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METHOD FOR FORMING ENSEMBLES OF COMPLEX SIGNALS BASED ON MODIFIED NSGA-III ALGORITHM

This paper presents a method for forming ensembles of complex signals based on structural transformation of time-domain segments and multi-objective optimization using a modified NSGA-III algorithm. It is shown that existing approaches mainly focus on optimizing individual signal characteristics and do not provide coordinated control of correlation and spectral properties in ensemble formation.

A comparative experimental study is performed to evaluate the effectiveness of the proposed method under interference conditions. The evaluation focuses on peak sidelobe level (PSL), integrated sidelobe level (ISL), and structural entropy.

The results demonstrate that the proposed approach enables coordinated reduction of correlation characteristics, formation of Pareto-optimal solutions, and improved efficiency of complex signal ensemble formation in interference environments.

Keywords: complex signals; optimization; evolutionary algorithm; time domain; correlation; spectrum; structural transformation; Pareto front.

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МЕТОД ФОРМУВАННЯ АНСАБЛІВ СКЛАДНИХ СИГНАЛІВ НА ОСНОВІ МОДИФІКОВАНОГО АЛГОРИТМУ NSGA-III

У статті розглянуто задачу формування ансамблів складних сигналів у часовій області на основі керованого структурного перетворення та багатокритеріальної еволюційної оптимізації. Запропоновано метод формування ансамблів складних сигналів на основі модифікованого еволюційного алгоритму NSGA-III, який поєднує структурне представлення сигналу у вигляді часових сегментів, параметризовану перестановку та узгоджене врахування кореляційних, енергетичних та спектральних характеристик сигналів.

Обґрунтовано, що існуючі підходи до оптимізації сигналів переважно орієнтовані на удосконалення окремих характеристик та не забезпечують узгодженого формування ансамблів сигналів у багатовимірному просторі критеріїв. Встановлено, що застосування класичних методів оптимізації є обмеженим у задачах комбінаторного характеру, пов'язаних з перестановками часових сегментів, тоді як еволюційні алгоритми дозволяють ефективно здійснювати пошук компромісних рішень та формувати множину Парето-оптимальних варіантів.

Для оцінювання ефективності запропонованого методу проведено експериментальне моделювання в умовах складного завадового середовища. Оцінювання виконано за показниками рівня бічних пелюсток (PSL), інтегральної енергії бічних пелюсток (ISL) та структурної ентропії сигналу. Отримані результати показали, що використання модифікованого еволюційного алгоритму NSGA-III забезпечує узгоджене зниження кореляційних характеристик сигналів, формування множини Парето-оптимальних рішень та підвищення ефективності формування ансамблів складних сигналів порівняно з класичним генетичним алгоритмом та неоптимізованим підходом.

Таким чином, запропонований метод забезпечує формування ансамблів сигналів з керованими властивостями в умовах складного завадового середовища та може бути використаний у телекомунікаційних системах спеціального призначення.

Ключові слова: складні сигнали, оптимізація, еволюційний алгоритм; часова область, кореляція, спектр; перетворення; Парето фронт.

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INTRODUCTION

In modern telecommunication systems, the formation and processing of complex signals play a key role in ensuring interference robustness, efficient spectrum utilization, and channel separation. Particular importance is given to methods that enable the formation of signal ensembles with controllable correlation, energy, and spectral characteristics. Depending on the specific tasks, signal analysis and synthesis involve time–frequency representation methods, spectral analysis, entropy-based approaches, as well as evolutionary optimization algorithms [1–21].

Despite the wide variety of existing approaches, most of them are focused on optimizing individual signal characteristics or system parameters, while the process of forming ensembles of complex signals in the time domain is considered only to a limited extent. This motivates the need for developing methods in which structural signal representation, controlled transformation of time-domain segments, and multi-objective optimization are treated as a unified and coordinated problem.

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

In practical problems of forming ensembles of complex signals, the choice of structural transformation methods and their parameters directly affects the mutual correlation level of signals, their spectral characteristics, and robustness to interference. The use of fixed or empirically selected transformation parameters does not ensure a coordinated achievement of the required characteristics, while the combinatorial nature of the solution space significantly limits the effectiveness of classical optimization methods.

In this regard, an important scientific and practical problem is the development of methods for forming ensembles of complex signals based on controlled structural transformation of time-domain segments using multi-objective optimization, which enables simultaneous consideration of correlation, energy, and spectral characteristics. Solving this problem is essential for improving the efficiency of telecommunication systems for special purposes operating under complex interference conditions.

ANALYSIS OF RESEARCH AND PUBLICATIONS

An analysis of recent research and publications [1–21] shows that existing approaches to the formation and optimization of complex signals are primarily focused on solving specific tasks, such as peak reduction, spectral parameter optimization, or improving interference robustness, without comprehensive consideration of the process of ensemble formation in the time domain.

A significant number of studies are devoted to the application of genetic algorithms and their modifications for solving optimization problems in telecommunication systems [1, 2, 8–10, 20, 21]. In these works, the main focus is placed on optimizing individual signal or network parameters, including peak power reduction, spectrum efficiency improvement, and enhancement of transmission characteristics, while the structural formation of signal ensembles is only partially addressed.

Optimization methods used in signal processing and synthesis, particularly in the design of filters and signals with predefined spectral properties, demonstrate the effectiveness of evolutionary approaches in complex multidimensional search spaces [12–16]. However, in such studies, optimization is typically performed for a fixed signal structure, without considering the possibility of controlled structural transformation through permutations of time-domain segments.

In studies devoted to the formation of complex-signal ensembles and the analysis of their properties [4, 11], the potential of structural transformations for improving correlation characteristics has been demonstrated. Nevertheless, in most cases, the parameters of such transformations are either predefined or selected empirically, without their integration into a multi-objective optimization framework.

Research in the field of cognitive radio and adaptive telecommunication systems [3, 18, 19] emphasizes the need for forming signals with controllable properties under dynamically changing interference conditions and limited spectral resources. However, existing approaches do not provide a coordinated consideration of correlation, energy, and spectral characteristics within a unified optimization model.

Therefore, the analysis of publications [1–21] indicates the absence of approaches in which the process of forming ensembles of complex signals is formulated as a multi-objective optimization problem with explicit consideration of signal structural representation in the form of time-domain segments, a control parameter governing their permutation, and the requirements for correlation and spectral characteristics under complex interference conditions.

MATHEMATICAL FORMULATION OF THE PROBLEM

At the stage of preliminary research, a method for forming ensembles of complex signals based on parameterized structural transformation of time-domain segments was proposed. The method includes a sequence of stages such as signal segmentation, structural transformation, and ensemble formation (Fig. 1).

The obtained experimental results have shown that the efficiency of the formed ensembles of complex signals is determined not only by the structural transformation procedure itself, but also by the choice of the control parameter θ and the need to simultaneously consider multiple criteria, including correlation, energy, and spectral characteristics.

In this regard, the problem of forming ensembles of complex signals can be formulated as a multi-objective optimization problem, which requires the application of specialized algorithmic approaches. To solve this problem, the use of evolutionary algorithms is appropriate, as they enable efficient search in a multidimensional solution space and allow the formation of a set of compromise solutions.

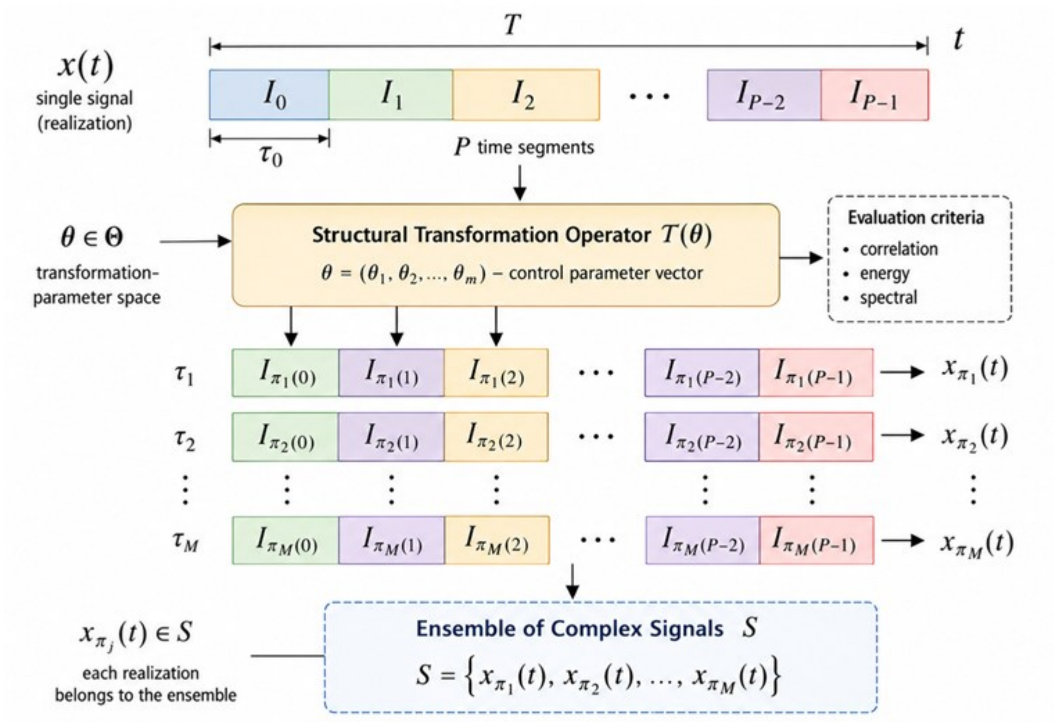

Fig. 1. Main stages of complex signal ensemble formation

Among the existing approaches, the NSGA-III algorithm is of particular interest, as it provides an effective solution for multi-objective optimization problems and ensures a uniform distribution of solutions along the Pareto front. However, the classical implementation of NSGA-III does not take into account the specific features of the signal formation problem, particularly the structural representation of signals in the form of time-domain segments.

Therefore, in this study, a modification of the NSGA-III algorithm is proposed. The modification includes the use of structural encoding of solutions in the form of permutations of time segments, the introduction of the control parameter θ as an element of the solution space formation, and the adaptation of crossover and mutation operators to the problem of segment permutation (Fig. 2).

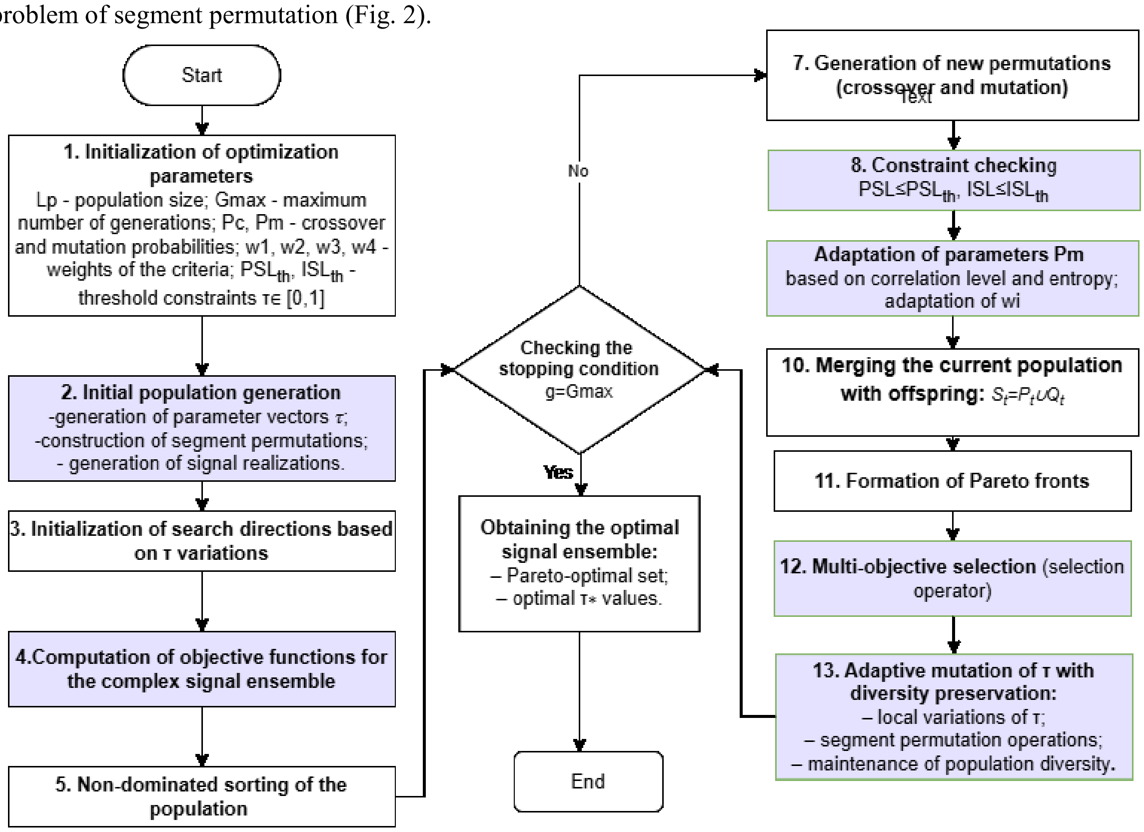

Fig. 2. Block diagram of the modified NSGA-III algorithm

To formalize the proposed algorithm, a set of mathematical relationships is used to describe the signal formation process and the criteria for its evaluation.

The base signal $s(t)$ is divided into a set of time-domain segments:

$$s(t) \rightarrow \{I_0, I_1, \dots, I_{P-1}\}. \quad (1)$$

The formation of a new signal realization is performed by permuting the segments according to the control parameter θ:

$$s^{\theta}(t) = \mathcal{P}_{\pi(\theta)}\{s(t)\}, \quad (2)$$

where $\pi(\theta)$ denotes the permutation of segment indices determined by the parameter θ.

The quality of the generated signals is evaluated using correlation-based metrics. The peak sidelobe level (PSL) is defined as:

$$PSL = \max_{k \neq 0} |R(k)|, \quad (3)$$

the integrated sidelobe level (ISL) is defined as:

$$ISL = \sum_{k \neq 0} |R(k)|^2, \quad (4)$$

the structural entropy of the signal is defined according to Shannon's formulation:

$$H = -\sum p_i \log p_i. \quad (5)$$

In this study, the entropy measure is used as an indicator of structural disorder; therefore, its reduction corresponds to the formation of a more ordered and controlled signal ensemble.

Thus, the problem of forming a signal ensemble is formulated as a multi-objective optimization problem:

$$min\{PSL, ISL. H\}. \quad (6)$$

The presented mathematical formulation serves as the basis for the implementation of the proposed algorithm and its subsequent experimental validation.

EXPERIMENTAL RESULTS

The effectiveness of the proposed method is confirmed through experimental modeling. During the simulations, input signals of limited duration were subjected to structural transformation by parameterized permutation of time-domain segments using the control parameter θ. This approach enables the formation of signal ensembles with controllable correlation properties, which is particularly important for ensuring interference robustness and channel separation in telecommunication systems for special purposes.

The evaluation of performance was carried out using the peak sidelobe level (PSL) of the autocorrelation function, the integrated sidelobe level (ISL), and entropy-based characteristics reflecting the degree of structural ordering of the signal.

The optimization of ensemble formation parameters was performed using the modified evolutionary NSGA-III algorithm, which allows simultaneous consideration of multiple conflicting criteria and the formation of a set of Pareto-optimal solutions. A classical genetic algorithm and a non-optimized signal formation approach were used as baseline methods for comparison.

Table 1 and Figure 3 present the results of the analysis of optimization process stability and the assessment of the appropriateness of stopping criteria selection. The study was conducted under different termination conditions of the evolutionary process, including those based on changes in the objective function ΔK, reaching a predefined PSL threshold, and stabilization of the Pareto front.

Table 1

Optimization criteria at algorithm stopping points

Stopping criterion	Параметр	PSL	ISL	H	Gen
$\Delta K<1\times10^{-4}$	$\varepsilon=1\times10^{-4}$	0,052	10,8	0,66	92
$\Delta K<1\times10^{-5}$	$\varepsilon=1\times10^{-5}$	0,048	9,7	0,63	148
PSL threshold	0,05	0,050	10,2	0,65	31
Pareto stable	$\delta=0{,}01$	0,047	9,5	0,63	193

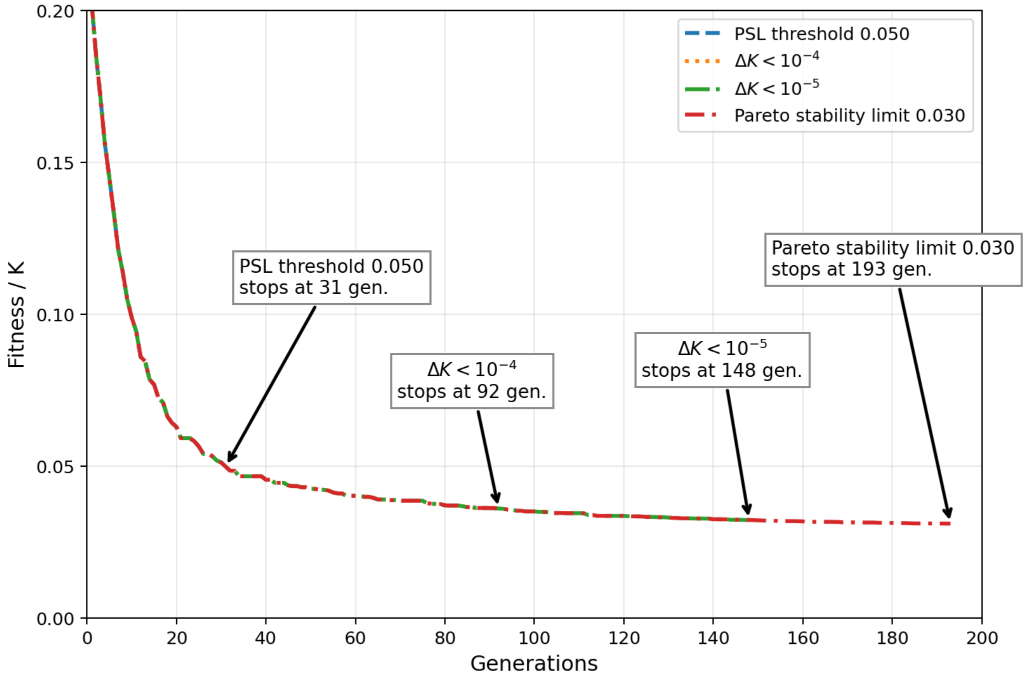

Fig. 3. Dynamics of the objective function and algorithm stopping criteria

As shown in Table 1 and Figure 3, the choice of the stopping criterion directly affects the achieved values of PSL, ISL, and the duration of the optimization process. The use of the threshold criterion PSL≤0,05 ensures termination of the algorithm at the 31st generation; however, it is associated with higher values of the integrated sidelobe level (ISL=10,2) and entropy (H=0,65).

Transition to the criterion $\Delta K<10^{-4}$ increases the number of generations to 92 (three times higher), while resulting in a 5,9% reduction in ISL and a 1,5% decrease in H compared to the PSL threshold criterion.

The use of a stricter criterion $\Delta K<10^{-5}$ further increases the optimization duration to 148 generations (60,9% higher compared to $\Delta K<10^{-4}$), while reducing ISL by an additional 10,2% and PSL by 7,7%. In the case of the Pareto front stabilization criterion, the algorithm terminates at the 193rd generation, which is 6,2 times higher than for the PSL threshold criterion, while achieving the minimum values PSL=0,047 and ISL=9,5.

Thus, the criterion $\Delta K<10^{-4}$ provides a balance between the achieved correlation characteristics of the signal and the duration of the optimization process.

At the next stage of the experiment, a convergence analysis of evolutionary optimization algorithms was performed, focusing on the dynamics of changes in PSL and ISL indicators during the process of signal ensemble formation using the modified NSGA-III algorithm, the classical genetic algorithm, and the non-optimized approach (Table 2, Figure 4).

Table 2

Calculated values of PSL and ISL

Generation	Modified NSGA-III PSL	Modified NSGA-III ISL	Classical GA PSL	Classical GA ISL	Non-optimized PSL	Non-optimized ISL
1	1,000	1,000	1,020	1,010	0,970	0,950
20	0,680	0,710	0,810	0,860	0,890	0,930
40	0,550	0,590	0,710	0,730	0,850	0,890
60	0,520	0,540	0,670	0,680	0,820	0,850
80	0,505	0,525	0,640	0,650	0,800	0,830
100	0,490	0,520	0,630	0,630	0,790	0,820

As shown in Table 2 and Figure 4, the modified NSGA-III provides the lowest PSL and ISL values after 100 generations. Compared to the classical genetic algorithm, the PSL value decreases from 0,630 to 0,490, i.e., by 22,2 %, while the ISL value decreases from 0,630 to 0,520, i.e., by 17,5 %. Compared to the non-optimized approach, PSL decreases by 38,1 %, while ISL decreases by 36,6 %.

The obtained experimental results indicate a more balanced reduction of correlation-based characteristics when using the modified NSGA-III evolutionary algorithm.

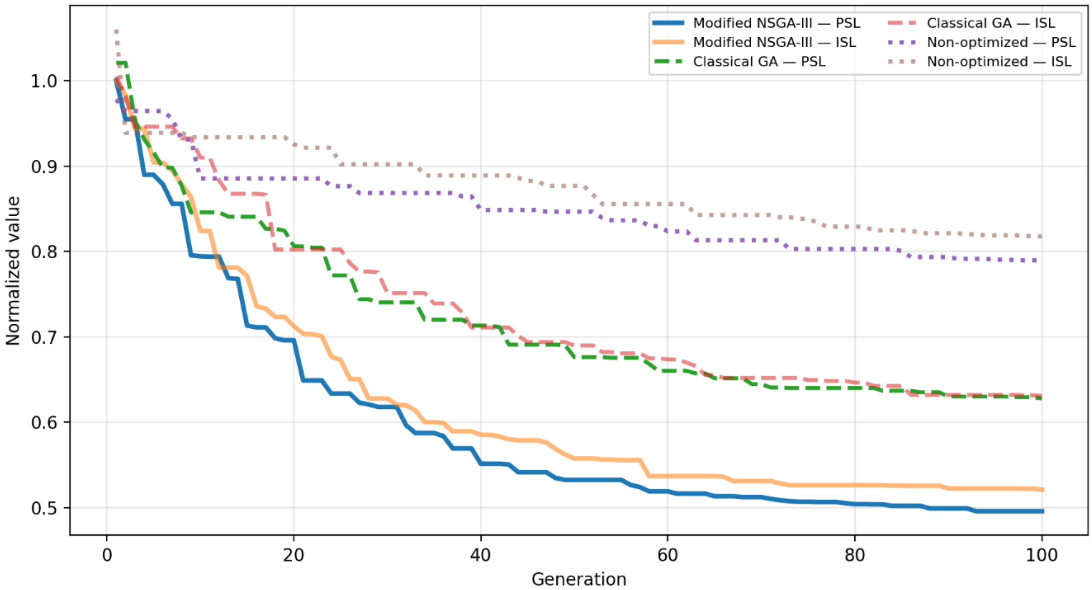

Fig. 4. Convergence dynamics of optimization algorithms

At the next stage of the experimental study, the influence of the control parameter θ on the characteristics of the formed signal ensemble was investigated. In particular, the variation of *PSL, ISL*, and the entropy measure *H* was analyzed as a function of the parameter θ, which determines the mode of structural signal transformation (Table 3, Figure 5).

Table 3

Calculated values of PSL, ISL, and H depending on the parameter θ

θ	PSL	ISL	H	θ
0,10	0,80	0,72	0,93	0.10
0,20	0,77	0,70	0,90	0.20
0,30	0,76	0,71	0,91	0.30
0,40	0,78	0,70	0,90	0.40
0,50	0,71	0,63	0,78	0.50
0.55	0,64	0,55	0,72	0.55
0,60	0,59	0,51	0,70	0.60
0,62	0,60	0,52	0,71	0.62
0,70	0,66	0,57	0,75	0.70
0,80	0,77	0,70	0,86	0.80
0,90	0,76	0,71	0,92	0.90

As shown in Table 3 and Figure 5, at θ=0,60, the PSL value decreases by 26,25 %, which leads to a corresponding reduction in the level of peak correlation interference between signals in the ensemble. The ISL value decreases by 29,17 %, indicating a reduction in the integrated level of mutual signal influence and contributing to interference mitigation in telecommunication systems for special purposes.

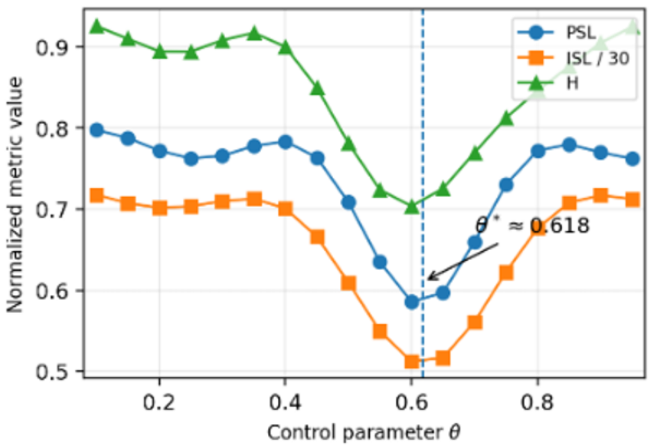

Fig. 5. Influence of the control parameter θ

The entropy measure H decreases by 24,73 %, which indicates a reduction in the degree of signal randomness and the formation of a more structured ensemble suitable for stable processing.

At the next stage of the experiment, the selection of an optimal solution based on a set of conflicting criteria is performed. For this purpose, a multi-objective optimization approach is employed, which allows simultaneous consideration of PSL and ISL indicators without reducing them to a single aggregated criterion.

Based on the results of the evolutionary search, a set of feasible solutions is obtained, from which a Pareto-optimal subset is identified. For these solutions, any further reduction of one indicator leads to an increase in the other (Figure 6).

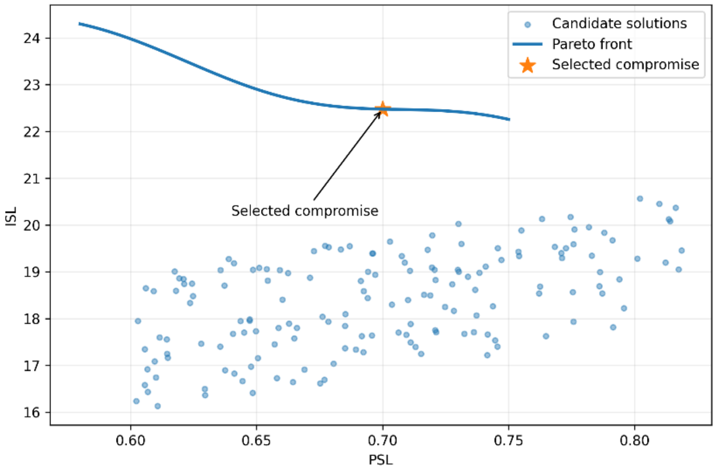

Fig. 6. Pareto-optimal set for the complex signal ensemble

As shown in Figure 6, the obtained Pareto set reflects the trade-off between PSL and ISL indicators. The selected compromise solution corresponds to PSL=0,70 and ISL=22. This indicates that further reduction of the peak sidelobe level (PSL) is accompanied by an increase in the integrated sidelobe level (ISL), and vice versa.

The choice of this solution is determined by the fact that it is not extreme with respect to any of the considered criteria and ensures a balanced trade-off between peak and integrated correlation components. In contrast to solutions with lower PSL values, which are associated with an increase in ISL, the selected solution avoids excessive growth of the total sidelobe energy while maintaining an acceptable peak sidelobe level.

At the next stage of experimental modeling, a spectral analysis of the generated signals was performed to evaluate changes in their correlation characteristics in the frequency domain. For this purpose, a comparison of the spectral characteristics of signals before optimization, after applying the classical genetic algorithm, and after applying the modified NSGA-III algorithm was conducted. The main focus was on evaluating the peak sidelobe level (PSL) and the integrated energy of out-of-band components, which characterizes the overall level of interference components in the signal (Table 4, Figure 7).

The ISL (proxy) metric is used as an approximate estimate of the integrated sidelobe energy, defined in the frequency domain as the total energy of out-of-band spectral components of the signal. This allows for assessing the level of interference components without direct computation of the autocorrelation function.

Table 4

Comparison of PSL and ISL for different optimization methods

Method	PSL	PSL, dB	ISL (proxy)	ISL, dB	PSL reduction, %	ISL reduction, %
Before optimization	0,336	− 9,48	0,0206	−16,86	0,0	0,0
Genetic algorithm (GA)	0,245	−12,22	0,0128	−18,93	27,1	37,9
Modified NSGA-III	0,178	−14,99	0,0081	−20,91	47,0	60,7

As shown in Table 4 and Figure 7, the application of evolutionary algorithms leads to a reduction in both the peak sidelobe level and the integrated energy of out-of-band signal components. When using the classical genetic algorithm, the PSL value decreases from 0,336 to 0,245, which corresponds to a reduction of 27,1 %, whereas the application of the modified NSGA-III results in a reduction of 47,0 %. Similarly, the ISL (proxy) value decreases from 0,0206 to 0,0128 (37,9 %) for the genetic algorithm and to 0,0081 (60,7 %) for the modified NSGA-III.

The results of the conducted experiment confirm that the use of the modified NSGA-III algorithm provides a significant reduction in both peak and integrated interference components of the signal.

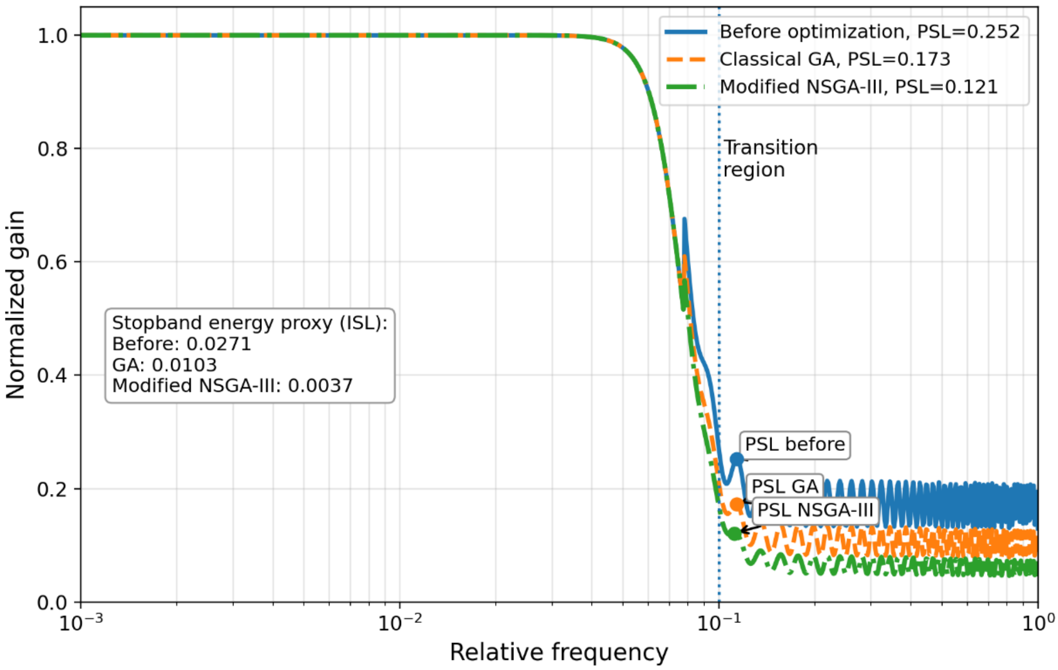

Fig. 7. Spectral characteristics of signals

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

The paper substantiates the feasibility of applying evolutionary algorithms to solve the problem of forming ensembles of complex signals, which is characterized by a high-dimensional and combinatorial nature. A modification of the NSGA-III algorithm is proposed, taking into account the specific features of the signal formation task. The approach is based on structural encoding in the form of permutations of time segments, the introduction of a control parameter for shaping the solution space, and the adaptation of crossover and mutation operators to the problem of structural signal transformation.

The results of experimental modeling confirm that the application of the modified NSGA-III evolutionary algorithm ensures a coordinated reduction of PSL and ISL indicators, the formation of a set of Pareto-optimal solutions, and an increase in the efficiency of forming ensembles of complex signals under interference conditions.

Further research should be focused on extending the proposed approach to multichannel and multiband systems, as well as on improving the evaluation criteria for signal ensembles, taking into account complex interference environments.

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