

MODERN SCIENTIFIC RESEARCH: ACHIEVEMENTS, INNOVATIONS AND DEVELOPMENT PROSPECTS

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ANALYSIS OF THE RESULTS OF TESTING A HYBRID GENETIC ALGORITHM USING THE RASTRIGIN FUNCTION

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Introductions. Genetic algorithm is a heuristic search algorithm that is used to solve optimization and modeling problems by random selection, combination and variation of the desired parameters using mechanisms similar to natural selection in nature. It is a type of evolutionary computation that solves optimization problems using natural evolution techniques such as inheritance, mutation, selection, and crossover. A distinctive feature of the genetic algorithm is the emphasis on the use of the "crossing" operator, which performs the operation of recombination of candidate solutions, the role of which is similar to the role of crossing in wildlife.

Aim. Conducting and analyzing the results of testing the developed hybrid genetic algorithm on a set of Rastrigin test functions.

Materials and methods.

Basic concepts of genetic algorithms.

The first work to simulate evolution was conducted in 1954 by Niels Barichella on a computer installed at the Institute for Advanced Study at Princeton University. His work, published in the same year, attracted widespread public attention. Since 1957, Australian geneticist Alex Fraser has published a series of works to simulate artificial selection among organisms with multiple control of measurable characteristics [1]. Fraser's simulations included all the most important elements of modern genetic algorithms. In addition, Hans-Joachim Bremermann published a series of papers in the 1960s that also took the approach of using a population of

solutions that can be recombined, mutated, and selected for optimization problems [2].

Artificial evolution became a well-known method of optimization after the work of Ingo Rechenberg and Hans-Paul Schwefel in the 1960s and early 1970s - their group was able to solve complex engineering problems according to evolutionary strategies. Another approach was the evolutionary programming technique of Lawrence J. Vogel, which was proposed to create artificial intelligence[3].

Evolutionary programming originally used finite state machines to predict circumstances, and used variety and selection to optimize prediction logic. Genetic algorithms became especially popular thanks to the work of John Holland in the early 70's and his book "Adaptation in natural and artificial systems" (1975). His research was based on experiments with cellular automata conducted by Holland and on his work written at the University of Michigan. Holland introduced a formalized approach to predicting the quality of the next generation, known as the Scheme Theorem[4].

In genetic algorithms, a certain set of points of this space (possible solutions) is distinguished from the whole search space, which in terms of natural selection and genetics is called a population. Each individual of the population is a potential solution to the problem, it is represented by a chromosome - the structure of elements (genes). In turn, an arbitrary chromosome gene takes on a meaning - an allele from some alphabet that specifies the code representation of points in the solution search space. In the simplest case, an individual can be an ambiguous string. The genetic algorithm works with coded structures regardless of their value. In this case, the code itself and its structure are described by the concept of genotype, and its interpretation in terms of the problem - the concept of phenotype. For possible solutions, the fitness function (FF) is determined, which allows to assess the proximity of each individual to the optimal solution - the ability to survive. The genetic algorithm for finding a solution is to model the evolution of an artificial population. The population develops (evolves) from one generation to another. The creation of new individuals in the

process of the algorithm is based on the modeling of the reproduction process. In this case, the decision-makers involved in the process of reproduction are called parents, and those obtained as a result of reproduction - descendants. In each generation, many offspring are created using parent parts and adding new parts with good properties.

Direct generation of new code strings from the two selected occurs using the crossover operator (crossing). Modeling of the process of mutation of new individuals is carried out using the mutation operator, which allows to make the phenotype of the offspring good properties by certain changes in its genotype. Usually the probability of using the mutation operator is small (<0.1).

Being a variety of random search methods, genetic algorithms allow you to find good but not optimal solutions. Their main advantage is that they allow you to find good solutions to very difficult problems in less time than other algorithms. A negative feature of evolutionary, including genetic methods, is that they require adaptation to each specific class of tasks by selecting certain characteristics and parameters. Such parameters include, first of all: the size of the population, the method of coding the solution, the set of genetic operators involved in each algorithm and the probability of their use, the criterion for stopping the search process[5].

The criterion for stopping may be, firstly, the passing of a certain number of generations, secondly, the achievement of the required quality of decisions and, thirdly, the lack of improvement in the quality of decisions due to the degeneration of the current population.

Genetic algorithm for searching global extremes

A monochromosomal person carries in each of its genes information about the corresponding coordinate x or y . The population is determined by many individuals, but the population is segmented by 4 people. This decision is due to an attempt to avoid convergence to the local optimum, as the task is to find a global extremum. Such a division, as practice has shown, in many cases does not allow to dominate one genotype in the whole population, but, on the contrary, gives the "evolution" of greater dynamics. The following algorithm is used for each such part of the

population:

1. Selection is similar to the ranking method. 3 persons with the best indicators of fitness function are selected (ie individuals are sorted in ascending / descending order of the user-defined function, which acts as an adaptation function) [6].

2. Next, the crossbreeding function is applied so that the new generation (or rather a new segment of the population of 4 people) receives 2 pairs of non-mutated genes from the individual with the best indication of fitness function and a pair of genes mutated from the other two individuals [7].

The principle of selection, crossing and mutation clearly looks like this (in generation N, the chromosomes of individuals are already sorted in the right order, and a small black square means a mutation fig.1):

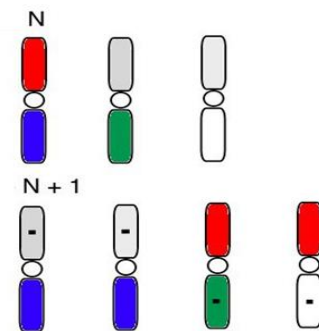


Fig.1. The principle of selection, crossing and mutation

Analytical form of the Rastrigin function: $-5 + x * x + y * y - 10 * (\cos(2 * 3.14 * x) + \cos(2 * 3.14 * y))$.

Visualization of the Rastrigin function is shown in Fig. 2

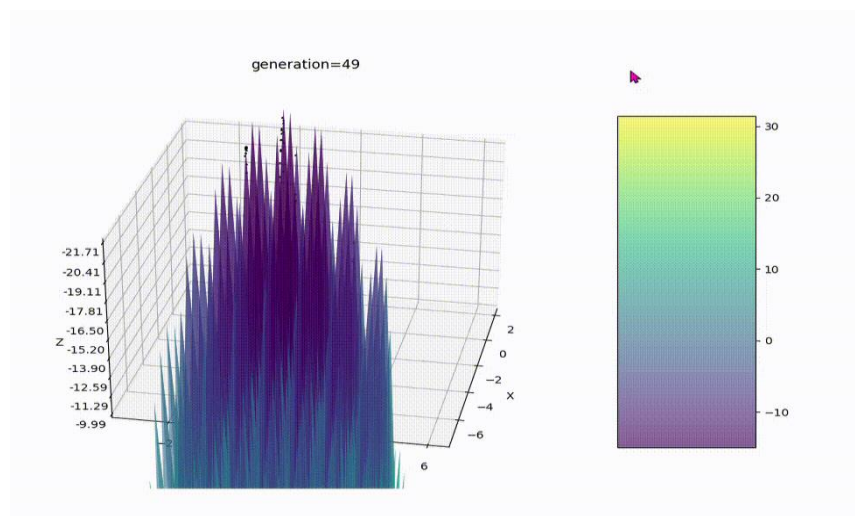
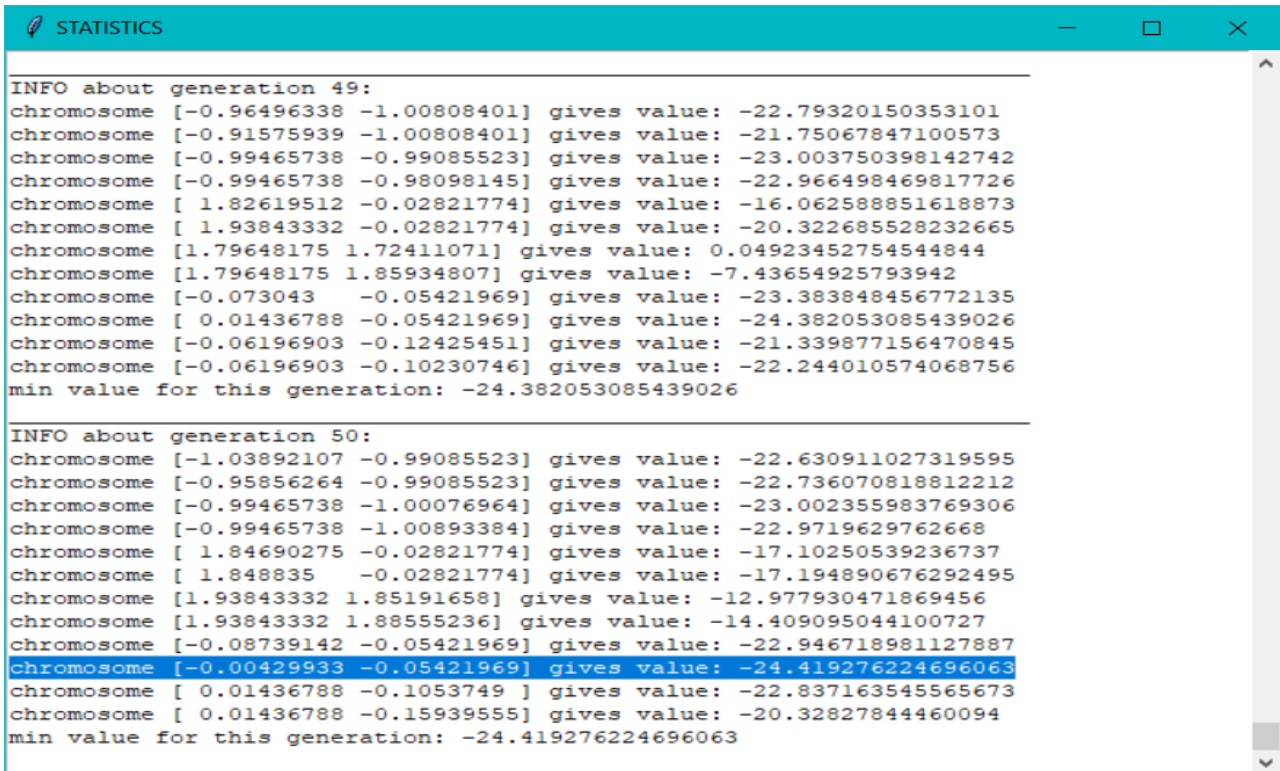


Fig. 2. Rastrigin function graph

The calculated data obtained are shown in fig. 3.



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STATISTICS
INFO about generation 49:
chromosome [-0.96496338 -1.00808401] gives value: -22.79320150353101
chromosome [-0.91575939 -1.00808401] gives value: -21.75067847100573
chromosome [-0.99465738 -0.99085523] gives value: -23.003750398142742
chromosome [-0.99465738 -0.98098145] gives value: -22.966498469817726
chromosome [ 1.82619512 -0.02821774] gives value: -16.062588851618873
chromosome [ 1.93843332 -0.02821774] gives value: -20.322685528232665
chromosome [1.79648175 1.72411071] gives value: 0.04923452754544844
chromosome [1.79648175 1.85934807] gives value: -7.43654925793942
chromosome [-0.073043 -0.05421969] gives value: -23.383848456772135
chromosome [ 0.01436788 -0.05421969] gives value: -24.382053085439026
chromosome [-0.06196903 -0.12425451] gives value: -21.339877156470845
chromosome [-0.06196903 -0.10230746] gives value: -22.244010574068756
min value for this generation: -24.382053085439026

INFO about generation 50:
chromosome [-1.03892107 -0.99085523] gives value: -22.630911027319595
chromosome [-0.95856264 -0.99085523] gives value: -22.736070818812212
chromosome [-0.99465738 -1.00076964] gives value: -23.002355983769306
chromosome [-0.99465738 -1.00893384] gives value: -22.9719629762668
chromosome [ 1.84690275 -0.02821774] gives value: -17.10250539236737
chromosome [ 1.848835 -0.02821774] gives value: -17.194890676292495
chromosome [1.93843332 1.85191658] gives value: -12.977930471869456
chromosome [1.93843332 1.88555236] gives value: -14.409095044100727
chromosome [-0.08739142 -0.05421969] gives value: -22.946718981127887
chromosome [-0.00429933 -0.05421969] gives value: -24.419276224696063
chromosome [ 0.01436788 -0.1053749 ] gives value: -22.837163545565673
chromosome [ 0.01436788 -0.15939555] gives value: -20.32827844460094
min value for this generation: -24.419276224696063
```

Fig. 3. The initial data of the Rastrigin function

Results and discussion. Estimation of chromosome fitness in a population is to calculate the fitness function for each chromosome in that population. The greater the value of this function, the higher the "quality" of the chromosome. The form of the fitness function depends on the nature of the problem to be solved. It is assumed that the fitness function always takes non-negative values and, in addition, to solve the optimization problem you need to maximize this function. If the original form of the fitness function does not satisfy these conditions, then the corresponding transformation is performed (for example, the task of minimizing the function can be easily reduced to the problem of maximization).

Conclusions. Testing the developed hybrid genetic algorithm on the classical test function of Rastrigin showed the adequacy and relevance of using heuristic algorithms for solving problems of finding a global optimum. It is determined that the improvement of methods for optimizing and expanding the use of genetic algorithms, stimulates the emergence of similar software products on the market, simplifies the structure of software, design an interface to work with commercial users, simplify the

language of teams that enable genetic programming. circle of users with different levels of professional training.

BIBLIOGRAPHY

1. Genetic algorithms. Key concepts and methods of implementation [Electronic resource]: article. - Access mode: http://www.znannya.org/?view=ga_general (access date: 15.01.2022);

2. Genetic algorithm - visual implementation [Electronic resource]: article. - Access mode: <https://habr.com/ru/post/254759/> (access date: 15.01.2022);

3. Function optimizer based on genetic algorithms [Electronic resource]: article. - Access mode: <https://github.com/likeblood/geneticOptimizer> (access date: 15.01.2022);

4. Hybrid genetic algorithm for solving the problem of optimizing the structure of the integrated circuit, National University "Kyiv-Mohyla Academy" MM Hlybovets, S.S. Gorokhovskiy, OV Kratkova, Software Engineering № 1 2011;

5. Skakalina E.V. IMPLEMENTATION OF A GENETIC ALGORITHM FOR OPTIMIZING THE DISTRIBUTION PROCESS / Elena Skakalina // Modern engineering and innovative technologies. – 2020. – Issue 14, Part. 2, pp. 6-13. ISSN 2567-5273, DOI: 10.30890/2567-5273.2020-14-02.

6. Genetic algorithm on Python, Anatoly (@likeblood): [Electronic resource]: article. - Access mode: <http://habr.com/ru/post/498308/> (access date: 15.01.2022);

7. NTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2015, VOL. 61, NO. 1, PP. 7–16 Manuscript received January 3, 2015; revised March 2015. [Electronic resource]: article. - Access mode: https://www.researchgate.net/publication/276528229_On_Some_Aspects_of_Genetic_and_Evolutionary_Methods_for_Optimization_Purposes (access date: 15.01.2022).