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METHOD FOR OPTIMIZING COMPLEX SIGNAL ENSEMBLES IN COGNITIVE NETWORKS

Introduction

In modern cognitive telecommunication networks with multiple access, a relevant problem is the simultaneous reduction of interference levels (both inter-channel and inter-symbol) and the improvement of ensemble properties of signal-code constructions.

The increasing number of users and shared spectrum utilization lead to a rise in multiple access interference, manifested through higher peaks of mutual correlation and side lobes of correlation functions, degradation of correlation–spectral indicators, and consequently a decline in quality of service.

Interference can be mitigated, among other means, by optimizing the time intervals of signals or sequence segments, which allows influencing the structure of signal interaction in the time domain and maintaining a balance between interference resistance and ensemble volume.

Therefore, there is a need to develop a method that enables adaptive optimization of time intervals and signal ensemble parameters, taking into account their energy, spectral, and correlation characteristics.

Such a method should combine global search in the space of possible combinations with local parameter refinement procedures, allowing the minimization of mutual interference, enhancement of ensemble coherence, and stable operation of the cognitive telecommunication network under dynamically changing environmental conditions.

Analysis of recent research and publications

An analysis of scientific studies by domestic and foreign authors [1–15] has shown that the novelty of the proposed approach lies in the combination of two optimization methods for solving nonlinear optimization problems that were previously used separately.

In works [1–4], parametric optimization of synthesized signals has been improved, and the influence of cross-correlation properties on the characteristics of cognitive telecommunications has been studied. The gradient descent, Newton, and Nelder–Mead methods proposed by the authors increase approximation accuracy; however, they do not account for nonlinearity and stochastic variability of the environment.

Studies [5–6] modeled complex signals using Volterra series and frequency filtering of pseudorandom sequences, which enables the formation of ensembles with low mutual correlation, though without considering time segmentation or local optimization effects.

Research [7] focused on improving noise immunity of wireless channels through adaptive noise compensation, but did not address signal ensemble properties as an optimization factor.

Among foreign studies [8–14], various approaches to waveform optimization in MIMO radars and communication systems have been proposed – in particular, the Cross-Correlation Signal Pruning method [8] and spatio-temporal optimization of phase codes [13,14]. However, most of them target correlation matching of signals rather than comprehensive time-domain ensemble optimization.

The approach in [15] is based on fast algorithms for constructing unimodular sequences with good correlation properties but neglects environmental parameter variations and fails to ensure adaptive convergence under stochastic disturbances.

Thus, the conducted analysis confirms the necessity of developing a combined method that integrates stochastic search with local nonlinear optimization.

Problem Statement

The problem addressed in this study is multimodal in nature and is accompanied by stochastic environmental uncertainty, which often causes classical deterministic methods to get trapped in local extrema or lose efficiency under varying interference conditions.

Based on this, a combined optimization strategy has been justified – one that integrates random search (for global exploration of the solution space and initialization of promising configurations of time segments and permutations) with local nonlinear optimization methods, namely gradient descent and the Levenberg–Marquardt algorithm (for fast convergence and precise parameter adjustment within local neighborhoods).

The proposed integration enables the identification of promising subregions of the solution space at the initial stages, followed by accurate suppression of correlation peaks and balancing of energy–spectral characteristics.

Thus, the development of an adaptive method for optimizing complex signal ensembles in the time domain based on the integration of random search with local optimization techniques is a relevant task aimed at improving ensemble interference immunity according to combined correlation–spectral criteria while maintaining (or increasing) ensemble volume.

The purpose of the article

The aim of the study is to develop a method for optimizing ensembles of complex signals in the time domain based on the integration of stochastic search and local nonlinear optimization.

Summary of the main material

The proposed method establishes a closed optimization loop for the signal ensemble, where the stochastic search ensures global exploration of the solution space, while local optimization provides precise parameter adjustment within the identified optimal regions.

This integration enables the reduction of mutual signal correlation without compromising the ensemble's energy consistency [1, 2].

In the article present a step-by-step implementtation of the proposed method, including analytical dependencies and experimental results (Fig. 1).

The proposed approach differs from traditional methods in that it focuses not on optimizing individual parameters, but on a comprehensive adaptive procedure of segmentation and permutation in the time domain.

This is achieved through the following stages:

Stage 1. Signal preparation (formulas 1–3).

Stage 2. Analysis of signal parametric characteristics (formulas 4–9).

Stage 3. Division of signals into time intervals (formulas 10–14).

Stage 4. Signal permutation (formulas 15–16).

Stage 5. Local parameter optimization (formulas 17–19).

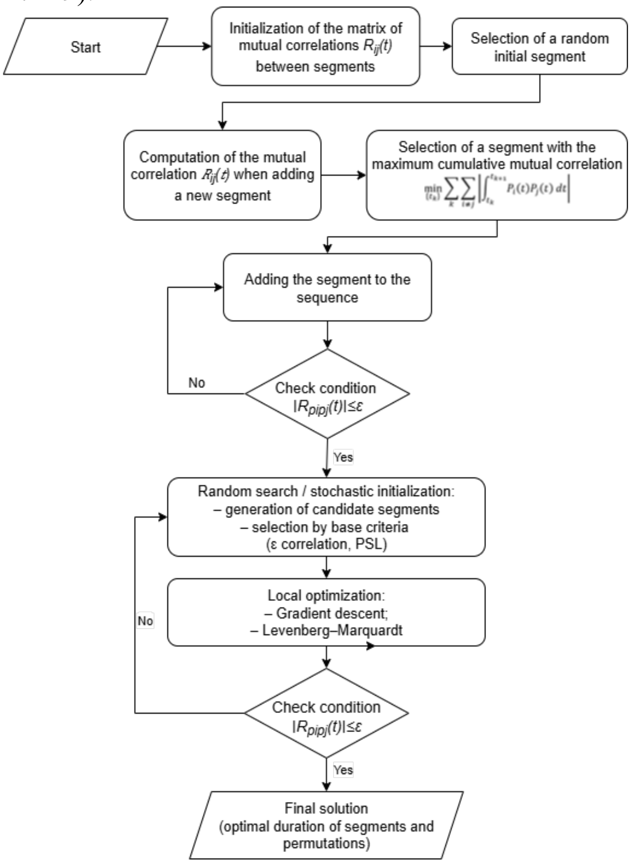

Fig. 1. Block diagram of the method for selecting time intervals

To substantiate the applicability of the proposed method, let us examine in more detail its structure, evaluation metrics, and specific features.

Stage 1. Signal preparation.

The first step involves collecting and preprocessing the signals that form the ensemble. At this stage, normalization, scaling, noise component suppression, and other procedures are performed to ensure data unification and improve the accuracy of subsequent processing [2, 3].

Normalization is carried out to align the amplitude scales of the signals and bring them to a common range. This is particularly important when dealing with ensembles, where differences in amplitude structure may cause uneven contributions to correlation estimates. The generalized normalization equation is expressed as:

$$P_{norm}(t) = \frac{P(t) - \mu}{\sigma} \cdot w + \delta, \qquad (1)$$

Where $P(t)$ – is the signal value at time t; μ – is the mean value of the signal; σ – is the standard deviation of the signal; w – is the scaling coefficient; and δ – is the offset parameter.

Filtering is used to reduce the influence of interference [1,3]. Depending on implementation conditions, two main approaches may be applied:

1. Linear convolution-based filtering:

$$P_f(t) = (h * P)(t), \quad (2)$$

where $h(t)$ – is the impulse response of the filter; $*$ – denotes the convolution operation.

2.Noise suppression by subtracting the estimated noise:

$$P_f(t) = P(t) - \alpha\,(\hat{n} * g)(t), \quad (3)$$

where α – is the filtering coefficient; $\hat{n}(t)$ – is the estimated noise component; $g(t)$ – is the window or spectral function used for noise estimation.

Thus, in the proposed method, Stage 1 ensures the creation of a consistent set of signals that are denoised and normalized to a common scale, forming the basis for subsequent parametric analysis and optimization.

Stage 2. Analysis of signal parametric characteristics [1–5]

The analysis of signal parametric characteristics includes the evaluation of such indicators as amplitude (*A*), frequency (*Fr*), duration (*T*), and energy signal. This stage is essential for further segmentation of the time domain and the implementation of balanced signal permutation, which form the core of the proposed method.

The traditional definition of signal energy is expressed as the integral of the squared amplitude. However, for ensembles of complex signals, this is insufficient, since it is necessary to consider not only the energy properties of signals but also their mutual correlation and ensemble consistency. Therefore, this study introduces an integral energy–correlation measure, which simultaneously accounts for the energetic, correlation, and ensemble characteristics of signals [4, 5, 6]:

$$J = \int_0^T |P(t)|^2 dt + \sum\nolimits_{i \neq j} \int_0^T P_i(t)\, P_j^*(t+\tau) dt + \\ + \frac{1}{T} \sum\nolimits_{i \neq j} \int_0^T P_i(t) \cdot P_j^*(t) dt \quad (4)$$

where $\int_0^T |P(t)|^2 dt$ – corresponds to the signal energy; $\sum_{i \neq j} \int_0^T P_i(t)\, P_j^*(t+\tau) dt$ – represents the mutual correlation between signals $P_i(t), P_j(t)$; $\frac{1}{T}\sum_{i \neq j} \int_0^T P_i(t) \cdot P_j^*(t) dt$ – characterizes the ensemble properties of the signals $P_i(t), P_j(t)$.

For the quantitative evaluation of the ensemble characteristics of signals, the following parameters are used: the time–bandwidth product (*B*), crest factor (*CF*), root mean square (*RMS*) value, and effective bandwidth (*BW*).

1. Time–bandwidth product (*B*) – It is defined as the product of the signal duration and its effective spectral width. The classical analytical expression is given by:

$$B = T \cdot BW, \quad (5)$$

The time–bandwidth product can also be defined using the energy-based approach:

$$B = \frac{E}{A_{max}^2 \cdot T}, \quad (6)$$

where E – the signal energy; A_{max} – max amplitude.

This analytical expression is applied when analyzing the ratio of the signal energy to its peak characteristics.

2. Crest factor (CF):

$$CF = \frac{A_{max}}{\sqrt{\frac{1}{T}\int_0^T (P(t))^2 \cdot dt}}\ , \quad (7)$$

3. The effective bandwidth (BW) is defined as the frequency range within which 95% of the signal's energy is concentrated:

$$BW = f_1 - f_2, \quad \text{де} \int_{f_2}^{f_1} |P(f)|^2 df = \\ = 0{,}95 \int_{-\infty}^{\infty} |P(f)|^2 df, \quad (8)$$

4. The root mean square (RMS) value defines the average power of the signal and represents its «equivalent constant magnitude». The analytical expression for calculating the RMS indicator is given by:

$$RMS = \sqrt{\frac{1}{T}\int_0^T (P(t))^2 \cdot dt}, \quad (9)$$

A distinctive feature of the proposed method is the combined application of RMS, CF, and effective bandwidth for a coherent evaluation, which enables precise tracking of the influence of preprocessing (normalization and filtering) on the ensemble properties [7].

To substantiate the necessity of Stages 1–2, OFDM-like signals of two modern mobile communication standards were simulated under conditions closely approximating real transmission scenarios: LTE with subcarriers spaced at SCS=15 kHz (72 active subcarriers, SNR ≈ 20 дБ); and 5G NR with subcarriers spaced at SCS = 30 kHz (144 active subcarriers, SNR ≈ 10 дБ).

The simulation was carried out within a time window defined by the following parameters: sampling frequency Fs = 10 MHz and duration T = 10 mc.

The obtained signals were sequentially processed using the normalization procedure according to (1) and a low-pass FIR filter (513 coefficients) with cutoff frequencies of approximately ≈1,2 MHz для LTE та ≈2,5 MHz for 5G NR.

The calculation results are presented in Table 1 and Figures 2–5.

Table 1

Metrics after normalization and filtering

System	*RMS*	*CF*	*BW*	f_{low}	f_{high}	*B*
LTE_{raw}	0,7203	3,772	4710000	150000	4860000	47100
LTE_{norm}	1,0	3,7716	4710000	150000	4860000	47100
LTE_{filt}	0,4644	3,7896	1005000	105000	1110000	10050
$NR5G_{raw}$	0,7417	3,7764	4710000	120000	4830000	47100
$NR5G_{norm}$	1,0	3,777	4710000	120000	4830000	47100
$NR5G_{filt}$	0,705	3,5203	2370000	90000	2460000	23700

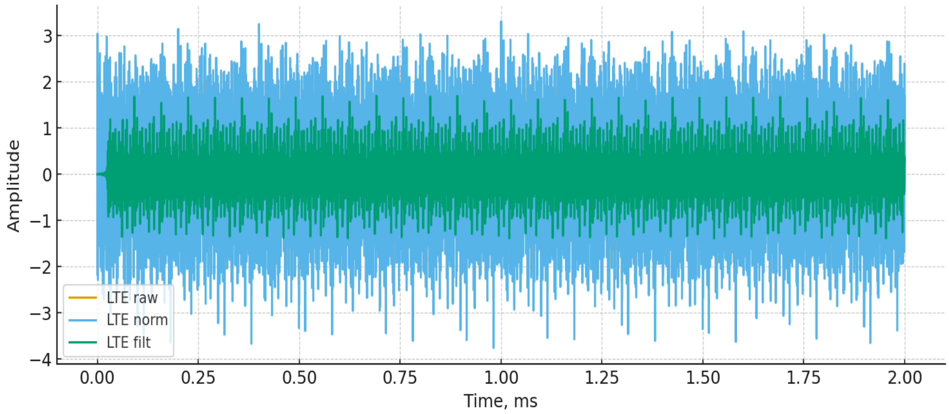

Fig. 2. Time-domain representation of the LTE signal

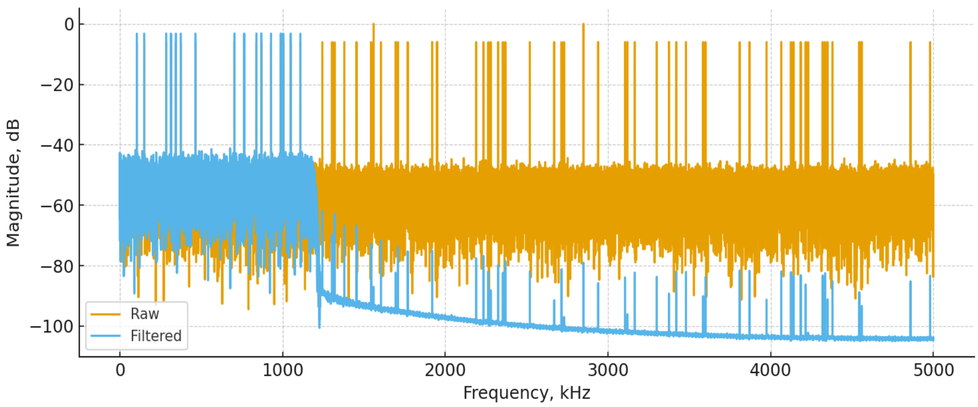

Fig. 3. Spectrum of the LTE signal

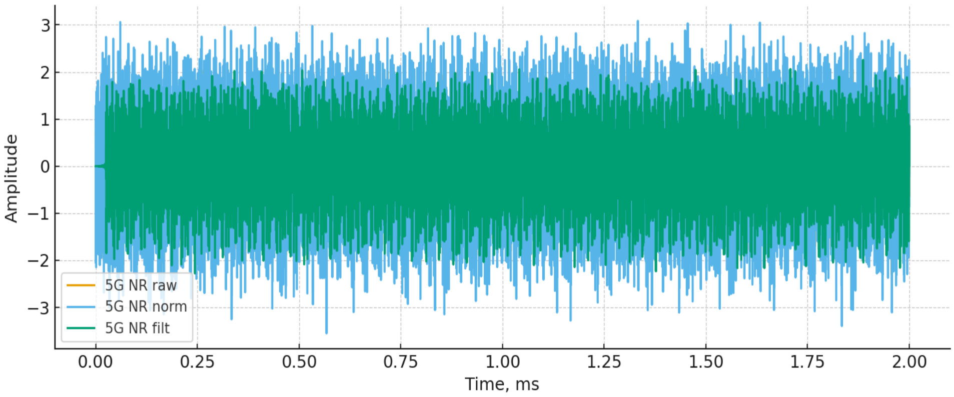

Fig. 4. Time-domain representation of the 5G NR signal

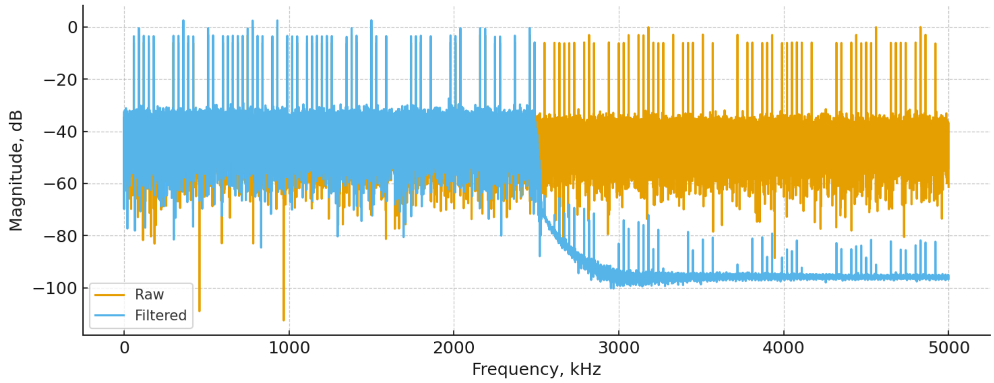

Fig. 5. Spectrum of the 5G NR signal

As shown in Figures 2–3 for LTE and Fig. 4–5 for 5G NR, the sequential application of normalization and filtering ensures the consistency of amplitude characteristics and reduces noise components.

In the time domain (Fig. 2 and 4), after normalization, the signals exhibit a unified scale ($RMS \approx 1$), while filtering decreases the impulsiveness of oscillations, as confirmed by the reduction in *CF*.

In the spectral domain (Fig. 3 and 5), a significant narrowing of the effective bandwidth (*BW*) is observed after filtering, particularly for LTE, where the spectral width decreased nearly fivefold. This results in a reduction of the signal time–bandwidth product and minimizes mutual spectral overlaps between ensemble signals, which is crucial for improving interference immunity at the subsequent stages of the method.

The next stage of the method involves dividing the signals into time intervals while taking into account their correlation properties, which forms the basis for subsequent permutation and optimization of the complex signal ensemble [8, 9].

Stage 3. Division of signals into time intervals.

At this stage, the signals are segmented into time intervals of varying lengths based on their correlation properties. The core of this process is the analysis of mutual correlations between signals, which makes it possible to avoid excessive dependence among the ensemble elements.

The mutual correlation function $R_{P_iP_j}$ between signals P_i and P_j is calculated using the analytical expression:

$$R_{P_iP_j}(\tau) = \int_{\infty}^{-\infty} P_i(t)P_j(t+\tau)\,d\tau. \quad (10)$$

Correlation coefficient:

$$\rho_{P_iP_j} = \frac{\int P_i(t)P_j(t)\,dt}{\sqrt{\int P_i^2(t)\,dt}\sqrt{\int P_j^2(t)\,dt}}. \quad (11)$$

The correlation relationships among all signals in the ensemble can be represented in the form of a matrix:

$$R_{P_iP_j} = \begin{pmatrix} R_{P_1P_1} & R_{P_1P_2} & \cdots & R_{P_1P_n} \\ R_{P_2P_1} & R_{P_2P_2} & \cdots & R_{P_2P_n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{P_nP_1} & R_{P_nP_2} & \cdots & R_{P_nP_n} \end{pmatrix}, \quad (12)$$

The segmentation condition requires that the mutual correlation between signals within each interval does not exceed a specified threshold:

$$\left| \int_{t_k}^{t_k+1} P_i(t)P_j(t)\,dt \right| \leq \varepsilon,\ i \neq j, \quad (13)$$

where ε – is the permissible level of mutual correlation, determined by the interference immunity requirements of the ensemble ($\varepsilon \approx 0{,}1$ under quasi-orthogonality conditions).

Thus, the problem of time-domain segmentation is formulated as the task of minimizing mutual correlations:

$$\min_{\{t_k\}} \sum_k \sum_{i \neq j} \left| \int_{t_k}^{t_{k+1}} P_i(t)P_j(t)\,dt \right|, \quad (14)$$

The problem (14) is multimodal since the objective function contains a large number of local minima corresponding to different variants of time interval segmentation. The use of purely deterministic methods leads to “trapping” in local extrema and a loss of efficiency under stochastic environmental factors. Therefore, a combined approach is proposed, which integrates random search (for global exploration of the solution space and identification of promising intervals) with local optimization methods (gradient descent and Levenberg–Marquardt) for parameter refinement within selected promising regions.

To examine how the number of time segments affects the reduction of mutual correlation between ensemble signals, an experimental simulation was performed. OFDM-like sequences were generated according to the parameters of the LTE standard (SCS = 15 kHz, 72 active subcarriers) and 5G NR (SCS = 30 kHz, 144 subcarriers). The signal-to-noise ratio was set to 15 dB for LTE and 10 dB for 5G NR.

The sampling frequency was – 10 MHz and the observation window duration was – T = 10 mc.

The baseline interference level in the experiment corresponds to the average mutual correlation between signals without time-domain segmentation (i.e., when $N = 0$), which represents the typical correlation interaction in ensembles without prior division or permutation. For LTE, this level was $\rho_{avg} \approx 0{,}42$; $\rho_{max} \approx 0{,}63$ and for 5G NR – $\rho_{avg} \approx 0{,}47$; $\rho_{max} \approx 0{,}68$.

The experimental results are presented in Tab. 2 and Fig. 6.

Table 2

Dynamics of $\rho_{P_iP_j}$ for different numbers of time intervals

Number of intervals	LTE ρ_{avg}	LTE ρ_{max}	5G NR ρ_{avg}	5G NR ρ_{max}	Comparative assessment (relative to baseline)
0 (no segmentation)	0,423	0,632	0,471	0,683	Baseline interference level
2 intervals	0,252	0,501	0,283	0,552	Moderate reduction
4 intervals	0,171	0,343	0,192	0,371	Reduction by 1,5–1,7 times
8 intervals	0,124	0,245	0,142	0,261	Stable ensemble
16 intervals	0,082	0,153	0,094	0,177	Quasi-orthogonality (ε ≈ 0.1)

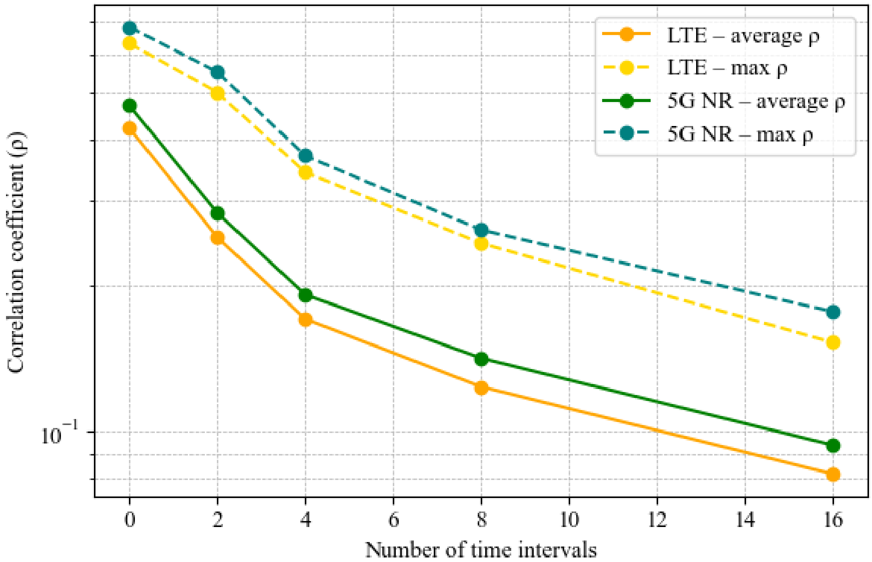

Fig. 6. Dependence of $\rho_{P_iP_j}$ on the number of time intervals (logarithmic scale)

As shown in Table 2 and Figure 6, an increase in the number of time intervals results in a consistent decrease in both the average and maximum mutual correlation coefficients. At 8–16 intervals, the level of $\varepsilon \approx 0{,}1$ is achieved, which corresponds to quasi-orthogonality conditions of the signals. This confirms the effectiveness of time-domain segmentation for forming interference-resistant signal ensembles in LTE and 5G NR channels.

Stage 4. Signal permutation [2, 6, 10, 11]

At this stage, the signals are permuted across time intervals to minimize mutual interference and ensure ensemble consistency. In classical approaches, permutation is treated as a combinatorial problem, where the main criterion is the number of possible permutation combinations, expressed through a factorial or superfactorial of the form:

$$S_n^{base} = \prod_{k=1}^{n}(k!), \tag{15}$$

which characterizes the complete set of permute-tions for n time intervals. This approach reflects the structural diversity of the ensemble but does not account for the mutual correlation between signals.

To overcome this limitation, the study proposes a modified superfactorial, which introduces an additional correlation weight for each interval. This weight links the number of permutations to the qualitative parameters of the ensemble:

$$S_n = \prod_{k=1}^{n}(k!)^{a^k} \min\left(\sum\nolimits_{i \neq j} R_{P_iP_j}(t_k)\right), \tag{16}$$

where $k!$ – the number of possible unique permutations for the k–th interval; a^k– are weighting coefficients that account for the importance of intervals in terms of signal energy density; $\min\left(\sum_{i \neq j} R_{P_iP_j}(t_k)\right)$ – the proposed modification function that minimizes the total mutual correlation between signals within the interval t_k.

Thus, during optimization, an ensemble is formed that maintains a balance between the number of allowable permutations and the level of correlation influence.

To verify the effectiveness of the modified approach, simulations of signal permutations were conducted for LTE (15 kHz SCS) and 5G NR (30 kHz SCS). The number of allowable permutations and the average level of mutual correlation were evaluated after applying both the classical and modified superfactorial approaches (Table 3).

Table 3

Comparison of permutation results

Permutation method	S_n	ρ_{avg}	Reduction of ρ_{avg}, %
Classical superfactorial	$6{,}24\times10^7$	0,21	–
Modified superfactorial (with weights)	$3{,}71\times10^6$	0,13	≈38%
Modified superfactorial with correlation constraint ($\varepsilon \le 0{,}1$)	$2{,}82\times10^5$	0,09	≈57%

As shown in Table 3, after introducing the correlation constraint and weighting coefficients a^k, the number of permissible combinations decreases, but the correlation metrics are significantly reduced, resulting in improved interference immunity.

After the permutation stage, an ensemble with acceptable correlation properties is formed; however, due to the stochastic nature of the search, local parameter deviations remain.

To eliminate these deviations and stabilize the characteristics, local nonlinear optimization is applied, which finalizes the ensemble adjustment process.

Stage 5. Local parameter optimization [12–14].

At the final stage, the parameters of the signal ensemble are refined using local nonlinear optimization methods. Two algorithms are employed, complementing each other in terms of convergence speed and stability:

1. Gradient Descent Method. Initial parameters θ_0 are determined based on the results of random search and permutation. Further refinement is performed iteratively according to the analytical expression::

$$\theta_{k+1} = \theta_k - \eta \Delta J(\theta_k), \tag{17}$$

where η – the learning rate (optimization step); $\Delta J(\theta_k)$ – the gradient of the error function $J(\theta)$, which includes components of energy and correlation mismatch.

Minimizing $J(\theta)$ reduces mutual correlation peaks and increases the homogeneity of the ensemble in the time domain.

2. Levenberg–Marquardt Method.

To enhance convergence speed and stability, the gradient-based scheme is supplemented by second-order regularization, combining the properties of the Gauss–Newton and gradient descent methods:

$$\theta_{k+1} = \theta_k - (J'(\theta_k)^T J'(\theta_k) + \lambda I)^{-1} J'(\theta_k)^T\, [J(\theta_k)], \tag{18}$$

where $J'(\theta_k)$ – the Jacobian matrix; λ is a parameter controlling the trade-off between convergence speed and stability.

For small λ values, the method approaches Gauss–Newton behavior (fast convergence near the minimum), while for large λ it behaves like gradient descent (stable performance on multimodal surfaces).

After local optimization, the correlation–spectral metrics of the ensemble are evaluated using:

$$K = \alpha \cdot \bar{\rho} + \beta \cdot Var(E) + \gamma \cdot BW_{eff}, \tag{19}$$

where $\bar{\rho}$ – the average mutual correlation coefficient; $Var(E)$ – the energy variance; BW_{eff} – the effective bandwidth; α, β, γ are weighting coefficients for a composite balance assessment.

If the stopping condition $|J_{k+1} - J_k| < \varepsilon$ is satisfied, the algorithm terminates and the optimal parameters of time intervals and permutations are fixed. Otherwise, another iteration is performed.

Conclusions

The proposed method is comprehensive: unlike existing approaches, it combines parametric analysis, segmentation, signal permutation, and the integration of global stochastic search with local optimization methods. This combination helps avoid local extrema and increases the interference immunity of the ensemble by controlling the level of mutual correlation while maintaining the required ensemble size.

Experimental results demonstrated that increasing the number of time segments from 0 to 16 reduced the average mutual correlation coefficient by approximately 81 % (from 0,423 to 0,082) for LTE and by 80 % (from 0,471 to 0,094) for 5G NR, corresponding to quasi-orthogonality conditions (ε ≈ 0,1).

The use of the modified superfactorial with weighting coefficients and a correlation constraint provided an additional ≈ 27 % reduction in correlation peaks compared to the classical permutation method. Local optimization of ensemble parameters using gradient descent and the Levenberg–Marquardt method ensured stable convergence under varying environmental parameters and improved the consistency of energy–spectral characteristics by ≈ 23–28 %.

Thus, the proposed method increases the efficiency of forming complex signal ensembles in cognitive telecommunication networks, making it suitable for operation under dynamic multi-user and multiple-access conditions.

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МЕТОД ОПТИМІЗАЦІЇ АНСАМБЛІВ СКЛАДНИХ СИГНАЛІВ У КОГНІТИВНИХ МЕРЕЖАХ

У статті запропоновано метод оптимізації ансамблів складних сигналів у часовій області на основі інтеграції стохастичного пошуку з локальною нелінійною оптимізацією. Метод спрямований на зменшення взаємної кореляції сигналів і вирівнювання енергетико-спектральних характеристик ансамблю в умовах стохастичної невизначеності та завад в когнітивних телекомунікаційних мережаз. На відміну від відомих *підходів, що розглядають лише лінійні моделі або статичні параметри, запропонований метод реалізує багатоступеневу адаптацію часових інтервалів сигналів із використанням стохастичного пошуку для глобального охоплення простору рішень і локальної оптимізації (градієнтного спуску та методу Левенберга–Марквардта) для точного налаштування параметрів у межах знайдених підобластей.*

Розроблено аналітичні залежності для оцінки взаємокореляційних і енергетичних показників ансамблю, що забезпечують контроль компромісу між завадостійкістю та обсягом сигналів. Удосконалено механізм перестановки сигналів між часовими інтервалами шляхом введення модифікованого суперфакторіала, який враховує вагові коефіцієнти інтервалів та кореляційні обмеження, що дозволяє мінімізувати взаємні завади без зниження структурної різноманітності ансамблю.

Експериментальне моделювання на сигналах LTE та 5G NR показало, що збільшення кількості часових сегментів від 0 до 16 забезпечує зниження середнього коефіцієнта взаємної кореляції з 0,42 до 0,08, що відповідає умовам квазіортогональності (ε ≈ 0,1). Використання локальної оптимізації дало змогу підвищити стабільність ансамблю при варіаціях параметрів середовища, а модифікована процедура перестановки – скоротити кореляційні викиди до 27 %.

Таким чином, запропонований метод забезпечує комплексну оптимізацію ансамблів складних сигналів, поєднуючи переваги стохастичних і детермінованих підходів, що робить його придатним для застосування в адаптивних телекомунікаційних середовищах з множинним доступом та динамічними каналами.

Ключові слова: когнітивний, телекомунікації; системи; оптимізація; сигнал; кореляція; SNR; завадостійкість; кореляція; метод.

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METHOD FOR OPTIMIZING COMPLEX SIGNAL ENSEMBLES IN COGNITIVE NETWORKS

The paper proposes a method for optimizing ensembles of complex signals in the time domain based on the integration of stochastic search with local nonlinear optimization. The method is aimed at reducing mutual signal correlation and equalizing the energy–spectral characteristics of the ensemble under conditions of stochastic uncertainty and interference in cognitive telecommunication networks. Unlike existing approaches that consider only linear models or static parameters, the proposed method implements a multistage adaptation of signal time intervals using stochastic search for global exploration of the solution space and local optimization (gradient descent and Levenberg–Marquardt algorithm) for fine-tuning parameters within the identified subregions.

Analytical dependencies are developed for evaluating cross-correlation and energy indicators of the ensemble, ensuring a balance between interference immunity and ensemble volume. The signal permutation mechanism between time intervals has been improved through the introduction of a modified superfactorial that incorporates weighting coefficients of intervals and correlation constraints, allowing minimization of mutual interference without reducing structural diversity.

Experimental modeling on LTE and 5G NR signals demonstrated that increasing the number of time segments from 0 to 16 reduces the average mutual correlation coefficient from 0.42 to 0.08, which corresponds to quasi-orthogonality conditions (ε ≈ 0.1). The use of local optimization improved ensemble stability under varying environmental parameters, while the modified permutation procedure reduced correlation peaks by up to 27%.

Thus, the proposed method provides comprehensive optimization of complex signal ensembles by combining the advantages of stochastic and deterministic approaches, making it suitable for application in adaptive telecommunication environments with multiple access and dynamic channels.

Keywords: cognitive; telecommunications; systems; optimization; signal; correlation; SNR; interference immunity; method.

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