Modern radio engineering and telecommunication systems
Современные радиотехнические и телекоммуникационные системы

UDC 621.391
https://doi.org/10.32362/2500-316X-2022-10-6-42-51

RESEARCH ARTICLE

Comparison of algorithms for multi-objective optimization of radio technical device characteristics

Alexander V. Smirnov @

MIREA – Russian Technological University, Moscow, 119454 Russia
@ Corresponding author, e-mail: av_smirnov@mirea.ru

Abstract
Objectives. The selection of a method for solving multi-objective optimization problems has many practical applications in diverse fields. The present work compares the results of applying different methods to the selected classes of problems by solution quality, time consumption, and various other criteria.
Methods. Five problems related to the multi-objective optimization of analog and digital filters, as well as multistep impedance-matching microwave transformers, are considered. One of the compared algorithms comprises the Third Evolution Step of Generalized Differential Evolution (GDE3) population-based algorithm for searching the full approximation of the Pareto set simultaneously, while the other three algorithms minimize the scalar objective function to find only one element of the Pareto set in a single search cycle: these comprise Multistart Pattern Search (MSPS), Multistart Sequential Quadratic Programming (MSSQP) method and Particle Swarm Optimization (PSO) algorithms.
Results. The computer experiments demonstrated the capability of GDE3 to solve all considered problems. MSPS and PSO showed significantly inferior results than to GDE3 for two problems. In one problem, MSSQP could not be used to reach acceptable decisions. In the other problems, MSPS, MSSQP, and PSO reached decisions comparable with GDE3. The time consumption of the MSPS and PSO algorithms was much greater than that of GDE3 and MSSQP.
Conclusions. The GDE3 algorithm may be recommended as a basic method for solving the considered problems. Algorithms minimizing scalar objective function may be used to obtain several elements of the Pareto set. It is necessary to investigate the impact of landscape features of individual quality indices and scalar objective functions on the extreme search process.

Keywords: multi-objective optimization, Pareto optimality, Pareto front, quality index, scalarizing objective function, population-based algorithm

• **Submitted:** 02.05.2022 • **Revised:** 20.05.2022 • **Accepted:** 15.09.2022

For citation: Smirnov A.V. Comparison of algorithms for multi-objective optimization of radio technical device characteristics. *Russ. Technol. J.* 2022;10(6):42–51. https://doi.org/10.32362/2500-316X-2022-10-6-42-51

Financial disclosure: The author has no a financial or property interest in any material or method mentioned.

The author declares no conflicts of interest.

НАУЧНАЯ СТАТЬЯ

Сравнение алгоритмов многокритериальной оптимизации характеристик радиотехнических устройств

А.В. Смирнов @

МИРЭА – Российский технологический университет, Москва, 119454 Россия
@ *Автор для переписки, e-mail: av_smirnov@mirea.ru*

Резюме
Цели. Вопрос о выборе метода решения задачи многокритериальной оптимизации из множества известных методов актуален для многих практических областей. Цель исследования – сравнить результаты применения разных методов на выбранных классах задач по качеству решений, затратам времени и другим критериям.
Методы. В работе сравниваются результаты применения различных алгоритмов при решении пяти задач многокритериальной оптимизации характеристик аналоговых и цифровых фильтров и многоступенчатых согласующих СВЧ-трансформаторов. Исследовались популяционный алгоритм GDE3, осуществляющий поиск одновременно всей аппроксимации множества Парето-оптимальных решений, и три алгоритма, основанные на скаляризации целевой функции, которые в одном цикле поиска находят один элемент указанного множества. Это многократный запуск покоординатного поиска MSPS, многократный запуск алгоритма последовательного квадратичного программирования MSSQP и алгоритм роя частиц PSO.
Результаты. Проведенное исследование показало, что популяционный алгоритм GDE3 позволяет успешно находить множества решений для всех рассмотренных задач. В двух задачах из пяти алгоритмы MSPS и PSO существенно уступили GDE3 как по качеству решений, так и по затратам времени на поиск одного решения. В одной из задач алгоритм MSSQP оказался неработоспособным. В других задачах алгоритмы, основанные на скаляризации, находили решения, не только не уступающие, а в некоторых случаях и превосходящие результаты GDE3. При этом затраты времени на поиск одного решения у MSPS и PSO оказались значительно бо́льшими, чем у GDE3 и MSSQP.
Выводы. Алгоритм GDE3 можно рекомендовать как базовый для решения подобных задач. Алгоритмы, основанные на скаляризации, целесообразно применять при поиске небольшого числа элементов множества Парето-оптимальных решений. Необходимо исследовать влияние особенностей рельефов отдельных показателей качества и скалярных целевых функций на процесс поиска решения.

Ключевые слова: многокритериальная оптимизация, Парето-оптимальное решение, фронт Парето, показатель качества, скаляризация целевой функции, популяционный алгоритм

• **Поступила:** 02.05.2022 • **Доработана:** 20.05.2022 • **Принята к опубликованию:** 15.09.2022

Для цитирования: Смирнов А.В. Сравнение алгоритмов многокритериальной оптимизации характеристик радиотехнических устройств. *Russ. Technol. J.* 2022;10(6):42–51. https://doi.org/10.32362/2500-316X-2022-10-6-42-51

Прозрачность финансовой деятельности: Автор не имеет финансовой заинтересованности в представленных материалах или методах.

Автор заявляет об отсутствии конфликта интересов.

INTRODUCTION

Multi-objective optimization (MOO) problems are of considerable interest in radio engineering and other fields of research [1]. Multicriteria optimization is aimed at finding an approximation of the set of Pareto-optimal solutions (POS) [2], which cannot be improved by one of the quality indices (QI) without deteriorating at least one of the other QIs.

Methods for solving MOO problems can be divided into two main classes [3, 4]. The first is based on solving the problem of minimizing the scalar objective function (OF) written in the generalized form [5]:

$$f(\mathbf{x}) = \sum_{j=1}^{M} \left(W_j \cdot \max\left(\frac{\left(Q_j(\mathbf{x}) - Q_{jt}\right)}{Q_{jt}^{\ q_j}}, 0 \right) \right), \qquad (1)$$

where $Q_j(\mathbf{x})$ and Q_{jt} are the current and target values of the jth QI; W_j is the weighting factor of the jth QI.

The exponent $q_j = 1$ provided that normalizing the QI deviation from the target value for bringing the summands in (1) to the same range of values is required. The exponent $q_k = 0$ provided that such normalization is not required. Equality (1) covers different scalarization techniques for MOO problem. Taking all $Q_{jt} = 0$ and considering the denominators equal to one, the problem of minimizing the QI weighted sum arises. Another technique is to set target values Q_{jt}, as well as $W_k = 1$ and $W_j >> 1$, where $j = 1, ..., M, j \neq k$. In this case, the problem of minimizing QI Q_k while fixing other QI near the target values arises. Methods based on scalarization allow one POS to be found in a search cycle.

The methods grouped in the second class (MOO population-based algorithms) permit the computation of several elements of approximation of the POS set in a single search cycle using agent population. The classification and description of algorithms of this type are given in [3, 4].

The sets of test functions [6] and quality criteria for approximating the POS set [3] are used to compare different methods for solving the MOO problem. Generally, the results of applying MOO population-based algorithms are evaluated using test functions, e.g., as in [7, 8]. Here, no comparison with the results of scalarization-based methods is performed. This can be justified in the case of test functions whose properties are all known; the quality of found approximations of the POS set can be evaluated objectively. In terms of practical applications, however, where nothing generally is known in advance about functions describing QI, it becomes necessary to solve the "Black Box Optimization" problem for collecting information on QI values while finding.

A determination of which algorithm would give the best approximation may be achieved only by comparing the results of different methods, including both population-based and scalarization-based approaches. Such comparison for a specific class of problems is performed in [9] to support a conclusion about the superiority of population-based algorithms in terms of the quality of obtained solutions. Nevertheless, a different result may be obtained for other types of problems. In [10], the possibility of applying population-based algorithms from the PlatEMO open source [11] running in the *MATLAB* environment to solve the MOO problem of the frequency response of analog electrical filters is investigated. Here, the authors conclude that, in the case of optimization by two QIs, population-based methods provide better solutions than scalarization-based approaches. While, in the case of optimization by three QIs, the opposite result is obtained, this conclusion is reached when not using the most effective algorithm for finding an extremum of the scalar OF in experiments. Different scalarization-based algorithms are compared in [12], albeit without considering population-based approaches.

The present work aims to compare the results of applying MOO algorithms of different classes on examples of several problems of optimizing the characteristics of radio engineering devices. Among the indicators characterizing the compared methods, the highest priority is given to obtaining the best results. In case these criteria are equal, a comparison may be performed in terms of search duration per one POS along with other indices.

PROBLEM FORMULATION AND SELECTION OF OPTIMIZATION ALGORITHMS

Problem 1. MOO of frequency response of analog filters. The QI definitions and methods for calculating them are given in [13] and other works by the author. Below is a list of QIs:

- uneven gain-frequency response in passband *DHp*, dB;
- minimum attenuation in stopband *Hs*, dB;
- exceeding gain-frequency response of a given level in transition band *DHt*;
- uneven delay-frequency response in passband *DTd*, %.

Frequency response is calculated on a dimensionless frequency scale normalized to the upper bound frequency of the low pass filter (LPF) passband. Here, it is necessary to minimize *DHp* and *DTd* together while fulfilling the constraints $DHt \leq 0$, $Hs \geq Hst$.

Problem 2. MOO of simultaneous frequency and time responses of analog filters. The QI definitions and methods for calculating them are given in [13]. In addition to the frequency domain QI mentioned above, the following time domain QIs are introduced:

- maximum voltage (overshoot) of the transient process *Um* normalized to the steady-state value;
- transient rising (front) duration *Tfr*;
- transient-process duration *Tss*.

The last two QIs are calculated on a dimensionless time scale referenced to the normalized frequency scale. Here, it is necessary to jointly minimize *Tss* and maximize *Hs* under the constraints $DHt \leq 0$, $Um \leq Umt$, and $Tfr \leq Tfrt$.

Problem 3. MOO of frequency responses of digital filters. The QI definitions and methods for calculating them are given in [5]. The QI list and formulation of optimization problem is the same as for Problem 1.

Problem 4. MOO of frequency responses of matching multistep microwave transformers (transitions). The following QIs are defined:

- maximum *KPmax* and minimum *KPmin* power transfer coefficients in the matching band;
- uneven power transfer coefficient in matching band *DKP* = *KPmax* – *KPmin*.

The method for calculating these QIs is not given here due to the limited scope of the paper and will be published separately. It is necessary to jointly minimize *DKP* and maximize *KPmin* at a given value of the matching bandwidth *DFM*.

Problem 5. Another MOO problem of frequency response of matching multistep microwave transformers. In addition to QI defined for Problem 4, the relative unevenness of the delay-frequency response in matching band *DTd*, %, is introduced. It is necessary to minimize *DKP* and *DTd* at given values of matching bandwidth *DFM* and maximum power transfer coefficient *KPt*.

We shall now consider the algorithms used for solving the above problems.

The population-based algorithm is implemented using the PlatEMO library mentioned above. The algorithm GDE3 (The Third Evolution Step of Generalized Differential Evolution) showing the best response values according to [10] is selected from 71 algorithms presented in the library. The specified parameters are the size of population *Npop* and the number of calculations of the QI set *Neval*. These values are found experimentally for each problem. For this purpose, search iterations with increasing *Npop* and *Neval* values were performed until the found approximation of the POS set is improved.

Below are the algorithms for finding extrema of scalar OFs.

Multistart Pattern Search (MSPS), which describes the repeated start of stepwise search, is implemented by SOFTD [13] in Problems 1 and 2 and by HODF in Problem 3 [5]. Both programs are written in C++. In Problems 4 and 5, the algorithm is implemented in the *MATLAB* environment.

Particle Swarm Optimization (PSO) is the particle swarm algorithm [3, 4] implemented in *MATLAB* by the *particleswarm*(..) function from the *Global Optimization Toolbox* module. According to the results presented in [12], this algorithm demonstrates its capacity to find global extrema of scalar OFs with complex landscape.

Multistart Sequential Quadratic Programming (MSSQP) is the repeated start of sequential quadratic programming algorithm implemented in *MATLAB* by the *fmincon*(..) function from *Optimization Toolbox* module. Unlike MSPS and PSO algorithms searching for minima of scalar OF of the type (1), the constraints on QI are not considered in MSSQP as penalty terms but are included in the Lagrange function that may be written in the following form:

$$L(\mathbf{x},\boldsymbol{\lambda}) = Q_k(\mathbf{x}) + \sum_{i=1}^{M-1} \lambda_i g_i(\mathbf{x}),$$
$$g_i(\mathbf{x}) = Q_j(\mathbf{x}) - Q_{jt},\ i = 1,\ldots, M-1,\ j = 1,\ldots, M,\ j \neq k, \qquad (2)$$

where λ_i are Lagrange multipliers; Q_j are quality indices; Q_{jt} are their target values.

In the strict sense, the algorithm is not intended for finding global extrema of OFs having a complex landscape containing many local extrema. However, as shown in [12], it obtains a good approximation to the global minimum of OF from most starting points evenly distributed in the search space for some problems. At the same time, the search duration turns out to be much shorter than for other algorithms.

The number of starts, *NT,* of the scalarization-based algorithms for finding one POS is selected in each problem so as to find a solution that could not be significantly improved by further *NT* increasing. Other parameters are set equal to default values.

PROBLEM SOLUTIONS

Problem 1. We shall consider experimental results for the analog LPF whose transfer function (TF) contains *NP* = 6 poles and *NZ* = 0 zeros. The lower bound frequency of the stopband on the frequency scale normalized to the upper bound frequency of the passband is *Fs* = 2. The results obtained using the GDE3 algorithm are shown in Fig. 1 in the form of Pareto front approximation graphs for *Hst* = 30 dB and *Hst* = 40 dB. In the first case, *Neval* = $1 \cdot 10^6$, while in the second case, *Neval* = $0.5 \cdot 10^6$. The search duration is 4 and 2 min, respectively. In both cases, *Npop* = 50.

The solutions obtained using algorithms based on scalarizing OFs are also presented in Fig. 1. Finding one solution takes an average of 2 min by MSPS algorithm, 10 s by MSSQP algorithm, and 5 min when using the PSO algorithm. The number of MSPS starts is 3000, while the number of PSO starts is 40; the number of MSSQP starts is 20. From the start results, the best one is selected. Here, it should be noted that about half of MSSQP starts gives the same best result when searching for each POS, with the remainder resulting in unacceptable solution. The results of the other two algorithms are distributed over a wide range of values in most experiments.

The comparison of QI solutions obtained by different algorithms shows that only MSSQP provides benefits for solution quality as compared to GDE3 at *DHp* small values. The other two algorithms based on scalarizing OFs show at best results similar to GDE3, being at a disadvantage to it at small values of *DHp*. In addition, they require significantly more time for finding solutions.

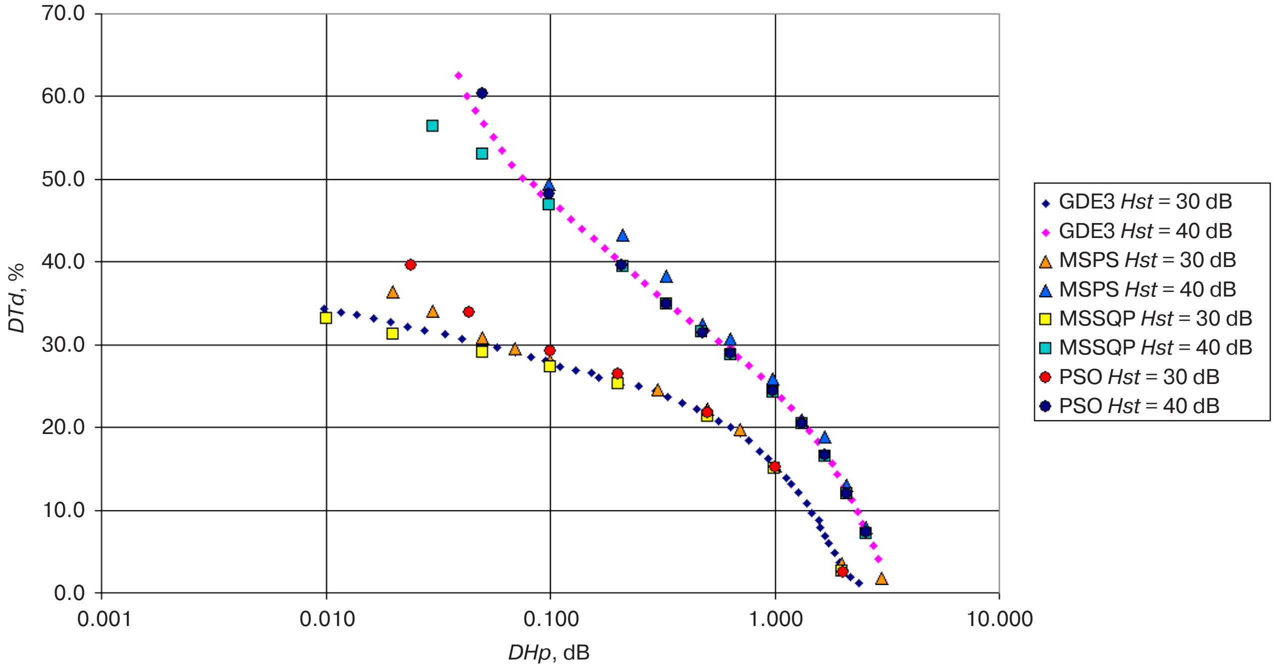

Fig. 1. Problem 1 solution

Problem 2. We shall consider experimental results for the same LPF as in Problem 1. The results obtained using the compared algorithms are shown in Fig. 2. The constraints are set to $Tfr \leq 0.5$, $Um \leq 1.1$, and $DHt \leq 0$ for the first series of experiments, while the constraint on *Tfr* is excluded in the second series.

First, it should be noted that the MSSQP algorithm cannot find admissible solutions, i.e., those satisfying all the restrictions, under the constraint on *Tfr* at all. In the absence of this constraint, the ability of MSSQP to find valid solutions appeared to be noticeably worse than that for GDE3 and PSO. The number of valid solutions in series of $NT = 200$ starts taking 40–60 s is measured in units. In both series of experiments, the MSPS algorithm also shows results significantly inferior to the GDE3 and PSO solutions.

In both series of experiments, the GDE3 and PSO algorithms show similar results in terms of QI. The GDE3 parameters are *Npop* = 50 and *Neval* = 200000, respectively, while finding an approximation of the POS

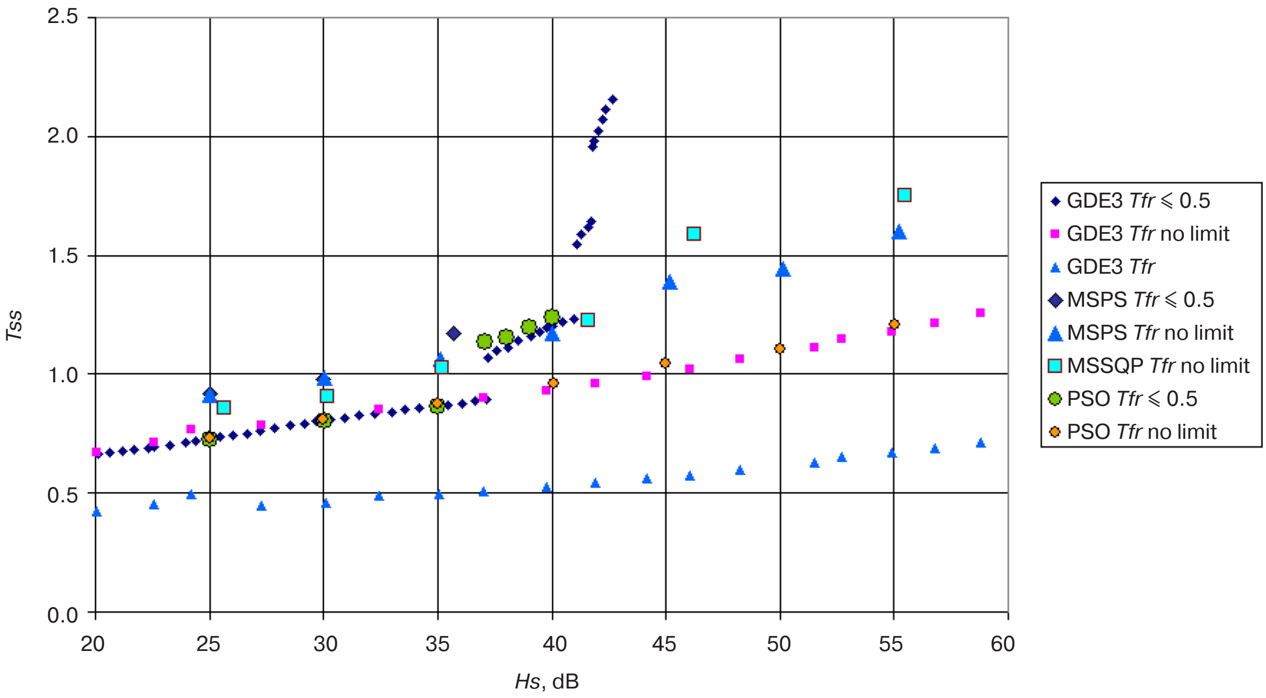

Fig. 2. Problem 2 solution

set takes about 7 min. For PSO, the number of starts is *NT* = 40; the duration of finding one solution is 8–10 min.

The Pareto front turns out to be discontinuous in the presence of a constraint on *Tfr*. To explain the reasons for this effect, the *Tfr* values obtained with no constraint imposed on this QI are plotted on the graph also shown in Fig. 2. As long as *Tfr* is less than constraint *Tfr* = 0.5, approximations of Pareto fronts obtained in the presence and absence of this constraint coincide. The constraint on *Tfr* is not active and does not affect search results. However, if *Tfr* value should exceed the specified threshold, the constraint becomes active, and the transition process becomes oscillatory in order to fulfill it. In this case, the Pareto front discontinuity is due to transitions of the moment when the condition of the transient process completion [5] from one wave to another is satisfied.

Problem 3. Experimental results for LPF with *NP* = 4 for pole and *NZ* = 4 for zero are shown in Fig. 3. The upper bound frequency of the passband on the frequency scale normalized to the sampling frequency is *Fp* = 0.1; the lower bound frequency of the stopband is *Fs* = 0.2. Using the GDE3 population-based algorithm, approximations of the Pareto front for problems of minimizing QI *DHp* and *DTd* at *Npop* = 50, under constraints *Hst* = 30 dB and *Hst* = 40 dB. The numbers of QI calculations are *Neval* = 10^6 and *Neval* = $1.5 \cdot 10^6$, the duration is 6 and 9 min, respectively.

Next, points of these approximations are obtained using algorithms based on scalarizing OFs. The MSPS algorithm gives the best results, since the solutions found by it cover the ranges of solutions obtained using GDE3 completely, not only equalling, but even slightly exceeding them in QI terms. In case of *Hst* = 30 dB, the set of MSPS solutions has the least low bound in terms of *DHp* parameters. In all experiments, the number of search starts is *NT* = 2000. The execution time per search ranges from 5 to 8.5 min.

The PSO algorithm for Problem 3 turns out to be worse than MSPS; here, the solutions found are within narrower ranges of QI values taking approximately the same time required for one search.

The MSSQP algorithm also loses to GDE3 and MSPS by the value of the lower bound of the *DHp* range. However, at *HSt* = 30 dB, the algorithm finds solutions within the *DHp* value range of 0.2–0.8 dB with lower *DTd* values compared to other algorithms. These solutions are located in the area of the search space into which other algorithms have not fallen. At the same time, the phase-frequency response of the solutions obtained using MSSQP differ from the phase-frequency response of the other algorithm solutions (Fig. 4) significantly, although the gain-frequency response is similar. At the same time, MSSQP results are close to those obtained by other methods at *Hst* = 40 dB.

Problem 4. We shall consider an example of the problem solution at matching the lines with the ratio of wave impedances Z_{w2}/Z_{w1} = 10, frequency matching bandwidth *DFM* = 1.2, and the number of transformer stages *Nst* = 4 and *Nst* = 5 (Fig. 5).

The search by GDE3 algorithm for both values of *Nst* is performed at *Npop* = 100 and *Neval* = $1 \cdot 10^6$, taking approximately 2 minutes. Since the results only insignificantly deteriorate with the number of QI calculations, the search duration is decreased by 10 times.

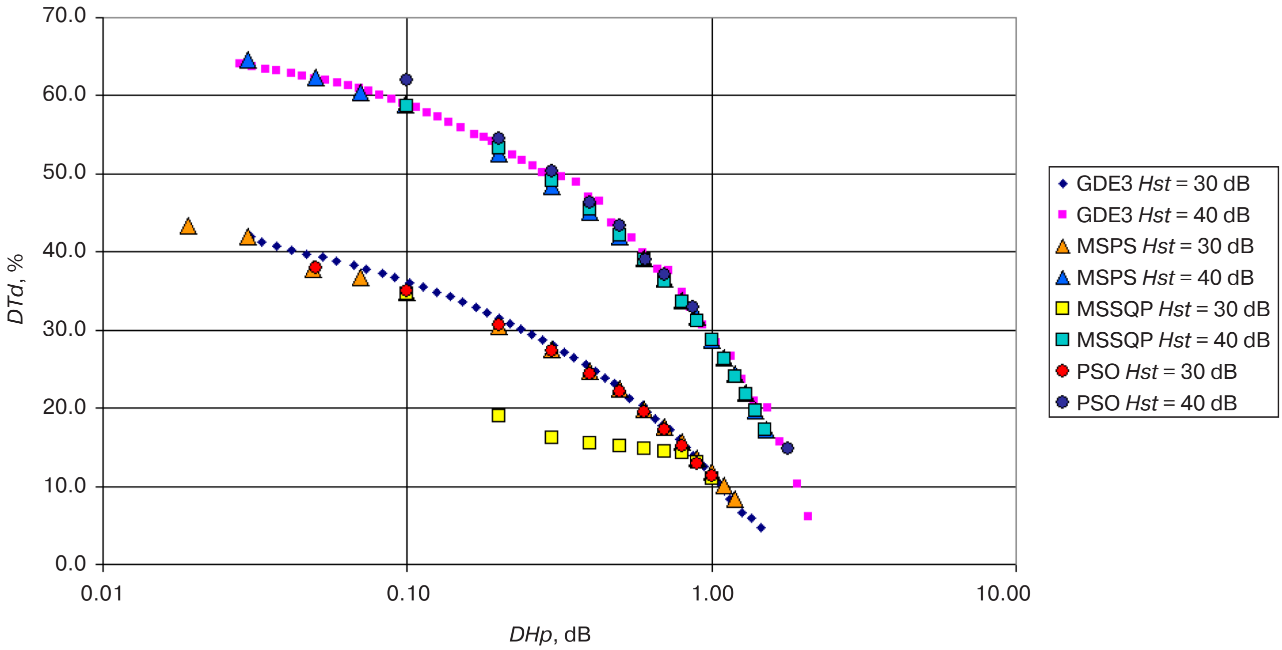

Fig. 3. Problem 3 solution

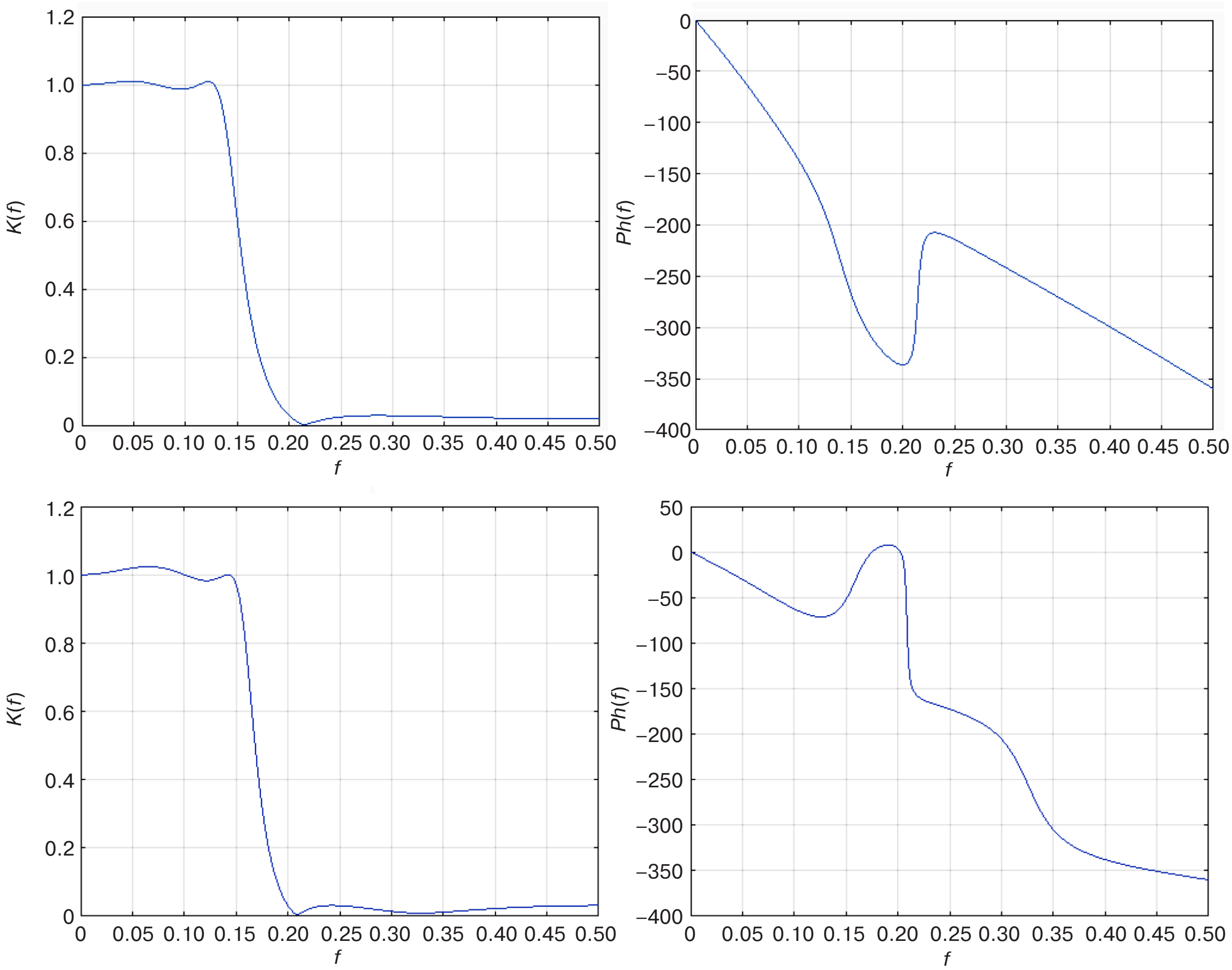

Fig. 4. Comparison of the gain-frequency response $K(f)$ and phase-frequency response $Ph(f)$ of filters found using MSPS algorithm (top) and MSSQP algorithm (bottom) at $HSt = 30$ dB and $DHp \leqslant 0.2$ dB

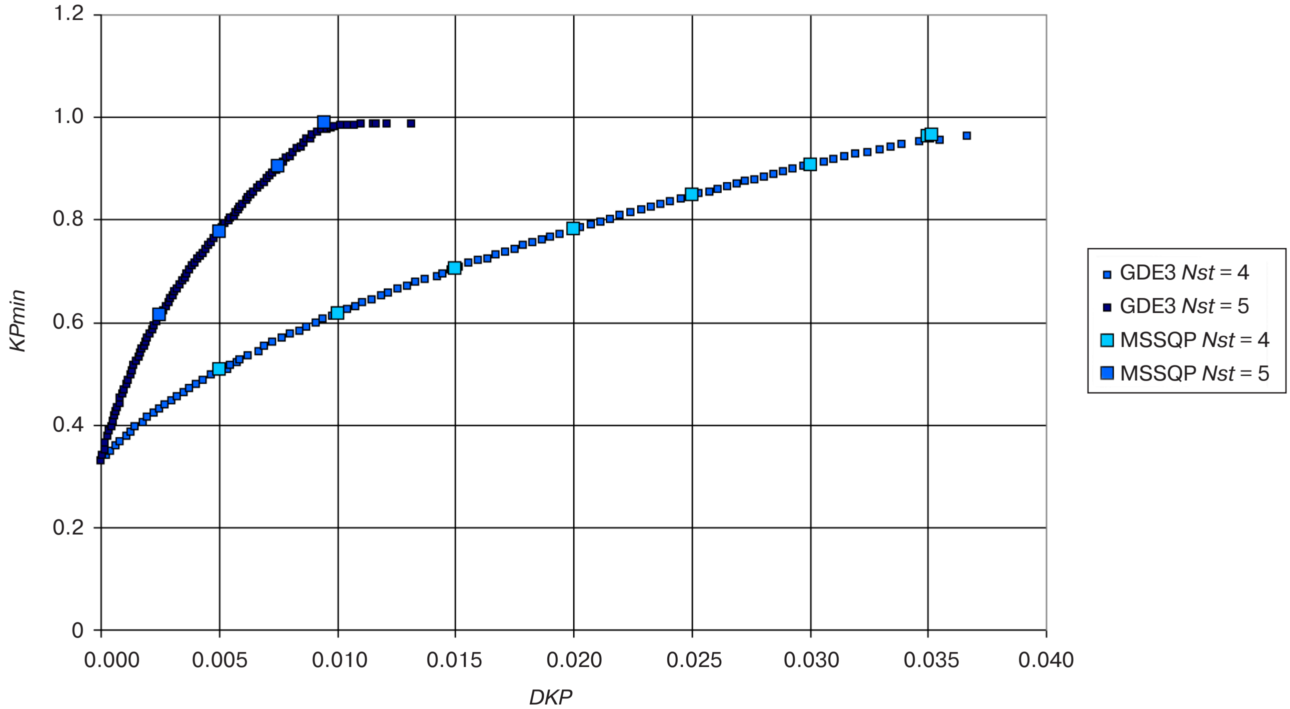

Fig. 5. Problem 4 solution

All three algorithms based on scalarizing OFs show the same results. Therefore, only the solutions obtained with MSSQP falling on Pareto front approximations found by GDE3 algorithm are shown in Fig. 5. However, the methods differ significantly in terms of search duration for a single solution. While MSPS and PSO require 40–50 s, MSSQP requires only 3–4 s. It should be noted that the rightmost points of the series obtained using MSSQP coincide with the results for Chebyshev approximations, while the points of GDE3 series located to their right are not POS.

Problem 5. The problem is solved under conditions $Z_{w2}/Z_{w1} = 12$, $DFM = 1$, and $KPt = 1$ for the number of stages $Nst = 3$, 4, and 5. Approximations of Pareto fronts obtained by the compared algorithms are shown in Fig. 6.

For GDE3 algorithm, parameters $Npop = 100$ and $Neval = 1 \cdot 10^5$ are set. No further increase in these parameters has any positive effect. With increasing number of steps *Nst*, the search duration increases within the range from 55 to 71 s. The upper bound of *DKP* values is set to 0.1. At $Nst = 5$, the Pareto front approximation turns out to be discontinuous within the range $DKP > 0.04$. This is due to the *DTd* value varying insignificantly within this range, thus making it difficult to estimate the solution dominances.

For the MSPS algorithm, $NT = 200$. The average search duration per solution for three *Nst* values is 7, 14, and 20 s. In all cases, the found solutions are significantly worse than those obtained using GDE3; moreover, increasing the number of *NT* starts yields no improvement. Since the PSO algorithm gives solutions coincident with MSPS solutions at close durations, its results are not included in Fig. 6.

The MSSQP algorithm demonstrates high efficiency in solving this problem. If $NT = 10$, then 60–100% of starts yield the same result matching GDE3 solutions over the entire range of values. The other starts result in unacceptable solutions with constraint violations. The average search duration for three *Nst* values is 1.6, 5.2, and 7.5 s. At the same time, the algorithm also finds solutions with the given DKP values in the area wherein the Pareto front approximation obtained using GDE3 has turned out to be discontinuous.

CONCLUSIONS

The study demonstrates that the GDE3 MOO population-based algorithm can be used to find a solution for all of the considered problems and can therefore be recommended for use in solving of such types of MOO problems to obtain an approximation of the POS set across a wide range of QIs. Thus, it is reasonable to check the applicability of the MSSQP algorithm to a particular problem, as well as the possibility of obtaining solutions superior in quality to those obtained by GDE3. However, due to the lack of answers to questions why MSSQP algorithm is effective for some problems and unsuitable for others, as well as how it finds solutions for Problem 3 inaccessible to other algorithms, further experimental

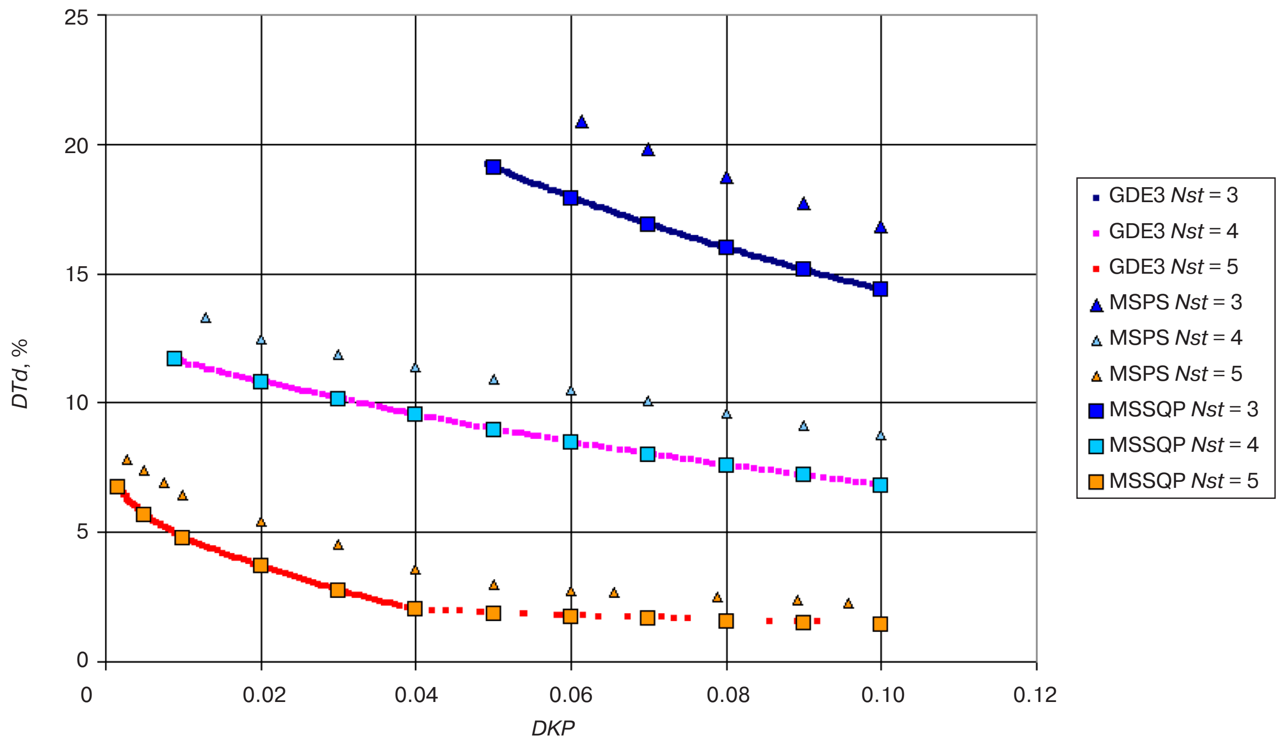

Fig. 6. Problem 5 solution

verification is required. For this it will be necessary to analyze the impact of landscape features of individual QI in MOO problems on the solution finding process. Despite active investigations in recent years, including the use of intelligent technologies [14, 15], in the field continues to be characterized by a lack of sufficiently general results.

The MSSQP algorithm (or, in case it cannot find suitable solutions, other algorithms based on scalarizing OFs) can be recommended for use in cases where it is necessary to find a small number of POS or to provide accurate values for part of QI, which is difficult when using population-based MOO algorithms.

REFERENCES

1. Gutkin L.S. *Optimizatsiya radioelektronnykh ustroistv po sovokupnosti pokazatelei kachestva* (*Optimization of Radio Electronic Devices with Aggregation of Quality Indices*). Moscow: Sovetskoe radio; 1975. 368 p. (in Russ).
2. Chernorutskii I.G. *Metody optimizatsii v teorii upravleniya: uchebnoe posobie* (*Optimization Methods in the Control Theory*). St. Petersburg: Piter; 2004. 256 p. (in Russ).
3. Karpenko A.P. *Sovremennye algoritmy poiskovoi optimizatsii. Algoritmy, vdokhnovlennye prirodoi:* uchebnoe posobie (*Modern Search Optimization Algorithms. Nature-Inspired Optimization Algorithms*). Moscow: Izd. MGTU im. Baumana; 2017. 446 p. (in Russ).
4. Jasbir S.A. *Introduction to optimum design*. 4th edition. Elsevier; 2017. 670 p. https://doi.org/10.1016/C2013-0-15344-5
5. Smirnov A.V. Optimization of digital filters performances simultaneously in frequency and time domains. *Russ. Technol. J.* 2020;8(6):63–77 (in Russ.). https://doi.org/10.32362/2500-316X-2020-8-6-63-77
6. Liu S., Lin Q., Tan K.Ch., Li Q. Benchmark problems for CEC2021 competition on evolutionary transfer multiobjective optimization. Technical Report. 2021. 24 p. https://doi.org/10.48550/arXiv.2110.08033
7. Ray T., Mamun M.M., Singh H.K. A simple evolutionary algorithm for multi-modal multiobjective optimization. 2022. 8 p. Available from URL: https://arxiv.org/pdf/2201.06718.pdf
8. Wang Z., Yao X. An efficient multi-indicator and many-objective optimization algorithm based on two-archive. 2022. 15 p. Available from URL: https://arxiv.org/pdf/2201.05435v1.pdf
9. Chen T., Li M. The weights can be harmful: Pareto search versus weighted search in multi-objective search-based software engineering. 2022. 40 p. Available from URL: https://arxiv.org/pdf/2202.03728.pdf
10. Smirnov A.V. Application of population algorithms in the problems of multiobjective optimization of electrical filters characteristics. *Modelirovanie, optimizatsiya i informatsionnye tekhnologii = Modeling, Optimization and Information Technology.* 2021;9(3) (in Russ.). https://doi.org/10.26102/2310-6018/2021.34.3.015
11. Tian Y., Cheng R., Zhang X., Jin Y. PlatEMO: A MATLAB platform for evolutionary multi-objective optimization. *IEEE Computational Intelligence Magazine*. 2017;12(4):73–87. https://doi.org/10.1109/MCI.2017.2742868

СПИСОК ЛИТЕРАТУРЫ

1. Гуткин Л.С. *Оптимизация радиоэлектронных устройств по совокупности показателей качества*. М.: Советское радио; 1975. 368 с.
2. Черноруцкий И.Г. *Методы оптимизации в теории управления*: учебное пособие. СПб.: Питер; 2004. 256 с.
3. Карпенко А.П. *Современные алгоритмы поисковой оптимизации. Алгоритмы, вдохновленные природой*: учебное пособие. М.: Изд-во МГТУ им. Н.Э. Баумана; 2017. 446 с.
4. Jasbir S.A. *Introduction to optimum design*. 4th edition. Elsevier; 2017. 670 p. https://doi.org/10.1016/C2013-0-15344-5
5. Смирнов А.В. Оптимизация характеристик цифровых фильтров одновременно в частотной и временной областях. *Российский технологический журнал*. 2020;8(6):63–77. https://doi.org/10.32362/2500-316X-2020-8-6-63-77
6. Liu S., Lin Q., Tan K.Ch., Li Q. Benchmark problems for CEC2021 competition on evolutionary transfer multiobjective optimization. Technical Report. 2021. 24 p. https://doi.org/10.48550/arXiv.2110.08033
7. Ray T., Mamun M.M., Singh H.K. A simple evolutionary algorithm for multi-modal multi-objective optimization. 2022. 8 p. https://arxiv.org/pdf/2201.06718.pdf
8. Wang Z., Yao X. An efficient multi-indicator and many-objective optimization algorithm based on two-archive. 2022. 15 p. URL: https://arxiv.org/pdf/2201.05435v1.pdf
9. Chen T., Li M. The weights can be harmful: Pareto search versus weighted search in multi-objective search-based software engineering. 2022. 40 p. URL: https://arxiv.org/pdf/2202.03728.pdf
10. Смирнов А.В. Применение популяционных алгоритмов в задачах многокритериальной оптимизации характеристик электрических фильтров. *Моделирование, оптимизация и информационные технологии.* 2021;9(3). https://doi.org/10.26102/2310-6018/2021.34.3.015
11. Tian Y., Cheng R., Zhang X., Jin Y. PlatEMO: A MATLAB platform for evolutionary multi-objective optimization. *IEEE Computational Intelligence Magazine*. 2017;12(4):73–87. https://doi.org/10.1109/MCI.2017.2742868
12. Смирнов А.В. Свойства целевых функций и алгоритмов поиска в задачах многокритериальной оптимизации. *Russ. Technol. J.* 2022;10(4):75−85. https://doi.org/10.32362/2500-316X-2022-10-4-75-85

12. Smirnov A.V. Properties of objective functions and search algorithms in multi-objective optimization problems. *Russ. Technol. J*. 2022;10(4):75−85 (in Russ.). https://doi.org/10.32362/2500-316X-2022-10-4-75-85
13. Smirnov A.V. Method of simultaneous optimization of radio devices performance in frequency and time domain. *Russ. Technol. J*. 2018;6(6):13–27 (in Russ.). https://doi.org/10.32362/2500-316X-2018-6-6-13-27
14. Mersmann O., Bischl B., Trautmann H., Preuss M., Weihs C., Rudolf G. Exploratory landscape analysis. In: *Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation* (*GECCO'11*). 2011. P. 829–836. https://doi.org/10.1145/2001576.2001690
15. Trajanov R., Dimeski S., Popovski M., Korošec P., Eftimov T. Explainable landscape-aware optimization performance prediction. In: *2021 IEEE Symposium Series on Computational Intelligence* (*SSCI*). 2021. https://doi.org/10.1109/SSCI50451.2021.9660124

13. Смирнов А.В. Метод одновременной оптимизации характеристик электрических фильтров в частотной и временной областях. *Российский технологический журнал*. 2018;6(6):13–27. https://doi.org/10.32362/2500-316X-2018-6-6-13-27
14. Mersmann O., Bischl B., Trautmann H., Preuss M., Weihs C., Rudolf G. Exploratory landscape analysis. In: *Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation* (*GECCO'11*). 2011. P. 829–836. https://doi.org/10.1145/2001576.2001690
15. Trajanov R., Dimeski S., Popovski M., Korošec P., Eftimov T. Explainable landscape-aware optimization performance prediction. In: *2021 IEEE Symposium Series on Computational Intelligence* (*SSCI*). 2021. https://doi.org/10.1109/SSCI50451.2021.9660124

About the author

Alexander V. Smirnov, Cand. Sci. (Eng.), Professor, Department of Telecommunications, Institute of Radioelectronics and Informatics, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). E-mail: av_smirnov@mirea.ru. https://orcid.org/0000-0002-2696-8592

Об авторе

Смирнов Александр Витальевич, к.т.н., доцент, профессор кафедры телекоммуникаций Института радиоэлектроники и информатики ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: av_smirnov@mirea.ru. https://orcid.org/0000-0002-2696-8592

Translated from Russian into English by Kirill V. Nazarov
Edited for English language and spelling by Thomas A. Beavitt