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Modified algorithm for searching for a global extremum of multi-parametric and multi-extremal functions

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ABSTRACT: The article deals with the modified algorithm for searching for a global extremum of multi-parameter, multi-extremal functions, based on methods of global optimization. The problems of the global extremum search algorithm and methods for their solutions are given. A brief description of the features of the global extremum search algorithm is given.

KEYWORDS: Method, algorithm, objective function, task, system, optimization.

I.INTRODUCTION

The problem of optimization is one of the central problems of modern computational and applied mathematics. The problems of global optimization encountered in practice are very diverse. Heuristic reasoning, experimental and, to a certain extent, theoretical results show that different methods of global search are most suitable for different classes of problems [1, 2].

II. STATEMENT OF A PROBLEM

The task set in [3] of minimizing the costs of production of oil and gas production

$$\left.\begin{aligned} &F(X)\rightarrow \min;\\ &f_j(x)\le 0 \ (j=\overline{0,m});\\ &a_i\le x_i\le b_i \ (i=\overline{1,n}),\end{aligned}\right\}(1)$$

complex in the form of a problem of nonlinear mathematical programming, posed in [3], in connection with the presence of a number of features, such as a significant number of parameters (n> 20), the complexity of calculating the objective function in comparison with the verification of constraints, its scale and the importance of the oil and gas industry, required the development of a special modification of the global search algorithm.

The main problem in the development of the algorithm was the achievement of high reliability and accuracy of operation with minimal expenditure of computer time. The algorithms given in [4,5] are taken as a basis, and the developed modification maximizes the number of calculations of the objective function (as requiring the greatest time) in solving problem (1).

III. THE CONCEPT OF THE PROBLEM DECISION

We give a brief description of the features of the algorithm.

1. The search area is the hyperparallelepiped: $a_i \le x_i \le b_i,\ i=\overline{1,n}$.

2. Determine the starting point of the search. Using the Monte Carlo procedure giving K_1 points uniformly distributed in the search domain D, a set of numbers

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$$\left\{ f_j(K_k) \right\} \begin{matrix} 1 \le K \le K_1; \\ 1 \le j \le m, \end{matrix} \quad (2)$$

which to some extent allows us to judge the degree of remoteness of the points X_k from the surfaces $f_j(X)=0$ $(j=\overline{0,m})$. After sorting the obtained numbers, number 1 is assigned to the point at which the minimax is reached

$$A = \min_k \left| \max_j f_j(X_k) \right| sign\left[\max_j f_j(X_k) \right]. \quad (3)$$

if $A \le 0$, then $X_1 \in \Omega$ (where area Ω means the satisfaction of all functional restrictions in (1)); if $A>0$, then $X_1 \notin \Omega$. Further, X_1samples K_1 through $X_1 + MШ\Xi_j$ are conducted from A, where $\Xi_j = (\xi_1, \xi_2, ..., \xi_n)$, and ξ_1 are random numbers uniformly distributed on the interval [-1, 1]. The best is chosen from these points. A series of K_1 samples continues until condition

$$A \le 0 \wedge |MШ| < 1, \quad (4)$$

where ∧ is the sign of logical multiplication; $MШ$ is the scale factor.

The point at which condition (4) was fulfilled for the first time is considered to be the starting point X_0. Thus, we get the starting point $X_0 \in \Omega$, which is sufficiently close to the boundary, never having calculated the objective function.

3. The best direction of search is determined by two points X_k

$$X_{k+1} = X_k + MШ_{k+1}\,\Xi^*, \quad (5)$$

where k is the step number when searching for each local minimum, and $MШ$ is calculated using the recurrence relation:

$$MШ_{k+1} = |MШ_{k+1}| sign\left(\frac{A_k}{A_k - A_{k-1}} \right) \left| \frac{A_k}{A_k - A_{k-1}} \right|^P, \quad (6)$$

where $P=const$is the regulating value $MШ$, depending on the degree of the objective function and constraints and is given for each task.

With this definition of the magnitude and sign of the working step, the search system at minimal costs will go to the hyperframe, where a refined search for a minimum will occur.

In addition, the values of $MШ_k$ are limited by the limits:

$$MШ_k = \begin{cases} 1, \; if \;\; 0 < MШ_k < 1; \\ MШ_k, \; if \;\; 1 \le MШ_k \le 100; \\ 100, \; if \;\; MШ_k > 100, \end{cases} \quad (7)$$

that allows to avoid an unjustified increase in the size of the working step.

4. The constraints on the parameters $a_i \le x_i \le b_i$ are taken into account by the formula

$$x_i = \begin{cases} x_i \;\; at \;\; a_i \le x_i \le b_i; \\ a_i(1+K_{ot}) - K_{ot}x_i \;\; at \;\; x_i < a_i; \\ b_i(1+K_{ot}) - K_{ot}x_i \;\; at \;\; x_i < b_i, \end{cases} \quad (8)$$

where K_{ot} is the reflection coefficient from the boundary. At K_{ot}= 0, the point that violated the restriction returns to the boundary. At K_{ot}> 0, the point "reflects" from the wall of the hyperparallelepiped to the inside of the coefficient search area. K_{ot} is set within $0 \le K_{ot} \le 1$ by the researcher before starting the search for each specific task. If the "reflected" points do not reduce the minimized function, then from the last improved point new series of samples are made with decreasing step size. Thus, a gradual approach to the border is being implemented.

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Taking into account the functional limitations $f_i(x) \leq 0$ the search is constructed as follows. If the point has violated the boundary, the system returns to the last improved state, which does not violate the constraint. From this point, new series of samples are made to find the "circumvention" of the restriction. If this direction can't be found, then the length of the working step decreases. At the same time, a gradual approach to the boundary is made and the minimum is at a given accuracy.

5. The condition for the end of the local search. If in the determination of the search-direction-improving function of the search function, none of the samples brought good luck, then the tests are repeated again. If a given number of consecutive series of tests does not improve the objective function, then the length of the working step decreases and the local minimum coordinates are refined, which continue until the condition

$$K_n = K_0 \wedge \xi > \Delta F^*, \quad (9)$$

where $K_n$is the number of successively failed test runs; K_0 is the coefficient characterizing the viewing density of the neighborhoods of the minimum; ξ-given search accuracy, measured in units of objective function; ΔF^* - the greatest increment of the objective function for the failed series of tests.

The coefficient K_0, like ξ, is specified for each task.

Obviously, the condition for the end of a local search consists of two parts connected by a logical multiplication symbol. The left-hand side adjusts the probabilistic side of the search process, and the right-hand side provides the specified accuracy.

6. Organizationofself-study.
In this algorithm, self-learning is used for the guiding hyperellipsoid, the essence of which is as follows. A hyperellipsoid is constructed, oriented along the previously achieved best direction. The semi-axes of the hyperellipsoid are determined by the following expressions:

$$b = \frac{1}{2}\sqrt{\frac{4 - \sum_{i=1}^{n}(x_i^{(k)} - x_i^{(k-1)})^2}{n}}; \quad (10)$$

$$b_1 = \sqrt{1 - (n-1)b^2},$$

where b_1 is the length of the semiaxis directed along the memory vector - of the best direction; $b_2 = b_3 = \ldots = b_n = b$ - other semiaxes.

The applied form of self-learning algorithm allows you to flexibly search in possible emergency situations.

In the rest, the developed algorithm of global search uses methods and heuristic methods that have passed a successful test of time and a large number of solved optimization problems.

The algorithm is implemented in C++ for the PC and tested for a number of complex test optimization tasks, where it showed itself on the best side.

This problem is solved with the help of the algorithm for NCOF = NCC = 301÷515, where NCOF - the number of calculations of the objective function; NCC is the number of constraint calculations.

With the help of the algorithm proposed by us, the problem is solved for NCOF = 29 and NCC = 40, and the achieved accuracy, which is much higher than reached to date.The achieved high accuracy with a significant reduction in the number of calculations (> 10 times) makes it possible to judge the correct heuristic techniques and the concept embodied in the algorithm developed by us.

VI.CONCLUSION AND FUTURE WORK

In the developed, based on methods of searching for a global extremum, a modified algorithm of global search, methods and heuristic methods that have passed a successful test of time and a large number of solved optimization problems are applied.

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REFERENCES

[1] Zhiglyavsky A.A., Zhilinskas A.G. Methods of searching for a global extremum. -M.: Science. 1991.-248p.
[2] Panteleev A.V., Metlitskaya D.V., Aleshina E.A. Methods of global optimization. Metaeviral strategies and algorithms. - M.: The University Book, 2013. - 244 p.
[3] Ishankhodjaev G.K., Sultanov M.B. Optimal planning and operational management of fuel and energy resources consumption // Problems of Informatics and Energy, 2018, No. 1, art. 64-70.
[4] Mishra S. K. Global optimization by sifferential evolution and particle swarm methods: evaluation on some benchmark functions. Munich Personal RePEc Archive (MPRA), 2006.
[5] Hirsch M. J., Meneses C. N., Pardalos P. M., Resende M. G. C. Global optimization by continuous grasp // Optimization Letters. 2006.

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