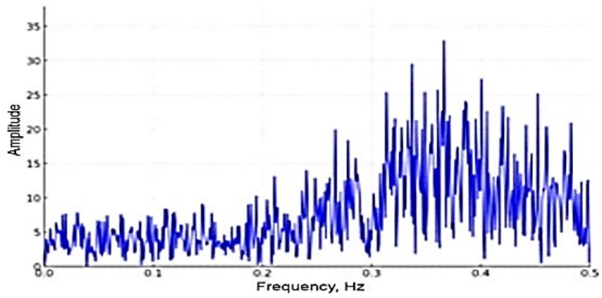

Fig. 3. Example of the spectrum of a chaotic signal.
Source: developed by the authors

The growing demand for information confidentiality has led to the use of stochastic signals-signals with random characteristics whose waveform is determined by underlying random processes (see Fig. 4). These signals offer enhanced data security due to their inherent unpredictability; however, their properties do not fully meet modern requirements for spectral efficiency.

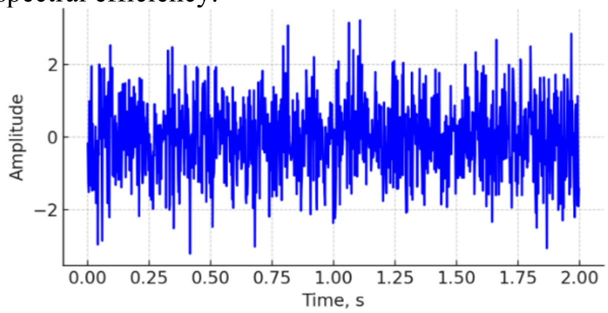

Fig. 4. Example of the spectrum of a stochastic signal.
Source: developed by the authors.

The main characteristics of stochastic signals are as follows:

Spectral Bandwidth. Stochastic signals exhibit a wide frequency spectrum due to their inherently random nature. The energy is typically spread across a broad range of frequencies without distinct peaks, unlike periodic signals.

2. Spectral noise characteristics. Stochastic signals are fundamentally noise-based. The type of noise-such as white noise, pink noise, or other variants-determines the corresponding spectral features of the signal. Each noise type contributes distinct statistical and spectral properties, influencing the signal's behavior across the frequency domain.

3. Correlation properties. Stochastic signals may exhibit varying degrees of correlation between their values at different points in time or space. These correlation levels influence the spectral efficiency by altering the waveform, energy distribution, and spectral bandwidth of the signal.

4. Spectral shape. The spectral shape of a stochastic signal can vary significantly depending on its nature and the conditions under which it arises. Some signals may exhibit a smooth, continuous spectrum, while others may display sharp peaks or spectral anomalies.

5. Signal energy distribution. The spectral energy of a stochastic signal may be unevenly distributed across the frequency spectrum. This non-uniform distribution is influenced by the signal's statistical properties and affects how energy is allocated among frequency components [8, 15]

The simulation results highlight the key advantages and limitations of the analyzed signal types, as summarized in Table 1.

An analysis of Table 1 indicates that, in terms of interference resistance, stochastic signals are the most effective. However, despite their broad spectral range, stochastic signals do not always guarantee efficient spectrum utilization under all conditions. For instance, white noise occupies the entire frequency range but carries no useful information, resulting in zero spectral efficiency. Therefore, the challenge of improving the spectral efficiency of information systems employing stochastic signals remains highly relevant.

Table 1

Comparison of Properties of Different Signal Types

Property	Harmonic Signal	Chaotic Signal	Stochastic Signal
Waveform	Single frequency, usually sinusoidal	Aperiodic, nonlinear	Variable; can take arbitrary forms
Mathematical Description	Sinusoidal function	Nonlinear differential equation	Random time-dependent function
Temporal Behavior	Periodic, predictable	Aperiodic, sensitive to initial conditions	Aperiodic, statistically independent
Spectral Characteristics	Line spectrum (single or multiple discrete frequencies)	Wideband, often fractal spectrum	Wideband, can vary (e.g., white noise, pink noise)
Predictability	Easily predictable, well-defined	Unpredictable for unauthorized observers, initial-state-sensitive	Unpredictable, random
Structure	Regular, deterministic	Complex, nonlinear	Statistically random
Examples	Sinusoidal wave	Logistic map, chaotic oscillators	White noise, Gaussian noise
Spectral Efficiency (bit/s/Hz)	1–2	5–10	3–7
Main Advantages	Simple generation and analysis; high energy efficiency	High noise immunity; large information capacity	Interference resistance; hard to intercept
Main Disadvantages	Low spectral efficiency; vulnerable to interference	Complex to analyze and process; potentially unstable	Difficult to decode; low energy efficiency

Source: developed by the authors.

Spectral efficiency refers to the data transmission rate achieved when transmitting information over a given bandwidth in a specified communication system. It quantifies how efficiently the limited frequency spectrum is utilized and is defined by the following key parameters (3):

1. Signal transmission rate – the maximum amount of information transmitted per unit time within a given frequency band.

2. Signal bandwidth – the range of frequencies over which the signal can be transmitted without distortion:

$$\eta = \frac{R}{\Delta F}, \quad (3)$$

Where η – the spectral efficiency of a signal (bit/s/Hz); R – the information transmission rate (bit/s); ΔF – the bandwidth of the signal (Hz) [7].

Assuming that:

he signal bandwidth (ΔF)varies from 0,1 Hz to 10 Hz;

The data transmission rate (R)is assigned for each signal type according to Shannon's theorem as follows: (Harmonic signal – 1,5 bit/s, Chaotic signal – 7,5 bit/s, Stochastic signal – 5 bit/s) Then:

As shown in Fig. 5, the data transmission rate depends on both the signal type and the efficiency of frequency resource utilization.

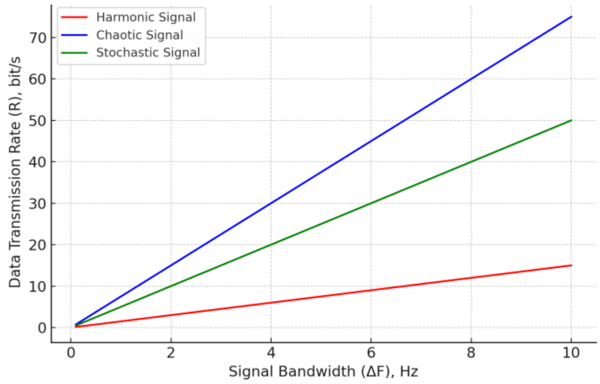

Fig. 5. Comparison of data transmission rates for different types of signals. Source: developed by the authors

Harmonic signals (red line) exhibit the lowest data transmission rate among all three signal types. This is due to their limited spectral efficiency; even with increased bandwidth, the growth in transmission rate remains marginal.

Chaotic signals (blue line) demonstrate the highest data transmission rate across the entire frequency range. Their complex structure enables more efficient spectrum usage and facilitates the transmission of greater amounts of information.

Stochastic signals (green line) occupy an intermediate position, achieving a higher transmission rate than harmonic signals but lower than chaotic ones. Their randomized structure and broad spectrum provide enhanced resistance to interference.

Overall, the graph confirms that chaotic signals are the most efficient in terms of spectral utilization, whereas harmonic signals are limited in their ability to transmit large volumes of data. Stochastic signals offer the highest interference resistance among the three and represent a compromise between spectral efficiency and transmission reliability.

The observed transmission rates can be interpreted through the relationship between the Shannon-Hartley theorem and the information entropy of the signals.

Information entropy is defined as the average amount of information (in bits) contained in each symbol (or sample) of a signal. It is estimated using Shannon's formula [21, 24]:

$$H(X) = -\sum_{i=1}^{k} p_i \log_2 p_i \ , \quad (4)$$

where $H(X)$ – information entropy of a signal (bit/symbol); k – the number of possible states (discrete levels) a signal can assume; p_i – the probability of occurrence of each individual state, x_i.

The calculation of signal entropy consists of three main steps:

1. Determining the discrete levels (states) of the signal

A harmonic signal typically possesses a limited number of discrete levels, such as three: positive (+1), zero (0), and negative (-1).

A stochastic signal may have a significantly larger number of discrete levels due to its random nature, typically four or more.

A chaotic signal also consists of several discrete levels, the number of which depends on the level of detail chosen for its analysis.

Fig. 6 presents a schematic representation of different signal types-harmonic, chaotic, and stochastic-highlighting their discrete amplitude levels used for entropy estimation.

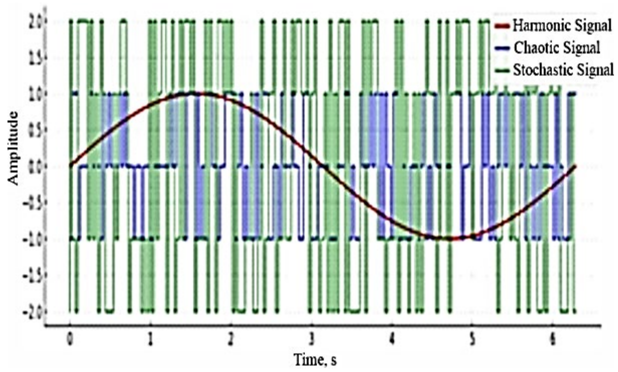

Fig. 6. Discrete amplitude levels of different signal types. Source: developed by the authors

The harmonic signal exhibits clearly defined and predictable states: -1, 0, and 1.

The stochastic signal contains a greater number of discrete levels, such as -2, -1, 1, and 2, which occur with equal probability.

The chaotic signal also features several levels (e.g., -2, -1, 1, 2), but their distribution is less uniform compared to that of the stochastic signal.

2. Calculating the probability of occurrence for each state p_i

In the next step, the probabilities of the signal occupying each discrete state are determined. The probability p_i is computed as the ratio of the time the signal spends in a particular state to the total observation time.

For example: For a harmonic signal with three discrete states $\{-1,0,1\}$, he zero state occurs approximately twice as frequently as the other two. Thus, the corresponding probabilities can be approximated as (5):

$$p_0 = 0,5;\ \ p_{-1} = 0,25;\ \ p_1 = 0,25. \qquad (5)$$

For a chaotic signal, which exhibits nonlinear dynamics and is characterized by the absence of periodicity, the probabilities of the discrete states may be close to a uniform distribution, but with slight deviations due to the system's sensitivity to initial conditions.

If a chaotic signal is represented using four discrete states {-2, -1, 1, 2}, the corresponding state probabilities may take the following form (6):

$$p_{-2} = 0,20;\ \ p_{-1} = 0,30;\ \ p_1 = 0,25;\ p_2 = 0,25. \quad (6)$$

The selected probability values reflect the inherent non-uniformity typical of chaotic systems, where certain states may be slightly more or less probable due to the internal structure of the signal's dynamics.

For a stochastic signal with four discrete levels $\{-2, -1, 1, 2\}$, each occurring with equal probability, the state probabilities are (7):

$$p_{-2} = p_{-1} = p_1 = p_2 = 0,25. \qquad (7)$$

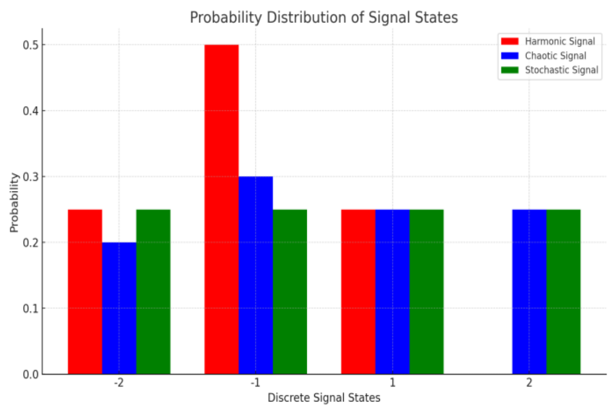

Fig. 7. Probability Distribution Of Signal States.
Source: developed by the authors

Figure 7 illustrates the probability values corres-pondding to the discrete states of each signal type.

3. Entropy Calculation.

Once the probabilities of the discrete states are determined, they are substituted into Shannon's formula (4) to compute the entropy of the signal:

harmonic signal $H = 1,5$ bits/symbol;

chaotic signal $H = 3$ bits/symbol;

stochastic signal $H = 2,5$ bits/symbol.

Thus, information entropy clearly indicates how predictable or random a signal is: low entropy corresponds to regular and predictable signals, while high entropy is associated with signals exhibiting a high degree of uncertainty, such as stochastic or chaotic signals.

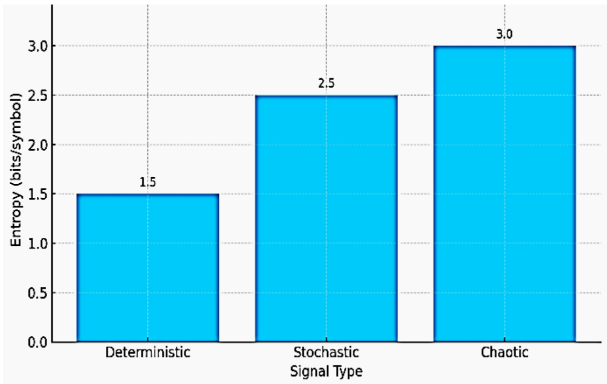

Fig. 8. Comparison of entropy levels for different signal types.
Source: developed by the authors

Accordingly, the data transmission rate (R) is defined as follows (8):

$$R = H(X) * f_s\ , \qquad (8)$$

where $H(X)$ – information entropy of a signal (bit/symbol); f_s – the sampling frequency (Hz), i.e., the number of signal symbols or measurements per second.

Spectral efficiency is calculated as the ratio of the data transmission rate R to the signal bandwidth ΔF accounting for additional system losses

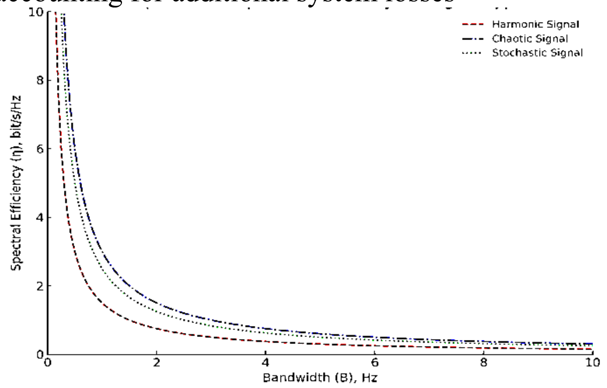

Fig. 9. Comparison of spectral efficiency for different signal types.
Source: developed by the authors

As shown in Fig. 9, simple harmonic signals provide the highest spectral efficiency at narrow bandwidths; however, their efficiency rapidly decreases as the signal bandwidth increases.

In contrast, chaotic signals exhibit the highest spectral efficiency among the three signal types across the entire bandwidth range. This behavior is attributed to their complex structure, which enables the transmission of larger volumes of information as the bandwidth increases.

However, due to the chaotic nature of these signals, further increases in signal bandwidth gradually reduce spectral efficiency. Moreover, processing such signals requires additional computational and energy resources.

Stochastic signals occupy an intermediate position between harmonic and chaotic signals, exhibiting a moderate level of spectral efficiency. They combine certain characteristics of both types: from harmonic signals, they inherit relatively simple generation, which facilitates efficient formation and processing; from chaotic signals, they inherit a wide bandwidth, which allows for the transmission of larger volumes of information and improved interference resistance.

Stochastic signals are generated based on random or pseudo-random processes, which can be implemented using standard algorithmic methods or physical noise sources. This makes their generation less resource-intensive compared to chaotic signals, which require complex nonlinear transformations for their formation.

Due to their statistically random nature and wide bandwidth, stochastic signals exhibit higher resistance to interference compared to harmonic signals. However, they are less efficient in utilizing the frequency spectrum than chaotic signals. At the same time, their spectral efficiency decreases more slowly than that of harmonic signals, but faster than that of chaotic signals, making them a compromise solution between interference immunity and data transmission efficiency.

Therefore, stochastic signals represent a promising solution for modern electronic communication systems, as they combine flexible signal generation, relative ease of implementation, and enhanced interference robustness-although they are inferior to chaotic signals in terms of spectral efficiency.

Spectral efficiency depends on a number of parameters determined by the physical characteristics of the signal, such as:

1. Signal power is one of the key physical characteristics that directly affects spectral efficiency, as increasing the power improves the signal-to-noise ratio (9), which in turn enables the use of more complex modulation schemes, thereby increasing spectral efficiency. However, increasing the signal power also requires greater energy consumption:

$$SNR = \frac{P_{signal}}{P_{noise}}, \quad (9)$$

Where P_{signal} – Signal power, W; P_{noise} – Noise power, W.

The dependence of spectral efficiency on the signal-to-noise ratio (SNR) has a logarithmic nature and is described by the Shannon-Hartley formula (10):

$$R = \Delta F log2\left(1 + \mathrm{SNR}\right), \quad (10)$$

from equation (11), it follows that (11):

$$\eta = log2\left(1 + \mathrm{SNR}\right), \quad (11)$$

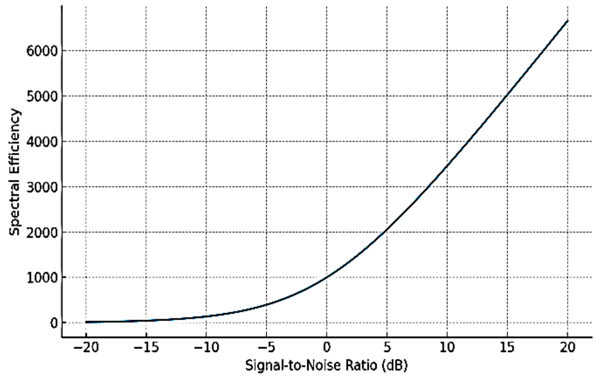

Fig. 10. Dependence of spectral efficiency on the signal-to-noise ratio.
Source: developed by the authors.

As shown in Fig. 10, the spectral efficiency of a signal depends on the signal-to-noise ratio (SNR) and follows a logarithmic trend in accordance with the Shannon-Hartley theorem. This implies that increasing the SNR leads to a higher spectral efficiency; however, the rate of this increase gradually diminishes. Three distinct regions can be identified on the graph:

At low SNR values (from -20 dB to 0 dB), spectral efficiency remains low and increases very slowly. This is due to the fact that, under such conditions, the noise level dominates the signal, significantly limiting the ability to transmit information effectively.

In the medium SNR range (approximately 0-10 dB), spectral efficiency grows more rapidly, as an increase in the signal-to-noise ratio substantially improves the conditions for data transmission.

At high SNR values (above 10 dB), the rate of spectral efficiency growth gradually decreases. This is explained by the logarithmic nature of the relationship: at high SNR levels, even a significant increase in SNR results in only a relatively small gain in efficiency.

This pattern explains why simply increasing signal power is not sufficient for optimal utilization of the frequency spectrum. It is also necessary to employ modern techniques for coding, modulation, and signal processing, which can enhance information transmission efficiency even under limited SNR conditions.

2. Complex signals have a wider time-bandwidth product and, consequently, a broader bandwidth, which allows for the transmission of more useful information per unit time. However, they require greater computational resources.

3. Signal shape (representation of signal amplitude as a function of time): the shape of a signal affects its spectral efficiency by determining how its energy is distributed across frequencies. Signals with different shapes-such as sinusoidal radio pulses, rectangular video pulses, or triangular pulses-have distinct spectral characteristics. For example, a rectangular video pulse has a broader frequency spectrum and therefore requires a higher channel bandwidth compared to a triangular video pulse or a sinusoidal radio pulse..

4. Temporal dynamics (signal modulation):the spectral efficiency of a signal depends on how its characteristics vary over time. Changes in signal amplitude can lead to the emergence of side lobes in the frequency spectrum, which appear in the bands adjacent to the signal's central frequency. This phenomenon results from nonlinear effects in the transmission channel interacting with the signal's varying amplitude. Similarly, variations in frequency or phase may cause spectrum broadening due to the generation of additional frequency components or changes in the spectral shape. These effects can stem from various processes, including signal modulation, noise, distortions in the transmission channel, or variations in the signal source itself.

5. Correlation properties:The interdependence between different frequency components of a signal can significantly influence its spectral efficiency. For example, the presence of harmonics in a signal can interact and produce new frequency components. Since harmonics are integer multiples of the fundamental frequency, they cause the spectrum to expand beyond the main frequency. This spectral expansion increases the required bandwidth for signal transmission and may demand higher channel capacity to ensure accurate and undistorted delivery.

6. Noise and Radio Interference:the presence of noise and radio interference affects a signal's spectral efficiency by introducing additional frequency components or attenuating existing ones. This results in changes to the signal's spectral shape, an increase in noise levels, and broadening of the bandwidth. Consequently, these effects lead to reduced spectral efficiency, as more frequency resources are consumed without a proportional increase in useful information transmission.

Given that in most cases it is not feasible to alter the data transmission rate or the signal bandwidth, it is reasonable to evaluate the spectral efficiency of an electronic communication system considering its dependence on the spectrum utilization factor. This relationship can be expressed as (12):

$$U = \Delta F \cdot S \cdot T \,, \tag{12}$$

Where S – geometric space (typically the area of the object); T – time [1, 15, 17]

In most cases, the influence of time is not taken into account, since message exchange is carried out continuously.

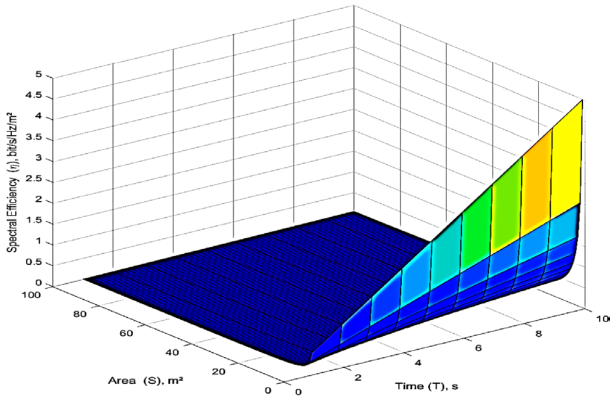

Fig. 11. Spectral Efficiency as a Function of Spectrum Utilization Factor.
Source: developed by the authors

From the graph (Fig. 11), it follows that: 1. As the area (S) increases, the spectrum utilization factor increases, which leads to a decrease in spectral efficiency.

2. As the time (T) increases, the spectrum utilization factor decreases, which contributes to an increase in spectral efficiency.

Thus, to improve spectral efficiency, it is necessary to either reduce the coverage area or increase the channel access time.

Thus, to improve spectral efficiency, it is necessary to either reduce the coverage area or increase the channel access time.

From the definition of spectral efficiency, it follows that spectral efficiency can be expressed as the ratio of the useful effect achieved by utilizing a given information system to the spectrum utilization factor (8):

$$\eta = \frac{M}{U} = \frac{M}{\Delta F \cdot S \cdot T} \,, \tag{13}$$

Where M – expected useful effect, i.e., the measuable outcome (e.g., data rate, system throughput, or mission success probability) achieved within the allocated spectrum and time constraints.

Considering that the expected useful effect is not always directly measurable, it is commonly replaced by the empirically derived spectrum utilization coefficient, as defined in equation (14):

$$U' = \Delta F' \cdot S' \cdot T', \qquad (14)$$

where $\Delta F'$ – bandwidth measured empirically; S' – actual coverage area; T' – operating time of the information system.

Hence, spectral efficiency can be expressed as the ratio between the empirically obtained spectrum utilization coefficient and its theoretically calculated value (15) [1, 16–19].

$$\eta = \frac{U'}{U} = \frac{\Delta F' \cdot S' \cdot T'}{\Delta F \cdot S \cdot T}. \qquad (15)$$

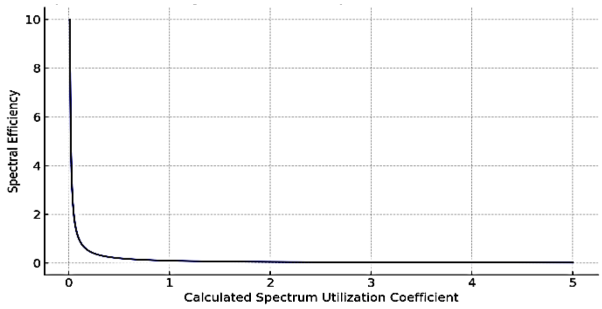

Fig. 12. Dependence of spectral efficiency on the calculated spectrum utilization coefficient.
Source: developed by the authors

As shown in Fig. 12, spectral efficiency depends on the ratio between actual spectrum usage and the calculated spectrum utilization coefficient. If the calculated coefficient significantly exceeds the actual usage, the resulting spectral efficiency will be low, indicating inefficient utilization of the spectral resource.

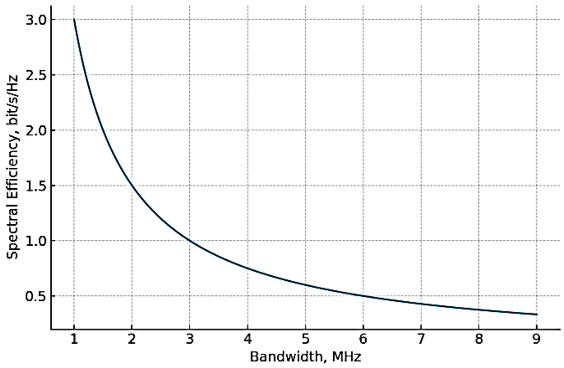

Fig. 13. Dependence of spectral efficiency on bandwidth.
Source: developed by the authors

As shown in Fig. 13, increasing the bandwidth allocated for signal transmission generally leads to a decrease in spectral efficiency. This indicates that transmitting a given amount of information over a wider frequency band requires less signal power, but results in a slower data transmission rate. On one hand, a wider bandwidth allows for the transfer of more data, but on the other, it reduces the efficiency of spectrum utilization [25].

Optimizing the use of stochastic signals in information systems with limited spectral resources remains a relevant challenge. Despite their robustness to interference and resistance to interception, stochastic signals face the problem of low spectral efficiency due to their wide spectral content and uneven energy distribution.

One way to improve the spectral efficiency of stochastic signals is through the application of advanced signal generation and processing techniques.

While traditional methods such as Fourier Transform, Wavelet Transform, and Hilbert Transform are widely used to enhance the spectral efficiency of stochastic signals, current conditions require the adoption of more innovative and sophisticated approaches. These will allow for more efficient signal analysis, reduction of excessive spectral width, and an increase in the volume of useful transmitted information [1, 2, 10, 15, 18]

Examples of the spectra of stochastic signals formed using the corresponding methods are presented in Figs. 14-18.

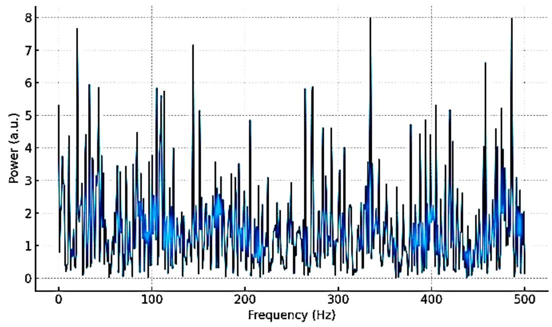

Fig. 14. Example of the spectrum of a stochastic signal formed using the Fourier transform method.
Source: develope by the authors

As shown in Fig. 14, the spectrum of the stochastic signal obtained using the Fourier transform exhibits a broad and uniform energy distribution. This indicates that the method provides a general overview of the signal's frequency structure, but does not account for temporal variations.

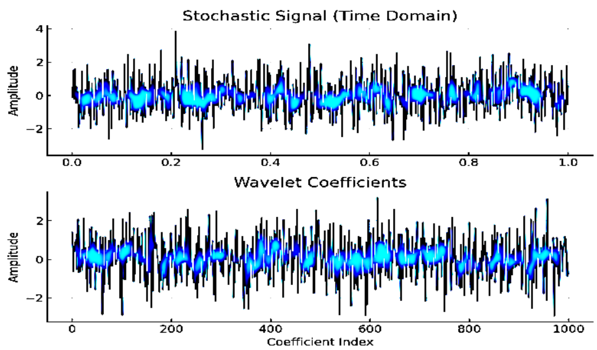

Fig. 15. Example of the spectrum of a stochastic signal formed using the wavelet transform method.
Source: developed by the authors

As shown in Fig. 15, the spectrum of the signal formed using the wavelet transform exhibits good time-frequency localization. This enables efficient analysis of short-term signal variations and the detection of transient processes. However, the choice of the basis function significantly affects the results and may introduce errors in the identification of frequency components [6, 25].

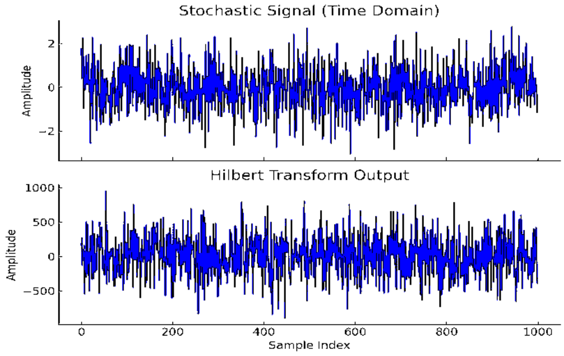

Fig. 16. Example of the spectrum of a stochastic signal formed using the Hilbert transform method.
Source: developed by the authors

As shown in Fig. 16, the spectrum of the signal obtained using the Hilbert transform allows for the extraction of instantaneous frequency and phase. This method is useful for analyzing time-varying signal characteristics; however, its sensitivity to noise may distort the results, particularly under low signal-to-noise ratio conditions.

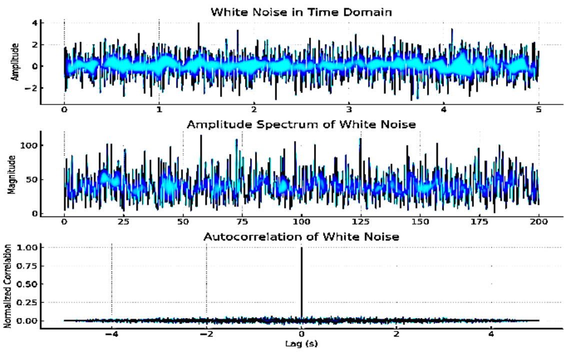

Fig. 17. Example of the spectrum of a stochastic signal formed using the Z-transform method.
Source: developed by the authors

As illustrated in Fig. 17, the discrete spectrum of the signal formed using the *Z*-transform method is presented. This approach enables the evaluation of system stability and the identification of frequency components in discrete processes. However, the method has limitations when applied to continuous signals and may produce inaccurate results outside the discrete interval.

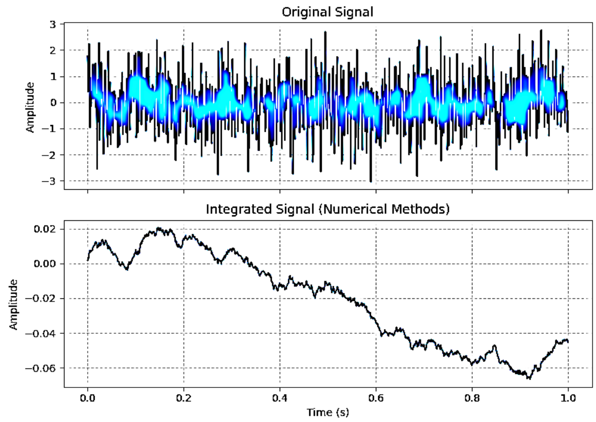

Fig. 18. Example of the spectrum of a stochastic signal generated by numerical methods.
Source: developed by the authors

Figure 18 illustrates a spectrum obtained using numerical methods.

It exhibits an arbitrary shape that depends on the modeling parameters. This method allows for the generation of signals with predefined properties; however, its accuracy is determined by the chosen algorithm (e.g., the Runge-Kutta method or the trapezoidal rule for numerical integration), Table 2.

Table 2

Comparison of Signal Processing Methods

Method	Advantages	Disadvantages	η (bit/s/Hz
Fourier Transform	Simple implementation; accurate frequency analysis; determines bandwidth.	No time localization; not suitable for non-stationary signals.	1–3
Wavelet Transform	Good time-frequency localization; effective for non-stationary signals; compression-friendly.	Results depend on basis function; computationally intensive.	3–7
Hilbert Transform	Extracts envelope, instantaneous frequency and phase; time-frequency analysis.	Limited use for non-stationary signals; sensitive to noise.	2–4
Z-Transform	Suitable for discrete signals; allows system stability evaluation.	Only works for discrete signals; complex for large datasets.	2–6
Numerical Methods	Enables modeling of signals with desired properties; flexible configuration.	High computational cost; accuracy depends on numerical integration method.	2–5

Source: developed by the authors

Table 2 presents the key advantages, disadvantages, and approximate spectral efficiency of modern methods for signal generation and processing.

Based on the data in Table 2, graphs were constructed to illustrate the spectral efficiency values for each of the listed signal processing methods.

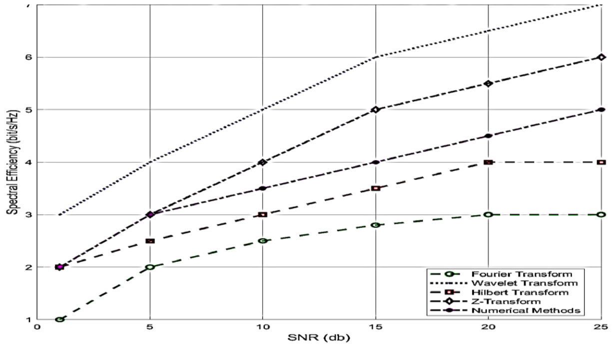

Fig. 19. Comparison of spectral efficiency across different signal processing methods.
Source: developed by the authors

Fig. 19 illustrates the spectral efficiency of various signal processing methods presented in Table 2.

The graph enables a direct comparison of these methods in terms of their effectiveness in utilizing the frequency spectrum. As seen from both Table 2 and Fig. 19, methods involving more complex Mathematical operations, such as wavelet transforms, demonstrate higher spectral efficiency (up to 7 bit/s/Hz), while classical methods like the Fourier transform exhibit lower performance levels (1–3 bit/s/Hz). Numerical methods and *Z*-transforms occupy an intermediate position, offering a balanced trade-off between flexibility, accuracy, and spectral efficiency.

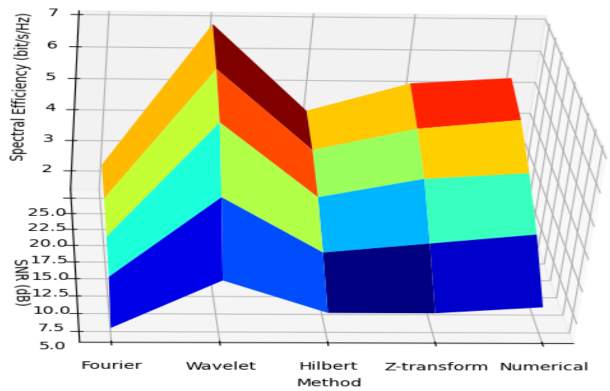

Fig. 20. Surface plot of signal processing methods.
Source: developed by the authors

As shown in Fig. 20, the spectral efficiency of signal processing methods depends not only on their mathematical complexity but also on their ability to adapt to non-stationary signals. The surface diagram illustrates the distribution of methods according to their strengths and weaknesses: methods with high spectral efficiency, such as the wavelet transform, are positioned at the top of the diagram, while methods with limited adaptability to time-frequency variations (e.g., classical Fourier transform) exhibit lower values. Numerical methods demonstrate a wide range of possible spectral efficiency values depending on the specific implementation.

Although the reviewed signal generation and processing methods are widely used to address a broad range of tasks, they often fail to maintain high spectral efficiency in challenging interference environments or when processing non-stationary signals in information systems.

Therefore, for the analysis of chaotic and stochastic signals, it is advisable to employ Volterra series and the Karhunen-Loève Transform (KLT). These techniques offer several advantages over traditional methods such as autocorrelation analysis, Fourier transform, or machine learning approaches-particularly in cases involving nonlinear and non-stationary signals.

Volterra series are capable of describing the interdependencies between signal components, accounttting for both linear and nonlinear relationships. This makes them highly suitable for modeling nonlinear systems and provides a powerful analytical tool for processing signals that cannot be adequately handled by traditional linear methods.

Key advantages of Volterra series include:

1. Consideration of interactions between signal components, including nonlinear dependencies. Volterra models capture both direct and cross-component influences, allowing accurate representtation of complex internal signal structures.

2. Accurate modeling of signals with complex structure and predictive capabilities regarding their temporal evolution. By incorporating higher-order kernels, the method enables precise reconstruction of signal behavior and supports forecasting of its dynamic changes

3. Applicability to both stationary and non-stationary processes. Unlike traditional linear methods, Volterra series are capable of analyzing signals whose statistical properties vary over time, making them suitable for real-world communication environments.

One of the most effective methods for reducing signal redundancy and extracting its principal components is the Karhunen-Loève Transform (KLT). This technique is widely used for the optimal representation of random signals and significantly reduces the complexity of subsequent signal processsing by eliminating low-energy, non-informative components.

The key advantages of applying the Karhunen-Loève Transform include:

1. Maximization of energy compactness by isolating the most significant frequency components of the signal, which enhances its representational efficiency.

2. Noise reduction, as the transform concentrates most of the signal's energy into a few principal components, effectively filtering out noise-dominated dimensions.

3. Optimal data compression and encoding, due to the orthogonal basis formed by the eigenfunctions of

the covariance matrix, enabling efficient representation and transmission of information with minimal loss.

Although autocorrelation analysis is widely employyed to identify patterns in signals and to estimate their power spectral density (PSD), this method exhibits several important limitations:

Ineffectiveness for nonlinear signals: Autocorrelation assumes linearity and stationarity of the underlying process. In the case of stochastic or chaotic signals-especially those with fractal properties-this approach often fails to capture the true interdependencies between signal components.

Inability to detect cross-frequency interactions: For signals with intermodulation, harmonics, or random spectral shifts (typical in stochastic or chaotic contexts), classical autocorrelation yields an averaged view that may obscure significant spectral relationships.

In contrast, time-frequency decomposition methods or nonlinear transforms-notably the Karhunen-Loève Transform (KLT)-provide more powerful tools for decorrelating signal components and extracting structure, even under severe noise conditions. As shown in studies such as [10, 11, 18] optimizing the spectral component selection in the KLT framework can significantly enhance the probability of correct recognition of complex signals, even in high-noise environments.

Despite the remarkable progress in applying machine learning (ML) techniques to signal analysis, these approaches also face several practical limitations:

High data requirements: ML models, particularly neural networks, demand large and representative datasets for training. For stochastic signals, such datasets may be unavailable or heavily corrupted by noise.

Limited interpretability: Unlike classical analytical methods, which offer clear mathematical relations between signal parameters and processing outcomes, most ML models function as "black boxes." This lack of transparency complicates their use in mission-critical systems, where each decision step must be formally justified and traceable.

Given these considerations, ML methods are best suited for classification, detection, and forecasting tasks, whereas spectral decomposition, modeling, and reconstruction are more reliably addressed using classical techniques with well-defined mathematical properties-such as basis orthogonality, component decorrelation, and minimum mean-square error (MMSE) optimization.

Table 3

Comparison with Traditional Methods

Method	Key Advantages	Key Limitations
Volterra Series	Capable of modeling nonlinear systems; enables signal behavior prediction	High computational complexity, especially for higher-order kernels
Karhunen-Loève Transform	Reduces redundancy; extracts principal components; optimizes subsequent processing	Requires significant computational resources at the initial processing stage
Autocorrelation Analysis	Easy to implement; useful for periodicity evaluation	Ineffective for nonlinear signals; does not account for interaction between frequency components
Machine Learning Methods	Flexible; high classification accuracy	Requires large training datasets; results are difficult to interpret

Source: developed by the authors.

Based on the analysis of Table 3, it is evident that the Volterra series and the Karhunen-Loève Transform (KLT) represent optimal tools for the analysis of chaotic and stochastic signals. The Volterra series enables the modeling of complex nonlinear interactions between signal components, while the KLT offers efficient dimensionality reduction and extraction of principal components, thus improving the accuracy of signal analysis.

However, the greatest potential lies in their combined application. Specifically, one may first apply the Volterra series to decompose and model the nonlinear interactions in the signal, followed by the KLT to reduce redundancy and extract the most significant spectral features.

This integrated approach offers several key advantages:

Increased spectral efficiency of signal analysis by minimizing the influence of noise and focusing computational resources on the most informative features.

Optimized computation, as the signal is first represented in a nonlinear model and then reduced to its relevant components for further processing.

Improved prediction and reconstruction accuracy, since the combination of these methods accounts for both the nonlinear dynamics and the stochastic nature of the signals.

Conclusions

This study provides a comprehensive comparative analysis of modern signal processing methods with regard to their spectral efficiency in handling stochastic and chaotic signals within electronic communication systems. The following key conclusions were drawn:

1. Classical methods, such as the Fourier Transform and autocorrelation analysis, remain useful for stationary and linear signals, but demonstrate significant limitations when applied to non-linear and non-stationary signals. In particular, they fail to capture complex interdependencies between spectral components and lack adaptability to time-varying signal structures.

2. More advanced techniques, including the Wavelet Transform and the Hilbert Transform, offer improved time-frequency localization and better performance in the analysis of non-stationary signals. However, their spectral efficiency varies significantly depending on parameter choices and computational complexity.

3. Numerical methods and the Z-transform occupy an intermediate position, providing flexibility and discrete analysis capabilities, yet still requiring optimization for robust performance in noise-affected environments.

4. Volterra series and the Karhunen-Loève Transform (KLT) have proven to be the most effective in terms of spectral efficiency and adaptability:

The Volterra series excels in modeling non-linear systems and capturing complex component interactions.

The KLT optimally reduces signal dimensionality and isolates principal components, maximizing energy compaction and facilitating efficient encoding.

5. A combined Volterra-KLT approach offers synergistic benefits, enabling:

Robust modeling of complex, stochastic signals.

Dimensionality reduction while preserving key information,

Enhanced resistance to noise and improved information throughput.

6. Machine learning methods, while promising in classification and detection tasks, are currently less suitable for signal modeling and spectral optimization due to their low interpretability and reliance on large training datasets.

In summary, improving spectral efficiency in systems dealing with stochastic signals requires a shift from purely classical techniques toward hybrid methods that combine nonlinear modeling with orthogonal transformations. The Volterra-KLT framework provides a powerful foundation for the development of next-generation adaptive communication systems [5, 11]. The Karhunen-Loève Transform facilitates the extraction of the principal components from a signal, thereby reducing redundancy and increasing spectral efficiency [17, 18].

REFERENCES

[1] Фалькович С. Е., Костенко П. Ю., Основи статистичної теорії радіотехнічних систем. Х.: ХАІ, 2005. 389 с.

[2] Van Trees H. L. Detection, Estimation, and Modulation Theory. Wiley, 2001. 1408 c.

[3] Cover T. Information Theory and Statistics. Wiley, 1991. 336 c.

[4] Oppenheim A. V. et al. Signals and systems. - Upper Saddle River, NJ : Prentice hall, 1997. Т. 2. С. 74–102.

[5] Roberts, Richard A., and Clifford T. Mullis. Digital signal processing. Addison-Wesley Longman Publishing Co., Inc., 1987.

[6] Mallat S. A Wavelet Tour of Signal Processing: The Sparse Way. Academic Press, 2009. 805 c.

[7] Cover T. M., Thomas J. A. Elements of Information Theory. 2nd Edition. Wiley-Interscience, 2006. 768 c.

[8] Васюта, К. С., Чечуй О. В., Глущенко М. О. Динамічний хаос в телекомунікаційних системах. *Системи обробки інформації.* 2010. Т. 1. С. 13–16.

[9] Костенко П. Ю., Слободянюк В. В., Волинець С. В., Крючка М. Л. Аналіз IID-скритності безперервних хаотичних сигналів. *Системи обробки інформації.* 2018. № 1(152). С. 20–26. https://doi.org/10.30748/soi.2018.152.03.

[10] Ling F. Nonlinear System Identification by Volterra and Wiener Models. *IEEE Signal Processing Magazine*. 2006. Vol. 14. P. 14–32.

[11] Tianxing C., Tianfang C. Signal processing of high-noisy chaotic data. Phys. scr. 2000. V. 6 l. № l. P. 46–48.

[12] Kostenko P., Vasiuta K., Symonenko S. Improving communication security by complicating chaotic process attractor using linear transform with Mandelbrot kernel. Radioelectronics and Communications Systems. 2010. No. 12(53). P. 636–643. http://doi.org/10.3103/s0735272710120022.

[13] Розенвассер Д. М. Спектральна еффективність корегуючого кодування. Проблеми телекомунікацій. 2012. № 4 (9). С. 86–95.

[14] Kay S. M. Fundamentals of Statistical Signal Processing: Detection Theory. Prentice Hall, 1998. Т. 2. С. 512.

[15] Papoulis A., Pillai S. U. Probability, Random Variables, and Stochastic Processes. 4th Edition. McGraw Hill, 2002. 852 c.

[16] International Telecommunication Union. Recommendation ITU-R SM.1046-3: Definition of spectrum use and efficiency of a radio system. Geneva, 2017.

[17] Mandelbrot B. B. Fractals and Chaos: The Mandelbrot Set and Beyond. Springer, 2004. 308 c.

[18] Dai Linglong, Wang Bichai, Yuan Yifei, Han Shuangfeng, Chih-Lin I, and Wang Zhaocheng. Non-orthogonal multiple access for 5G: solutions, challenges, opportunities, and future research trends. *IEEE Communications Magazine*. 2015. Vol. 53, no. 9. P. 74-81.
[19] Харлай Л. О., Кунах Н. І., Манько О. О., Скубак О. О., Нікіфоренко К. Б. Методи підвищення інформаційно-пропускної здатності волоконно-оптичних трактів. Інфокомунікаційні та комп'ютерні технології. № 2 (02), 2021. С. 82–94.
[20] Бондарєв О. Огляд методів множинного доступу до бездротового зв'язку. Частина 1. Як поділити спектр: Частотно-часовий поділ. URL: https://habr.com/ru/companies/etmc_exponenta/articles/677524/ (дата звернення: 07.03.2024).
[21] Shannon C. E. A Mathematical Theory of Communication. Bell System Technical Journal. 1948. Vol. 27. P. 379–423.
[22] Hofstätter, Harald (25 October 2015). "Calculation of the Feigenbaum Constants". www.harald-hofstaetter.at. Retrieved 7 April 2024.
[23] Proakis J. G., Manolakis D. G. Digital Signal Processing: Principles, Algorithms, and Applications. Prentice Hall, 2007. 992 с.
[24] Coifman R., Wickerhauser M. V. Entropy-based Algorithms for Best Basis Selection. IEEE Transactions on Information Theory. 1992. Vol. 38. No. 2. P. 713–718.
[25] Войтенко А., Романюк С. Застосування вейвлет-перетворення для аналізу сигналів. Системи обробки інформації. 2020. № 2. С. 25–31.
[26] Первунінський С. М., Дідковський Р. М. Обчислення ймовірності помилки приймача фазоманіпульованного шумового сигналу методом характеристичних функцій. *Наукові праці ОНАЗ ім. О.С. Попова*. 2011. № 1. С. 33–42.

Гарячий М. В., Щербінін С. О.

АНАЛІЗ МЕТОДІВ ПІДВИЩЕННЯ СПЕКТРАЛЬНОЇ ЕФЕКТИВНОСТІ ІНФОРМАЦІЙНИХ СИСТЕМ

У статті розглядаються основні фізичні властивості сигналів, що використовуються в сучасних інформаційних системах, та їхній вплив на спектральну ефективність. З огляду на зростаючі вимоги до швидкості передачі даних, захисту інформації та ефективного використання спектру в умовах обмежених ресурсів, зростає актуальність дослідження не тільки традиційних (детермінованих) сигналів, але й складніших - хаотичних і стохастичних.

Метою дослідження є виявлення й обґрунтування фізичних і статистичних характеристик хаотичних та стохастичних сигналів, що впливають на їхню здатність забезпечувати високу спектральну ефективність, з одночасним збереженням завадостійкості та інформаційної безпеки в системах передавання даних.

Особлива увага приділяється порівнянню сигналів різної природи: гармонійних, хаотичних і стохастичних. Гармонійні сигнали, хоча й прості в реалізації та обробці, мають низьку спектральну ефективність і слабкий захист від перешкод. Хаотичні сигнали демонструють найвищу ефективність використання спектру, але потребують складних методів генерації та обробки. Стохастичні сигнали, в свою чергу, виступають компромісом між ефективністю та стійкістю до завад, демонструючи хорошу адаптацію до умов зашумленого середовища.

У роботі використано як класичні методи аналізу (перетворення Фур'є, вейвлет-перетворення, перетворення Гілберта, Z-перетворення), так і інноваційні підходи – ряди Вольтерра та перетворення Кархунена-Лоєва, які дозволяють врахувати нелінійність, нестаціонарність і складну структуру сигналів. Проведено моделювання, побудовано графіки залежності спектральної ефективності від параметрів сигналів (ширини смуги, SNR, часу, геометричних характеристик тощо) та здійснено порівняльний аналіз методів обробки.

Результати дослідження показали, що комбіноване застосування рядів Вольтерра (для врахування нелінійних взаємозв'язків) і перетворення Кархунена-Лоєва (для декореляції та зменшення надмірності) дозволяє значно підвищити спектральну ефективність стохастичних та хаотичних сигналів. Такий підхід забезпечує оптимізацію використання частотного ресурсу, знижує рівень шуму, та дозволяє адаптувати систему до змін середовища, що особливо важливо для військових, мобільних та супутникових систем зв'язку.

Практичне значення результатів полягає у можливості впровадження запропонованих рішень у безпроводові інфокомунікаційні системи, системи бойового управління, сенсорні мережі, засоби захищеного зв'язку, де високі вимоги до надійності, конфіденційності та ефективності використання спектру є критично важливими.

Ключові слова: аналіз сигналів, спектральна ефективність, хаотичні сигнали, стохастичні сигнали, завадостійкість, частотний ресурс.

Gariachiy M., Shcherbinin S.

ANALYSIS OF METHODS FOR ENHANCING SPECTRAL EFFICIENCY IN INFORMATION SYSTEMS

This article is devoted to the study of the physical properties of deterministic, chaotic, and stochastic signals used in modern information systems with the aim of enhancing their spectral efficiency. Special attention is given to chaotic and stochastic signals, which, due to their unique structures, ensure a high level of information security. However, they require further development to achieve optimal utilization of the frequency spectrum.

The study addresses a pressing issue in communication systems: the need to balance high spectral efficiency with robust data protection and interference resilience. Deterministic signals, such as harmonic signals, traditionally used in narrowband systems, are characterized by simplicity and predictability but suffer from low spectral efficiency and poor resistance to interference. In contrast, chaotic and stochastic signals exhibit significant advantages in terms of security and interference immunity but require advanced signal processing techniques to overcome challenges associated with their wide spectral bandwidth and energy consumption.

The research methodology integrates mathematical modeling and signal analysis. Traditional approaches, such as Fourier transformation, wavelet transformation, and Hilbert transformation, are compared with innovative techniques, including Volterra series and Karhunen-Loève transformation. The comparative analysis is based on evaluating spectral efficiency, interference resilience, and the energy requirements of different signal types.

The results demonstrate that chaotic signals outperform deterministic and stochastic signals in terms of spectral efficiency across broader frequency ranges. However, chaotic signals require more sophisticated processing methods to ensure their stability and reliability in modern communication systems. Stochastic signals, while offering superior interference resistance and information security, exhibit lower spectral efficiency due to their broad frequency spectrum and uneven energy distribution.

Innovative approaches, such as Volterra series and Karhunen-Loève transformation, significantly improve the spectral efficiency of chaotic and stochastic signals by reducing redundancy and optimizing frequency utilization. These findings highlight the need for integrating advanced signal processing methods into information systems to enhance their performance and reliability.

The study's results have practical implications for the development of advanced communication systems, such as cellular networks, the Internet of Things, and satellite communication systems, where high data confidentiality and efficient spectrum usage are critical.

Keywords: signal analysis, spectral efficiency, chaotic signals, stochastic signals, interference resistance, frequency resources.

Стаття надійшла до редакції 24.06.2025 р.
Прийнято до друку 03.09.2025 р.