UDC 621.391

OPTIMIZATION OF THE PARAMETERS OF SYNTHESIZED SIGNALS USING LINEAR APPROXIMATIONS BY THE NELDER-MEAD METHOD

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ABSTRACT

Context. The article presents the results of a study of the effectiveness of using the Nelder-Mead method to optimize the parameters of linear approximations of synthesized signals. Algorithms have been developed and tested that integrate spectral, temporal, and statistical analyzes and provide reasonable optimization. The effectiveness of the application of the Nelder-Mead method was proven by experiment. The obtained results substantiate the improvement of the properties of the mutual correlation of signals and the reduction of the maximum deviations of the side lobes, which opens up prospects for the further application of the method in complex scenarios of signal synthesis.

Objective. The purpose of the work is to evaluate the effectiveness of the application of the Nelder-Mead method when adjusting the parameters of linear approximations to optimize the mutual correlation and minimize side deviations of complex synthesized signals.

Method. The main research method is the comparison of various optimization algorithms for the selection of the most effective approaches in linear approximations of synthesized signals, taking into account such criteria as accuracy, speed and minimization of deviations. Scientific works [1, 2, 4–6, 8, 9] present algorithms, including the Nelder-Mead method and differential evolution. The effectiveness of these methods is achieved due to adaptive optimization procedures that improve the characteristics of signals.

It is worth noting that the methods have disadvantages associated with high requirements for computing resources, especially when processing large data. This can be minimized using combined optimization methods that take into account the interaction of signal parameters. Another important direction of improvement is the optimization of methods for adaptation to dynamic changes in the characteristics of complex signals, which allows to achieve high adaptability and reliability of real-time systems.

Results. As a result of the experiment using the Nelder-Mead method, an increase in the similarity of spectral densities was achieved from 0.52 in the first iteration to 0.90 in the fourth, with a significant decrease in the distance between the peaks of the spectrum from 1.2 to 0.4, which indicates high adaptability and the accuracy of the method in adjusting the parameters of the synthesized signals.

Conclusions. The effectiveness of the Nelder-Mead method for adjusting the specified parameters of the synthesized signals was experimentally proven, which is confirmed by a significant improvement in the similarity of the spectra with each iteration. This opens the way for additional optimizations and application of the method in various technological areas.

KEYWORDS: optimization method, synthesized signals, Nelder-Mead method, approximation by linear functions, spectral characteristics, ensemble properties of signals, iteration algorithm, noise immunity, side lobe emissions.

NOMENCLATURE

$J(x)$ is an objective function

$x(t)$ is a signal;

$y(t)$ is a set value for deviation;

T is a duration;

E is an energy;

BW is a spectrum width;

C is a cross-correlation;

$P(t)$ is a deviation of the signal at the moment of time;

t is a time index;

λ, μ, ξ, ν is a parameters that regulate the weight between the deviation criterion and the side lobes;

x_i^0 is the initial value of the *i*-th variable;

x_r is a displayed point;

x_c is a centroid, calculated as the arithmetic mean of all points of the simplex, except for the worst one;

x_h is the worst point of the simplex, the point with the highest value of the objective function;

α is a “reflection” coefficient;

x is a set of parameters for an ensemble of signals;

S_x is a spectral density of an ensemble of signals with parameters *x*;

S_0 is a given spectral density;

H_x is a signal function with parameters *x*;

H_0 is a given signal function;

$w_1 w_2$ is a weighting factors that determine the importance of the similarity of the spectral densities and the level of blurring of the side lobes;

$Sim_{ensemble}$ – the similarity function, which takes into account the similarity between the spectral characteristics of the signals in the ensemble;

$Blur_{resis\tan s}$ is a blur function that takes into account the blurring of the side lobes of the signal function;

DOI 10.15588/1607-3274-2024-3-4

α, β is a weighting factors that regulate the importance of ensemble properties and immunity properties, respectively;

$S_i(t), S_j(t)$ is a functions of the spectral density of two different distributions of signals ("true" distribution and approximation of this distribution);

$\log\left(\frac{S_i(t)}{S_j(t)}\right)dt$ is a logarithm of the ratio of the distribution densities at each moment of time *t*, which reflects the local difference between them;

σ is a standard deviation or scale of uncertainty or noise;

t is a time parameter;

S(*t;*θ) is a signal or its spectral component depends on certain parameters θ$;

$\int_{\infty}^{-\infty} \exp\left(-\frac{t^2}{2\sigma^2}\right)$ is a Gaussian function that decreases on either side of the center.

INTRODUCTION

Optimizing the parameters of synthesized signals using methods with constraints that use approximation by linear and nonlinear functions is a promising and relevant area of research [1–14]. These methods make it possible to obtain signals with specified spectral, temporal, statistical and other characteristics, including a high level of immunity. They turn the problem of signal synthesis into the problem of optimizing the chosen objective function, which contains physical or technological limitations [2, 6, 8]. Various approaches are used to study the properties of synthesized signals, in particular, the analysis of their frequency, time characteristics and resistance to interference. Solving this problem is important and necessary for improving the efficiency of telecommunication systems, because it ensures their stable and reliable operation in conditions of various disturbances.

The object of study is the process of optimizing synthesized signals according to given parameters.

The subjects of study are optimization algorithms and methods, in particular the Nelder Mead method.

The purpose of this work is to evaluate the effectiveness of the Nelder-Mead method for optimizing the parameters of linear approximations of synthesized signals in order to improve their properties.

1 PROBLEM STATEMENT

Let us consider the most effective methods of approximating functions for solving optimization problems in signal synthesis. Classical optimization methods with constraints, which are based on the approximation of the objective function by linear functions, are widely used for the synthesis of signals with defined characteristics. Such methods include the Nelder-Mead method, methods based on gradients, Newton's method, and others [1, 3, 5]. We will analyze the effectiveness of the Nelder-Mead method for the synthesis of complex signal ensembles, in particular, focusing on improving the cross-correlation properties and significantly reducing the maximum deviations of the side lobes of the target function.

Methods based on linear approximation of the objective function systematize scientific optimization problems using the universal algorithm presented in Fig. 1.

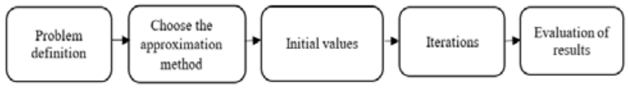

Figure 1 – General optimization algorithm by linear approximation

These methods, in particular, make it possible to simplify the optimization process through the linear representation of complex dependencies, which is the key to effectively solving a wide range of current scientific problems.

Linear approximation provides ease of use and implementation, especially when initial data or functional dependencies are too complex for direct analysis. It allows you to estimate the influence of various parameters on the target function with high accuracy, without delving into the excessive complexity of real processes. The main stages of this algorithm include defining the problem, choosing an approximation method, calculating parameters, verifying the obtained results, and correcting the model for the purpose of optimization.

2 REVIEW OF THE LITERATURE

Research in the field of optimizing the parameters of synthesized signals using the Nelder-Mead method and other evolutionary algorithms is actively considered in the scientific works of various authors. The works [1, 4, 5, 6, 8, 9, 10, 12, 13] analyze various aspects of linear and nonlinear signal approximations, demonstrating significant progress in improving the spectral characteristics and efficiency of signals. However, these studies also reveal underexplored areas, such as the impact of algorithmic constraints on system scalability and stability under diverse conditions. Special attention is drawn to the works [2, 3, 11, 14], which investigate the use of Nelder-Mead and other optimization methods for improving block diagrams of signal processing and their analytical models. It was found that despite the effectiveness in specific scenarios, there are problems with the integration of these approaches into wider systems, which requires further research into the adaptation and scaling of the algorithms. The comparative analysis of optimization methods presented in [7] indicates the differences in efficiency and areas of application of various approaches, offering additional opportunities for improving interoperability and interaction in complex scenarios. Also an important aspect is the development and optimization of automatic control systems, as stated in [8], where the Nelder-Mead algorithm is used to achieve higher accuracy and control adaptability.

These works formed the basis for further research devoted to the evaluation of the effectiveness of optimiza-

DOI 10.15588/1607-3274-2024-3-4

tion methods for linear approximations of synthesized signals, namely the Nelder-Mead method for complex signal ensembles, where high accuracy and adaptability to variable conditions are critical. The use of such methods will allow not only to improve the characteristics of signals, in particular their spectral efficiency and mutual correlation, but also to ensure a high level of immunity and performance in complex and dynamic telecommunications systems that require high reliability and adaptation to environmental changes.

3 MATERIALS AND METHODS

Let us consider in more detail the stages of the general optimization algorithm by linear approximation.

Preliminary Stage. An optimization problem is determined with the formalization of the objective function and constraints. For demonstration, consider the problem of signal synthesis. [3].

Let the signal be the specified value for the deviation, and the objective function is defined as the sum of the squares of the deviations of the side lobes from the specified value [5] by the formula (1):

$$J(x) = \sum_t x(t) - y(t))^2 . \quad (1)$$

Limitations determine such parameters of the ensemble of signals as their duration, energy, spectral width, mutual correlation, etc. This approach is essential to minimize the discrepancies between the side lobes and the desired signal profile, ensuring optimal signal quality and performance. By focusing on the deviations of the side lobes, we can effectively control and optimize the overall signal structure.

Suppose there are restrictions on the duration of the signal duration, energy, spectrum width, cross-correlation, then the mathematical system of restrictions will look like this in the sample:

$$\begin{cases} g_1(x) = T - T_{\max} \le 0, \\ g_2(x) = E - E_{\max} \le 0, \\ g_3(x) = BW - BW_{\max} \le 0, \\ g_4 = C - C_{\max} \le 0 \\ .... \end{cases} \quad (2)$$

The cross-correlation determined by the formula (3) [7, 6]:

$$C_{xy}(\tau) = \frac{\sum_t x(t_i) y(t_i)}{\sqrt{\sum_t x(t_i)^2 \cdot \sum_t y(t_i)^2}} . \quad (3)$$

The discrete approximation for sequences is calculated by the formula (4):

$$C_{xy}[n] = \sum_{m=-\infty}^{\infty} x[m] \cdot y[m+n] . \quad (4)$$

In this case, it is also necessary to consider the parameter of the signal energy, which is determined as the square of its amplitudes. For the signal *x(t)* it is calculated using the mathematical formula: $E = \int_{-\infty}^{\infty} |x(t)|^2 dt$. In the case of a discrete signal or sequence $x[n]$, it takes the form of the mathematical expression [2, 4, 11]:

$$E = \sum_{n=-\infty}^{\infty} |x[n]|^2 . \quad (5)$$

The side lobes of the signal reflect the deviation of the signal amplitude from its average value $P(t) = x(t) - x_{aver}$. This indicator is an important parameter for evaluating signal quality and stability. To quantify these deviations, the sum of the squares of the deviations is used, which is determined by the following formula (6) [5]:

$$J_{side} = \sum_t P^2(t). \quad (6)$$

To consider the objective function in the optimization problem along with the cross-correlation and constraints, the general optimization problem will look like this formula (7):

$$\min J(x) + \lambda \cdot C + \mu \cdot (T - T_{\max}) + \nu \cdot (E - E_{\max}) + \xi \cdot (BW - BW_{\max}). \quad (7)$$

1 Stage. Determination of initial values of variables. At this stage, the initial values of the variables to be optimized are determined. These values can be chosen arbitrarily or with the help of expert judgments. The choice of initial values is important because they can affect the rate of convergence of the optimization algorithm and whether it reaches a global or only a local optimum. Initial values obtained from previous experiments or simulations can be used for the task of optimizing signal parameters. If the initial values of the variables are chosen arbitrarily or with the help of expert estimates, they can be specified by a formula [10,13]:

$$x^0 = \left[x_1^0, x_2^0, x_3^0, \ldots x_n^0\right] \quad (8)$$

2 Stage. Iterative method for finding optimal values of variables. This stage involves the use of an iterative method to find new values of variables that are closer to the optimal ones. At each iteration, the method updates the values of the variables, trying to decrease (or increase) the objective function. Examples of such methods are Nelder Mead, gradient descent, Newton, or heuristic optimization algorithms such as genetic algorithms [6, 13].

3 Stage. Evaluation of the optimization result and checking for compliance with constraints. To evaluate the optimization result, it is necessary to check whether the obtained variable values satisfy the constraints of the problem. If not, then it is necessary to continue the execution of the optimization method.

DOI 10.15588/1607-3274-2024-3-4

4 At the final stage, the model is corrected and further optimized (if necessary).

Let us consider in more detail the solution of the optimization problem using the Nelder-Mead method. The Nelder-Mead method is one of the most popular constrained optimization methods. It provides an effective search for the optimum within the permissible values of the variables, as it works by successive refinement of the estimate of the global minimum of the function [6, 9].

The Nelder-Mead method, also known as the deformed simplex method, is one of the direct optimization methods that does not require the calculation of function gradients. It is especially useful in problems where it is difficult or impossible to calculate the gradient, or where the function has numerous local extrema [14].

The general view of the optimization algorithm according to the Nelder-Mead method is presented in Fig. 2.

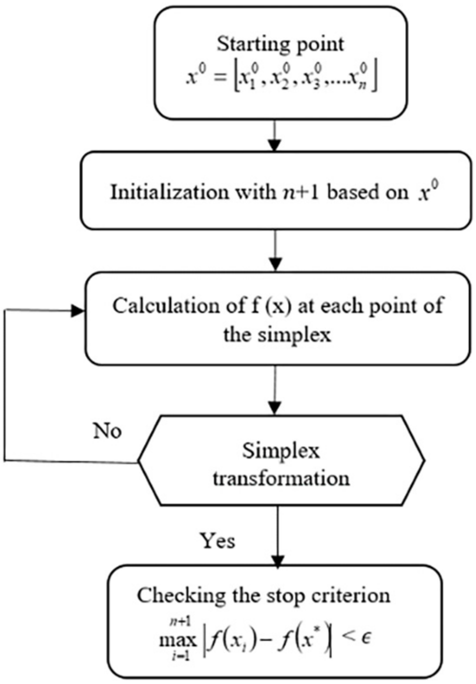

Figure 2 – Optimization algorithm based on the Nelder-Mead method

The main stages of calculation by the Nelder-Mead method are the following.

1. Initialization. Selection of initial simplex consisting of n +1 points in n – dimensional space. These points need not lie on the same hyperplane to form a dimensional simplex. Each point of the simplex is initialized so that they are located close enough to each other, but at the same time form a structure sufficient to start the optimization process.

2. Evaluation of the function. Calculation of the value of the objective function at each of n +1 points of the simplex. Ranking points by function value from best (lowest value) to worst (highest value).

3. Simplex transformation. It consists of a step – reflection – that is, the calculation of the mapped point relative to the worst point to investigate whether a better value can be found outside it, and extension – that is, if the mapped point shows an improvement, the method will try to "stretch" the simplex in that direction to investigate further. The formula for this step of the algorithm looks like this formula (10) [2]:

$$x_r = x_c + \alpha(x_c - x_h). \quad (9)$$

This formula allows you to calculate a new point x_r, which is a "mirror" of the worst point x_h relative to the centroid x_c, directing the search in a direction that can improve the value of the objective function. If no improvement can be found, the simplex is compressed towards the best point. If compression also fails, reduction is performed, where the simplex is reduced in size around the best point.

4. Checking the stop criterion. To check the stopping criterion in the Nelder-Mead method, the concept of standard deviation or another indicator of the dispersion of the function values among the points of the simplex is used. One approach is to check whether the maximum difference between the function values at the simplex vertices $f(x_i)$ and the function value at the best point $f(x^*)$ does not exceed a given threshold $\in$. If the condition is fulfilled, the optimization process ends, there is no need for further iterations [8], formula (10):

$$\max_{i=1}^{n+1} \left| f(x_i) - f(x^*) \right| < \in. \quad (10)$$

For practical testing, consider the application of the optimization algorithm based on the Nelder-Mead method for the synthesis of signals with specified ensemble properties and noise immunity. This method is optimal for application in the case of minimizing the difference between the spectral characteristics of the generated signals and the given target spectral density, as well as for controlling the blurring of the sidelobe deviation level. Mathematically, the function for the task of creating an ensemble of signals with a given similarity of spectral densities and a defined level of blurring of the side lobes is defined as [6] formula (11):

$$f(x) = w_1 \cdot \|S_x - S_0\|^2 + w_2 \cdot \|H_x - H_0\|^2. \quad (11)$$

This function defines the main minimization criterion for solving the problem of synthesis of signals with defined properties. The goal is to find such a set of parameters x that minimizes the function. The general form of the functional for optimization using the Nelder-Mead method for the synthesis of signals with given ensemble properties and immunity properties can be formulated as formula (12) [3]:

$$f(\theta) = \alpha \cdot Sim_{ensemble}(S) + \beta \cdot Blur_{resistans}(S(\theta)). \quad (12)$$

DOI 10.15588/1607-3274-2024-3-4

This approach allows the signal parameters to be precisely tailored to optimally meet the given criteria and ensure efficiency in a wide range of applications, from telecommunications to radar.

For a given objective function, different measures can be chosen to evaluate the similarity and blurring of signals. The choice of a specific measure depends on the specifics of the task and the desired characteristics of the signal. For similarity function can be selected:

– Kullback-Leibler similarity measure. It is especially valuable in scenarios where complex signal ensembles need to be analyzed, such as those used in telecommunications, cryptography, or radar. This measure not only allows us to measure the distance between two probability distributions, but also provides insights into the effectiveness of representing one distribution by another. For complex signal ensembles, the Kullback-Leibler measure provides a deeper understanding of how effectively a particular modulation or coding scheme can reproduce the properties of the original signal [7].

This is important in situations where highly complex signals need to be accurately reconstructed, such as in satellite communication systems, where every lost or distorted bit can lead to serious errors in data transmission. A measure is used to measure the distance or difference between two probability distributions, allowing us to estimate how much one signal distribution deviates from a reference distribution. The mathematical expression that describes the Kullback-Leibler similarity measure can take the form [9, 10]:

$$Measure_{KL}\left(S_i,S_j\right)=\int_{\infty}^{-\infty} S_i(t)\log\left(\frac{S_i(t)}{S_j(t)}\right)dt. \quad (13)$$

The integral is calculated over all possible values of t, which makes it possible to estimate the total difference between the distributions over the entire range of their definition.

– Gaussian similarity measure. This measure is based on considering the spectral density of signals as Gaussian processes, which allows us to estimate the differences between them through the parameters of their distributions. Unlike the Kullback-Leibler similarity measure, it does not evaluate the difference between probability distributions, but focuses on the analysis of deviations between two signals taking into account noise or uncertainty:

$$Measure_G\left(S_i,S_j\right)=\exp(-\frac{1}{2}\int_{\infty}^{-\infty}\left(\frac{S_i(t)-S_j(t)}{\sigma}\right)^2 dt). \quad (14)$$

The exponential function transforms the result into a range from 0 to 1, where a value closer to 1 means a smaller total deviation between $S_i(t), S_j(t)$, i.e. a higher similarity. Function blurring $Blur_{resis\tan s}$ may include the following measures [5, 8]:

– Gaussian blur measure: used to estimate the fuzziness of the side lobes of a signal by modeling them as a Gaussian process. This helps determine the level of smoothing of unwanted spectral components:

$$Measure_G Blur(S(t;\theta))=\int_{\infty}^{-\infty}\exp\left(-\frac{t^2}{2\sigma^2}\right)\left|S(t;\theta)\right|dt. \quad (15)$$

Gaussian function that decreases on either side of the center. The integral of this function along t gives a general estimate of the effect of Gaussian blur on the signal.

– Riemann-Lebesgue blur measure: takes into account the integral sum of deviations from the “reference” (“ideal”) level of the side lobes, which allows for a more accurate assessment of their impact on the overall signal purity:

$$Measure_{RL}Blur(S(t;\theta))=\int_{\infty}^{-\infty}\frac{\left|\varphi\left[S(t;\theta)\right](w)\right|}{1+w^2}dw. \quad (16)$$

Differentiated application of various measures allows for the adaptation of the optimization algorithm to solve specialized tasks in the field of signal synthesis and analysis. The use of the Kullback-Leibler similarity measure provides a deep understanding of the efficiency of reproducing complex signals, which is critically important for telecommunications and cryptography. The Gaussian similarity measure accounts for deviations between signals considering noise, enhancing the accuracy of evaluation. The Gaussian blur measure and the Riemann-Lebesgue blur measure help assess the level of smoothing of unwanted spectral components, improving signal clarity in radar systems and wireless cognitive systems. This approach enables precise tuning of signal parameters, ensuring high efficiency in various applications.

4 EXPERIMENTS

To demonstrate the effectiveness of the Nelder-Mead optimization method in the synthesis of an ensemble of signals with given properties, a Matlab code was developed. The results of the program execution are presented in Figures 3 (a,d.c), which illustrate the process (dynamics) of the current spectral density (blue region) compared to the target spectral density (red region) at each iteration.

The closer the blue line (area) is to the red, the better the optimization result (Table 1).

Parameters: similarity, distance between peaks, error of spectral densities, step size, objective function value, smoothing factor, computation time, sample size, and significance level – show the evolution of the optimization process with each iteration of the Nelder Mead method, and the gradual approximation of the current spectral density to target An additionally introduced smoothing factor is used to eliminate noise and stabilize

DOI 10.15588/1607-3274-2024-3-4

the spectral analysis data, while the computation time reflects the time required for each iteration of data processing, which is important when evaluating the algorithm's performance. Sample size refers to the number of data points used in the spectral analysis and is important to ensure the reliability of the results. Finally, the level of significance was used to statistically check the dynamics of changes between iterations, confirming their significance or insignificance in the course of the experiment.

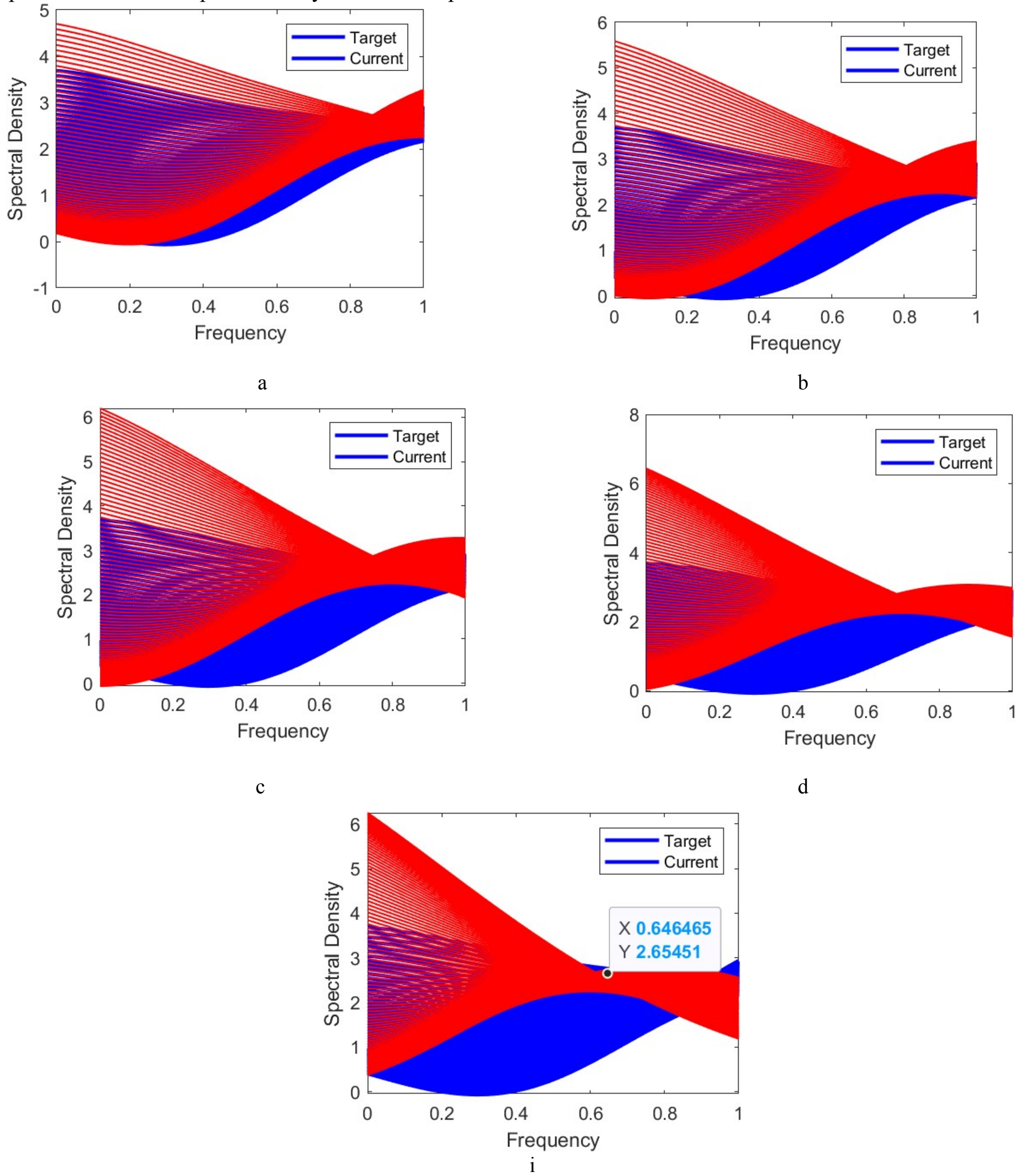

Figure 3 – Iterative optimization process of approximation of the current spectral density value to the target value: a – First iteration, b – The second iteration, c – The third iteration, d – The fourth iteration, i – The fifth iteration

Table 1 – Dynamics of signal spectral density parameters by optimization iterations

Iteration	Similarity	Distance between peaks	Error of spectral densities	Step size	Objective function value	Smoothing factor	Calculation time (sec)	Sample size	Level of significance
1	0.52	1.2	0.5	1.2	0.02	0.1	15	1000	0.05
2	0.68	0.9	0.3	0.9	0.01	0.1	12	1000	0.05
3	0.82	0.6	0.2	0.6	0.005	0.1	10	1000	0.05
4	0.90	0.4	0.1	0.4	0.002	0.1	8	1000	0.05

DOI 10.15588/1607-3274-2024-3-4

Table 1 shows how the similarity process of spectral densities between signal parameters and the target spectrum changes with each iteration of the Nelder-Mead algorithm. This confirms the effectiveness of the method in adapting the signal parameters to achieve optimal values according to the relevant criteria.

5 RESULTS

As can be seen from Table 1 and Fig. 3–7, the similarity of spectral densities increases with each iteration. At the first iteration, the similarity is 0.52, that is, the initial parameters of the signal are very different from the specified spectral density. And on the fourth iteration, the similarity already reaches 0.90, which means that the synthesized signals become more similar to a signal with a given spectral density.

In the fourth iteration, the similarity increased by 78% compared to the first iteration. The distance between the peaks of the spectral densities also decreases with each iteration. In the first iteration, the distance is 1.2, and in the fourth iteration – 0.4. This means that the signal spectra are becoming more and more similar.

The error of the spectral densities also decreases with each iteration.

From the point of view of ensemble properties, the synthesized signals with each iteration become more and more similar to a signal with a given spectral density. This means that they will have similar statistical characteristics such as mean, variance, autocorrelation function.

Fig. 3 (a–i) and table 1 demonstrate that in this experiment, the speed, accuracy and stability of convergence of the Nelder-Mead method is also high. For 4 iterations, it increases the similarity of spectral densities from 0.52 to 0.90, that is, by 90%, which is equal to an increase of 1.7 times.

The Nelder-Mead method used in this experiment proves its high convergence speed and ability to precisely tune signal parameters, which is critical for applications where high accuracy of spectral characteristics is required, such as in communication, radar, and acoustics systems. Optimization that allows for greater similarity of spectra can significantly improve the quality of signal transmission, reducing errors and interference.

The further development of the direction of this research is that the Nelder-Mead method can provide higher efficiency in optimizing the parameters of complex signal ensembles when it is integrated with other technological approaches to further improve the results. In particular, the use of machine learning can help in the selection of initial parameters for an algorithm based on previously analyzed data, which can potentially reduce the number of iterations required and improve the convergence of the algorithm.

Training models on existing data sets can help determine optimal initial parameters for the Nelder-Mead algorithm, reducing the time to reach the optimal configuration. Also, machine learning models can adaptively adjust optimization parameters based on changing environmental conditions or real-time input, thus providing more stable and efficient results. This extension of the Nelder-Mead method can significantly improve its versatility and open up new opportunities for its application in diverse and demanding technological areas.

6 DISCUSSION

The closest analogue to the proposed Nelder-Mead method for optimizing ensembles of complex signals is the method proposed in the work [12]. Unlike the approaches suggested in this paper, the authors of the referenced article applied the differential evolution method for optimizing the parameters of synthesized signals. However, the disadvantage of their methods lies in the low speed due to the need to calculate the distances between instances and the necessity and ambiguity of integrating the indicator into the complex measures of the informativeness of the instances.

Another relevant article [2], which proposes an approach for optimizing signal processing block diagrams using the Nelder-Mead method. The difference in this work is the focus on optimizing the block diagrams of signal processing, whereas our paper addresses the optimization of parameters of synthesized signals. The disadvantage of the method proposed by the authors is the need for numerous iterations to achieve acceptable results, which can lead to significant computational costs.

The advantage of the Nelder-Mead method proposed in this paper lies in its ability to provide an efficient search for the optimum within the permissible values of the variables without requiring the calculation of function gradients, significantly reducing calculation time and increasing convergence speed. However, this drawback can be seen as an advantage in the case of large samples: if we use a computationally simple distribution (e.g., a regular grid) and know the minimum and maximum values of each parameter, the computational cost of the proposed metrics will be lower than using a set of matched filter.

CONCLUSIONS

Optimization of synthesized signal parameters using methods with constraints based on linear and nonlinear function approximations is a promising and relevant area of scientific and practical research. These methods allow obtaining signals with specified spectral, temporal, statistical, and other characteristics, including a high level of noise immunity. They transform the signal synthesis task into an optimization problem of the chosen objective function, which includes physical or technological constraints. Solving this problem is necessary to improve the efficiency of cognitive telecommunication systems, as it ensures their stable and reliable operation under various interference conditions.

The scientific novelty of the article lies in the improvement of the Nelder-Mead method for optimizing ensembles of synthesized signals by developing algorithms that integrate spectral, temporal, and statistical analyses and provide comprehensive justified optimization.

DOI 10.15588/1607-3274-2024-3-4

The practical results of the study show that the Nelder-Mead method is effective for tuning the parameters of linear approximations of synthesized signals. It has been experimentally proven that the use of this method significantly improves the mutual correlation properties of signals and reduces the maximum deviations of side lobes.

The obtained results justify the **prospects for further application** of the method in complex signal synthesis scenarios.

The urgent problem of mathematical support development is solved to automate the sampling at diagnostic and recognizing model building by precedents.

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Received 31.06.2024.
Accepted 02.09.2024.

УДК 621.391

ОПТИМІЗАЦІЯ ПАРАМЕТРІВ ЛІНІЙНИХ АПРОКСИМАЦІЙ СИНТЕЗОВАНИХ СИГНАЛІВ ЗА ДОПОМОГОЮ МЕТОДУ НЕЛДЕРА-МІДА

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АНОТАЦІЯ

Актуальність. В статті представлено результати дослідження ефективності використання методу Нелдера-Міда для оптимізації параметрів лінійних апроксимацій синтезованих сигналів. Розроблено та апробовано алгоритми, що інтегрують спектральний, часовий та статистичний аналізи та забезпечують обгрунтовану оптимізацію. Ефективність застосування методу Нелдера-Міда доведено за допомогою експерименту. Отримані результати обгрунтовують поліпшення властивостей взаємної кореляції сигналів та зменшення максимальних відхилень бічних пелюсток, що відкриває перспективи для подальшого застосування методу в комплексних сценаріях синтезу сигналів.

DOI 10.15588/1607-3274-2024-3-4

Мета. Метою роботи є оцінка результативності застосування методу Нелдера-Міда при налаштуванні параметрів лінійних апроксимацій для оптимізації взаємної кореляції та мінімізації побічних відхилень складних синтезованих сигналів.

Метод. Основним методом дослідження є порівняння різних алгоритмів оптимізації для вибору найбільш перспективних підходів у лінійних апроксимаціях синтезованих сигналів. Існують різні показники для порівняння, такі як точність оптимізації, швидкість виконання алгоритмів, та мінімізація відхилень.

У наукових роботах [1, 2, 4, 5, 6, 8, 9], представлені різні методи та алгоритми оптимізації, включаючи метод Нелдера-Міда та диференціальну еволюцію. Найбільш ефективні з них основані на використанні адаптивних методів оптимізації та ітераційних процедур для поліпшення характеристик сигналів.

Варто відзначити, що запропоновані методи мають недоліки, пов'язані зі складністю і вимогами до обчислювальних ресурсів, особливо при великих обсягах даних або високих вимогах до точності. Ці недоліки можна суттєво зменшити шляхом застосування комбінованих методів оптимізації, які враховують різні аспекти моделювання, такі як взаємозв'язки між параметрами сигналу та їх вплив на загальні властивості системи. Іншим важливим напрямком вдосконалення є оптимізація методів для адаптації до динамічних змін у характеристиках складних сигналів, що дозволяє досягти високої адаптивності та надійності систем.

Результати. В результаті експерименту з використанням методу Нелдера-Міда було досягнуто збільшення схожості спектральних щільностей з 0,52 у першій ітерації до 0,90 у четвертій, зі значним зменшенням відстані між піками спектру з 1,2 до 0,4, що свідчить про високу адаптивність та точність методу в налаштуванні параметрів синтезованих сигналів.

Висновки. Експериментальним шляхом доведено ефективність методу Нелдера-Міда для налаштування заданих параметрів синтезованих сигналів, що підтверджується значним покращенням схожості спектрів з кожною ітерацією. Це відкриває шлях для додаткової оптимізації та застосування методу в різноманітних технологічних областях.

КЛЮЧОВІ СЛОВА: метод оптимізації, синтезовані сигнали, метод Нелдера-Міда, апроксимація лінійними функціями, спектральні характеристики, ансамблеві властивості сигналів, ітераційний алгоритм, завадостійкість, викиди бічних пелюстків.

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DOI 10.15588/1607-3274-2024-3-4