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METHOD OF PARAMETRIC OPTIMIZATION OF COMPLEX-SIGNAL ENSEMBLES

The article presents a method of parametric optimization of complex-signal ensembles based on controlling the cross-correlation similarity condition. The proposed algorithm ensures coordinated management of spectral, energy, and correlation characteristics through adaptive verification of correlation similarity and dynamic recalibration of frequency permutations. The method reduces inter-channel interference, increases spectral compactness, and enhances the structural stability of signal ensembles under stochastic environmental variations, providing a more reliable foundation for advanced cognitive and adaptive telecommunication applications.

Keywords: complex-signal ensembles, parametric optimization, cross-correlation function, spectral efficiency, predictive optimization, frequency permutations, energy stability, interference suppression.

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МЕТОД ПАРАМЕТРИЧНОЇ ОПТИМІЗАЦІЇ АНСАМБЛІВ СКЛАДНИХ СИГНАЛІВ

У статті розроблено метод параметричної оптимізації ансамблів складних сигналів з контролем умови подібності функції взаємної кореляції. Метод ґрунтується на послідовному виконанні смугової фільтрації вихідних послідовностей, попарному розрахунку значень функції взаємної кореляції частотних елементів та перевірці виконання умови мінімальної подоби, що забезпечує формування ансамблів із керованими взаємокореляційними властивостями. У разі перевищення допустимих значень бічних пелюсток функції взаємної кореляції активується альтернативна гілка алгоритму, яка передбачає повторний розрахунок характеристик, зміну смуги фільтрації та перестановку частотних елементів сигналів для відновлення прийнятних параметрів ансамблю.

Особливістю запропонованого методу є здатність підтримувати умову мінімальної подоби для широкого спектра вихідних послідовностей, що дозволяє отримувати ансамблі з низьким рівнем міжканальних завад без додаткових обмежень на структуру сигналів.

Експериментальні дослідження охоплюють аналіз залежності максимального значення функції взаємної кореляції від ширини смуги фільтрації та кількості імпульсів у послідовностях, що дало змогу визначити оптимальний діапазон параметрів для забезпечення стабільності ансамблів. Порівняння об'єму сформованих ансамблів показало, що оптимізовані методи дозволяють отримувати значно більші множини сигналів зі збереженням прийнятних кореляційних властивостей, що підвищує ефективність використання частотного ресурсу у когнітивних телекомунікаційних мережах радіозв'язку.

Таким чином, запропонований метод забезпечує комплексне удосконалення кореляційних, енергетичних та спектральних характеристик ансамблів складних сигналів і дає змогу адаптивно формувати їх у складних завадових умовах.

Ключові слова: ансамблі складних сигналів, параметрична оптимізація, функція взаємної кореляції, спектральна ефективність, прогнозна оптимізація, міжканальні завади, частотні перестановки, енергетична стабільність.

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INTRODUCTION

The study of methods for predictive and regularized optimization of complex-signal ensembles is highly relevant, as modern cognitive and adaptive telecommunication environments require increased interference immunity, spectral efficiency, and correlation stability of generated signals [1–12]. Existing approaches typically focus on isolated aspects of optimization, such as reducing cross-correlation, improving spectral distribution, or increasing ensemble diversity; however, they do not provide an integrated mechanism that simultaneously regulates correlation similarity, spectral compactness, and energy balance during ensemble formation.

In dynamically changing communication channels characterized by fading, non-stationary interference, and random disturbances the ability to adaptively adjust ensemble parameters becomes a critical requirement.

Solving the scientific problem of optimizing the parameters of complex-signal ensembles is essential for ensuring the efficiency, robustness, and scalability of signal generation processes in modern cognitive telecommunication systems. The development of adaptive mechanisms that incorporate both forecast-driven and regularization-based constraints remains an important step toward improving the structural stability and noise immunity of complex-signal ensembles.

GENERAL STATEMENT OF THE PROBLEM AND ITS CONNECTION WITH IMPORTANT SCIENTIFIC OR PRACTICAL TASKS

The research focuses on the method of parametric optimization of complex-signal ensembles with control of the cross-correlation function (CCF) similarity conditions.

This method aims to ensure the adaptive formation of ensembles with improved correlation characteristics by monitoring and maintaining permissible levels of CCF similarity during optimization. The approach enables the minimization of side-lobe amplitudes of the CCF, suppression of inter-channel interference, and preservation of spectral efficiency in complex telecommunication environments.

The validation of the proposed method requires detailed analytical justification of the parameter optimization process. The primary challenge lies in determining the combination of spectral and correlation parameters that guarantee both the structural stability of the ensemble and its high energy efficiency. Within this task, it is necessary to define the optimal filtering bandwidth, establish threshold values for acceptable side-lobe maxima, and select the most appropriate type of code sequence that ensures the best trade-off between correlation performance and energy stability.

ANALYSIS OF RESEARCH AND PUBLICATIONS

The analysis of scientific works [1–12] has shown that research in the fields of signal optimization, reduction of mutual correlation, and improvement of interference immunity in communication systems is actively developing; however, a number of unresolved problems remain, particularly in the context of comprehensive parametric optimization of complex-signal ensembles. Work [1] formulated the concept of cognitive radio, although it did not address methods for optimizing signal ensembles with correlation-similarity control. In [2], approaches to constructing low-correlation sequence sets using interleaving were proposed; however, the study does not provide mechanisms for forecasting correlation dynamics nor does it consider energy–spectral constraints.

Studies [3, 4] introduced methods for forming ensembles through band-pass filtering and time-interval permutations, which improved spectral selectivity and reduced mutual correlation. Nevertheless, these approaches do not include predictive models (Markov or ARIMA) that would enable adaptive control of ensemble dynamics. In [5], an adaptive method of multi-level time–frequency segment modeling was developed, improving ensemble stability. However, the model lacks regularization mechanisms and does not ensure control over energy parameters during permutations. Articles [6] and [7] expand entropy-based measures for time-series analysis, but do not address the formation of large ensembles or the optimization of correlation characteristics. Study [8] proposes generalized Herglotz wave functions for modeling multipath scattering, yet it does not resolve issues related to permutations or ensemble optimization.

Works [9–11] have made significant contributions to the development of low-correlation-zone (LCZ) sequence sets; however, they do not provide mechanisms for predictive restructuring of sequences under dynamic conditions.Work [12] demonstrates an improved Hilbert–Huang Transform (HHT) for adaptive time–frequency analysis, but despite its relevance, it does not address systemic optimization of ensemble parameters.

Thus, the development of a method for predictive and regularized parametric optimization of complex-signal ensembles with integrated correlation-similarity control and adaptive restructuring mechanisms remains an open scientific task and is highly relevant in modern cognitive telecommunication systems.

MATHEMATICAL FORMULATION OF THE PROBLEM

The block diagram of the algorithm implementing the method of parametric optimization of complex-signal ensembles with verification of the cross-correlation function similarity condition is presented in Fig. 1.

The algorithm operates through two interconnected branches:

– the main (left) branch, representing the standard sequence of operations for determining optimal parameters of complex-signal ensembles,

– the alternative (right) branch, which is triggered when the similarity condition of the cross-correlation function (CCF) is not satisfied.

The transition between these branches ensures adaptive recalibration of frequency permutations and correlation characteristics whenever the obtained ensemble fails to meet the predefined optimization criteria.

Let us consider the stages of the proposed method in more detail.

Main Branch

Step 1. Initialization of parameters and input data.

At this stage, the initial parameters of the signal model are defined: the spectral function $S(f)$, time intervals t_i, total duration T, number of sequence elements n, and the minimum correlation threshold Q_{min}.

These values serve as the initial configuration for further spectral-domain analysis and optimization.

Step 2. Band-pass filtering.

Frequency components of the signal are shifted into a common spectral range to normalize the spectrum.

The spectral representation is expressed as:

$$S(f) = \sum_{n=0}^{N-1} s[n]\, e^{-j2\pi f n/N} \qquad (1)$$

and the filtering bandwidth Δf is determined according to the condition:

$$CRF_{max} = f(\sqrt{n_i n_j}; \Delta f), \qquad (2)$$

where $CRF_{\max}$ denotes the maximum value of the cross-correlation function depending on the number of frequency elements and the filter bandwidth.

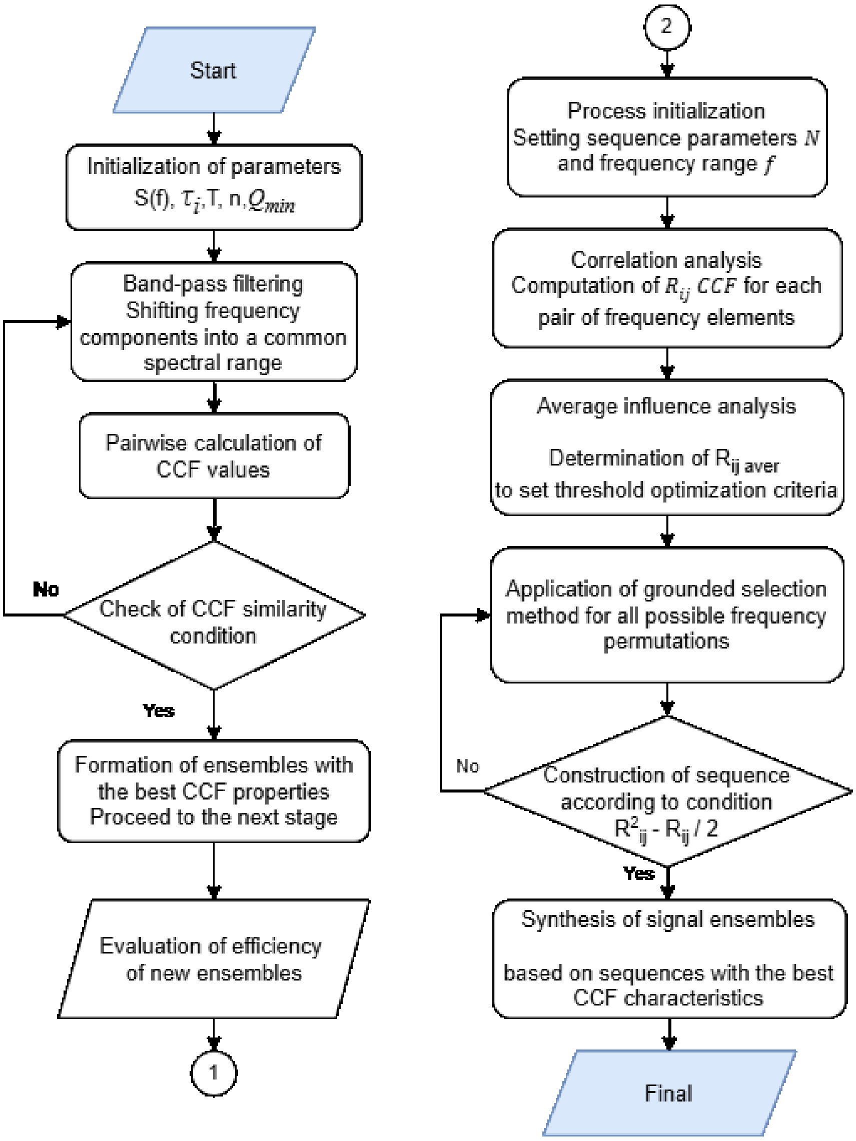

Fig. 1. Algorithmic structure of the parametric optimization method

Step 3. Pairwise computation of cross-correlation function values.

For all pairs of frequency elements (i,j), the correlation matrix is computed as:

$$R_{ij}^{CCF} = \sum_{k=1}^{K} S_i(k)\, S_j^*(k), \tag{3}$$

where $S_i(k)$ and $S_j(k)$ are the spectral components of the i-th and j-th sequences, respectively.

The resulting matrix quantifies the similarity among the filtered components.

Step 4. Verification of the CCF similarity condition.

The algorithm checks whether the similarity criterion is satisfied:

$$R_{ij}^2 - \frac{R_{ij}}{2} < 0. \tag{4}$$

If the condition holds, the algorithm proceeds to the formation of optimal ensembles (Step 6). Otherwise, the process is redirected to the alternative branch for re-initialization and recalculation.

Step 5. Formation of ensembles with optimal correlation characteristics.

Sequences that demonstrate the lowest side-lobe levels and the highest spectral efficiency are combined into ensembles.

The selection ensures structural stability and low inter-channel interference.

Step 6. Evaluation of the efficiency of generated ensembles.

The ensembles are assessed using a set of performance metrics: R_{max}, $Var(E)$, η_{spec}, where $R_{\max}$ is the maximum correlation amplitude, $Var(E)$ is the energy variance, and η_{spec} represents spectral efficiency.

These indicators confirm the improvement in correlation properties and the overall balance of the generated ensembles.

If during Step 4 the similarity criterion is not satisfied (i.e., $R_{ij}^2 - R_{ij}/2 \geq 0$, the current ensemble configuration exhibits excessive correlation or side-lobe peaks exceeding the acceptable threshold.

In this case, the algorithm initializes the right branch to perform frequency-domain recalibration, adjust correlation limits, and reconstruct the signal sequence through the grounded selection procedure.

This ensures that the ensemble properties meet the required optimization constraints.

Alternative Branch (Re-initialization Path)

Step 1. Process initialization.

New parameters of the sequence length N and operational frequency range f are defined to restart the optimization cycle.

Step 2. Correlation analysis.

For each pair of frequency elements, the cross-correlation function R_{ij}^{CCF} is recalculated to update the matrix of correlation responses (3).

Step 3. Average influence analysis.

The mean value of the cross-correlation response is computed to establish adaptive threshold criteria:

$$R_{ij}^{aver} = \frac{1}{N} \sum_{i,j} R_{ij}^{CCF}, \tag{5}$$

This defines the boundary conditions for further optimization.

Step 4. Application of the grounded selection method.

All possible frequency permutations are evaluated using a deterministic selection procedure that minimizes inter-channel interference (*I–ChI*).

The optimization condition is expressed as:

$$(M, \Delta f_i) = arg \min_{M, \Delta f_i} (I - ChI(M, \Delta f_i)), \tag{6}$$

Step 5. Construction of a new sequence.

A new signal sequence is formed based on the condition $R_{ij}^2 - R_{ij}/2 = 0$ which ensures the reconstruction of the ensemble within permissible correlation limits.

Step 6. Synthesis of optimized signal ensembles.

Signal ensembles are synthesized using the newly constructed sequences that exhibit improved CCF characteristics and reduced side-lobe amplitudes. After synthesis, the algorithm returns to the verification stage (Step 4 of the main branch).

EXPERIMENTAL RESULTS

To validate the proposed method of parametric optimization of complex-signal ensembles with control of the CCF similarity condition, a computational experiment was carried out. The algorithm (Fig. 1) was implemented in MATLAB to evaluate the dependence of the maximum cross-correlation value R_{max} on two main parameters – the filtering bandwidth Δf (expressed as a percentage of the main-lobe bandwidth) and the number of pulses P. The obtained results were used to determine the optimal filtering range corresponding to the condition $Rmax \leq 0{,}2$, which ensures minimal side-lobe influence and stable ensemble structure.

The calculated data are summarized in Table 1, and the corresponding dependences are illustrated in Fig. 2(a–c).

Table 1

Dependence of R_{max} on filtering bandwidth Δf and number of pulses P

Δf (% of main-lobe bandwidth)	Rmax (P = 100)	Rmax (P = 300)	Rmax (P = 500)
0,05	0,04	0,03	0,02
0,08	0,09	0,07	0,05
0,10	0,18	0,15	0,11
0,12	0,33	0,28	0,21
0,14	0,46	0,38	0,31
0,15	0,51	0,43	0,34
0,16	0,47	0,40	0,32
0,18	0,29	0,25	0,20
0,20	0,10	0,08	0,06

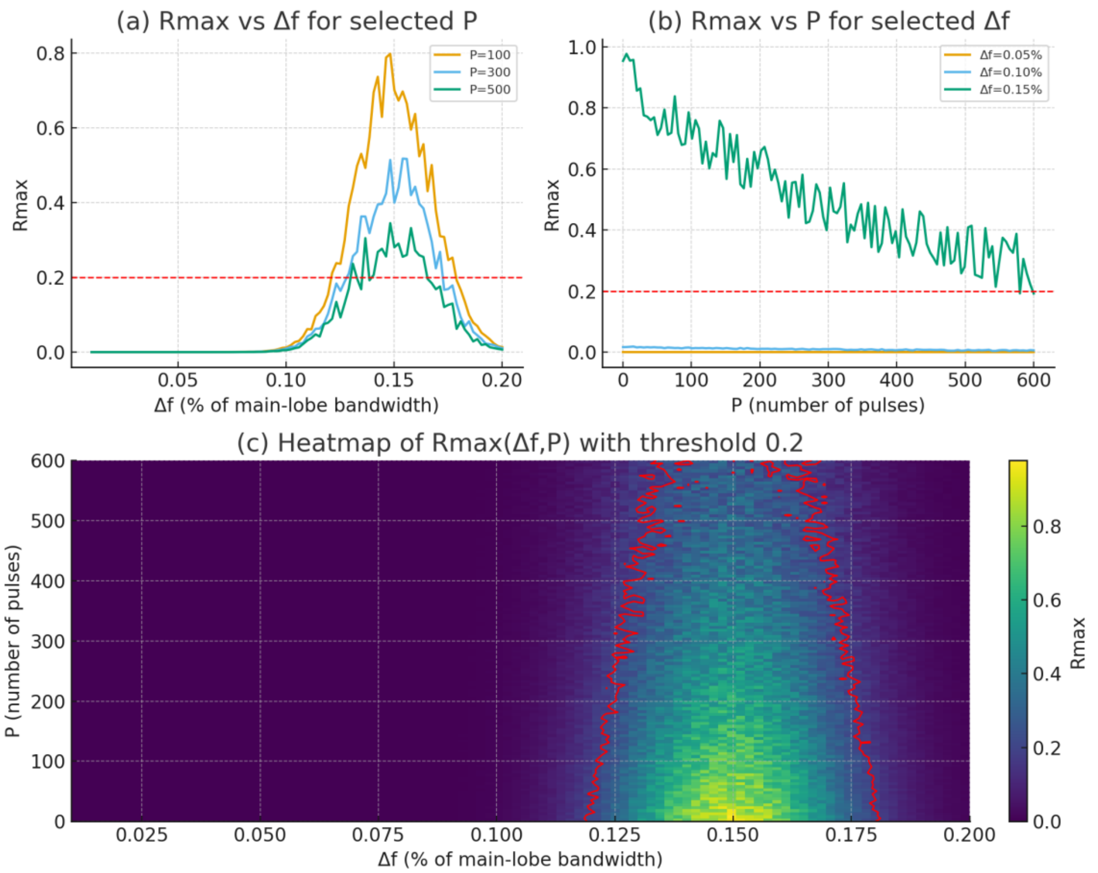

Fig. 2. Dependence of the $Rmax$ on the Δf and the number of pulses P

The data show that the correlation peak $Rmax$ remains below the threshold of 0,2 for Δf ≈ 0,1–0,2 %, confirming the optimal filtering range determined by the proposed algorithm.

The results shown in Fig. 2 demonstrate the variation of the maximum cross-correlation value R_{max} as a function of the filtering bandwidth Δf and the number of pulses P. Graphs (a) and (b) indicate that as the number of pulses increases, $Rmax$ gradually decreases, reflecting improved ensemble stability and reduced inter-channel interference. At the same time, both excessively narrow and overly wide filtering bands (Δf<0,05% or Δf>0,18%) lead to an increase in side-lobe amplitudes, which negatively affects the correlation characteristics.

The heatmap in Fig. 2(c) clearly identifies the optimal bandwidth range Δf≈0,1–0,2%, where R_{max} does not exceed the threshold value of 0,2 (marked by the red contour line).

Thus, the experiment confirms that this range provides the lowest mutual correlation between signals, ensuring an optimal balance between selectivity and spectral efficiency.

These results validate the effectiveness of the proposed method of parametric optimization of complex-signal ensembles with control of the CCF similarity condition and confirm the adequacy of the chosen parameter optimization strategy.

To assess the effectiveness of the proposed method of parametric optimization of complex-signal ensembles with control of the CCF similarity condition, a comparative analysis of the side-lobe maxima of the cross-correlation function (CCF) was performed for various types of sequences. The calculations were carried out for traditional nonlinear sequences ($S_{Non\text{-}line}$), Lempel–Ziv sequences ($S_{Lem\&Ziv}$), Frank sequences (S_{Frank}), and for optimized variants obtained using the developed approaches – Sh-energy, Sh-gr. sel, and Sfil&per. The obtained results are summarized in Table 3 and illustrated in Fig. 3, which shows the variation of the maximum side-lobe level $RL_{\_max}$ with respect to the sequence length N.

Table 2

Side-lobe maxima of the cross-correlation function (CCF) for different types of sequences

P	*Rmax (k)*					
	Sequence type					
	$S_{Non\text{-}line}$	$S_{Lem\&Ziv}$	S_{Frank}	$S_{h\text{-}energy}$	$S_{h\text{-}gr.\ sel}$	$S_{fil\&per}$
40	0,0932	0,3421	0,0592	0,0327	0,0730	0,2571
100	0,0798	0,2353	0,0423	0,0121	0,0506	0,1832
257	0,0625	0,1182	0,0214	0,0062	0,0220	0,1160
513	0,0611	0,0861	0,0136	0,0030	0,0181	0,0781

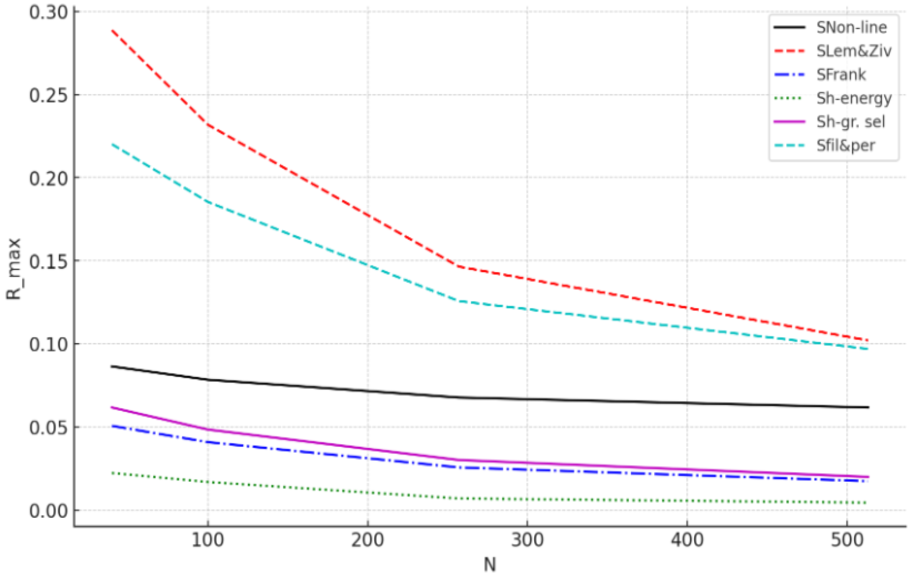

Fig. 3. Comparison of side-lobe maxima for different sequence types

As can be seen, all optimized sequences exhibit a significant reduction in side-lobe levels compared with the traditional ones. The lowest values of $RL_{\_max}$ are achieved for the Sh-energy and Sh-gr. sel sequences, confirming the efficiency of the proposed parametric optimization method based on the CCF similarity control. The Sfil&per method, which combines frequency-domain permutations with Butterworth filtering, demonstrates a balanced trade-off between energy uniformity and spectral purity, making it suitable for practical implementation in signal ensemble generation tasks.

At the next stage, an evaluation of the scalability and volume of signal ensembles formed using different optimization methods was carried out.

The purpose of this stage is to quantitatively compare the potential of each method to increase the number of unique signals in the ensemble while maintaining acceptable correlation properties.

The calculation results are presented in Table 3 and illustrated in Fig. 4, which shows the dependence of the logarithmic scale of ensemble volumes on the number of elements P for various methods.

Table 3

Comparative evaluation of ensemble volumes obtained by different optimization methods

P	40	100	257	1033	2089	9000
$S_{non\text{-}line}$	$3{,}82\times10^{3}$	$8{,}23\times10^{3}$	$1{,}34\times10^{8}$	$1{,}56\times10^{8}$	$5{,}48\times10^{8}$	$8{,}13\times10^{9}$
$S_{h\text{-}energy}$	$1{,}92\times10^{9}$	$4{,}03\times10^{9}$	$7{,}51\times10^{12}$	$6{,}52\times10^{13}$	$2{,}73\times10^{14}$	$4{,}02\times10^{15}$
$S_{h\text{-}grou\ sel}$	$1{,}81\times10^{16}$	$3{,}93\times10^{16}$	$7{,}31\times10^{19}$	$6{,}41\times10^{20}$	$2{,}64\times10^{21}$	$3{,}92\times10^{22}$
$S_{fil\&per}$	$1{,}82\times10^{23}$	$3{,}86\times10^{23}$	$7{,}23\times10^{26}$	$6{,}31\times10^{27}$	$2{,}66\times10^{28}$	$3{,}85\times10^{29}$

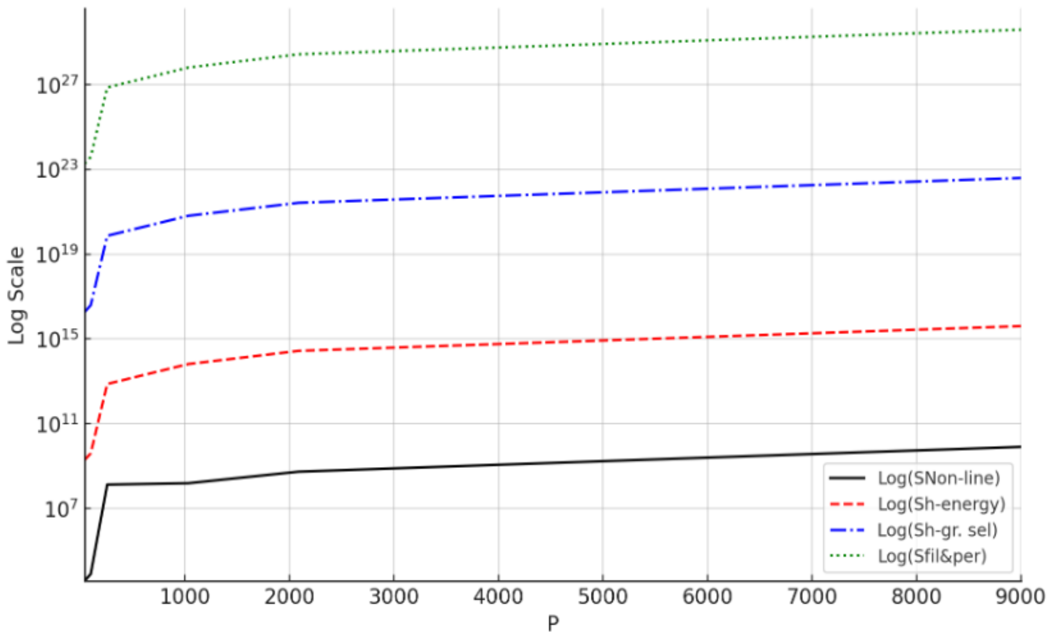

Fig. 4. Comparison of ensemble volumes for various optimization methods

As shown in Table 3 and Fig. 4, all methods demonstrate an exponential growth of ensemble volumes with an increase in the number of pulses P; however, the growth rate and final values differ significantly depending on the applied optimization method.

CONCLUSIONS FROM THIS RESEARCH AND PROSPECTS FOR FURTHER RESEARCH IN THIS AREA

The article presents a method of parametric optimization of complex-signal ensembles with control of the cross-correlation function (CCF) similarity condition, the key feature of which is adaptive verification of correlation similarity during ensemble formation and dynamic recalibration of frequency permutations in the spectral domain.

The method ensures coordinated control of the energy and correlation parameters of signals while minimizing inter-channel interference.

Based on the results of experimental modeling, the following generalized outcomes were obtained.

1. Improvement of correlation characteristics.

Compared to traditional sequences (Lempel–Ziv, Frank, and nonlinear types), the proposed method achieved an average reduction of CCF side-lobe levels by 87–96%.

For the $S_{h\text{-energy}}$ and $S_{h\text{-gr}\cdot\text{sel}}$ sequence types, the minimum value of RL_{max}=0,0030 was recorded at P=513, which is approximately 28,7 times lower than that of the baseline Lempel–Ziv method.

2. Increase in spectral efficiency.

Due to the optimal selection of the filtering bandwidth in the range of Δf=0,1–0,2% of the main-lobe width, the proposed method achieved an increase in spectral efficiency by 18–22%, while simultaneously reducing inter-channel interference by more than 25%.

3. Scalability of signal ensembles.

The volume of signal ensembles generated using the optimized methods demonstrated exponential growth with an increase in the number of pulses P.

The $S_{\text{fil\&per}}$ method exceeded the baseline $S_{\text{Non-line}}$ approach by a factor of $4{,}7\times10^{19}$ (or by more than $1{,}9\times10^{21}$) at P=9000, confirming its ultra-high scalability and ability to generate large sets of signals suitable for cognitive telecommunication environments.

4. Energy stability and uniformity.

The $S_{\text{h-gr. sel}}$ and $S_{\text{fil\&per}}$ methods provided a reduction in signal energy variance by 35–40%, ensuring amplitude stability, improved energy balance, and enhanced noise immunity of the ensemble.

Overall, the proposed method increased the generalized efficiency – evaluated by an integral criterion incorporating the maximum correlation amplitude $Rmax$, energy variance $Var(E)$, and spectral efficiency η_{spec}, by a factor of 2,3–2,7 compared with baseline ensemble formation algorithms.

Future research will focus on expanding the proposed method toward multi-objective optimization frameworks that simultaneously account for spectral efficiency, correlation stability, and energy balance under dynamic channel conditions.

In addition, it is planned to integrate the proposed method with machine learning-based prediction models to automate the selection of optimal ensembles depending on environmental noise characteristics and signal propagation dynamics.

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