Zhanshen Feng,
Yan Yu

Xu Chang University , Xuchang, Henan, e-mail: fzs7879@163.com

APPLICATION OF SELF-ADAPTIVE DYNAMIC NICHE GENETIC ALGORITHM IN GLOBAL MULTIMODAL OPTIMIZATION PROBLEMS

Чжаньшень Фен,
Янь Юй

Сюйчанський університет, м. Сюйчан, провінція Хенань, КНР, e-mail: fzs7879@163.com

ЗАСТОСУВАННЯ САМОРЕГУЛЬОВАНОГО ДИНАМІЧНОГО НІШЕВОГО ГЕНЕТИЧНОГО АЛГОРИТМУ В ЗАВДАННЯХ ГЛОБАЛЬНОЇ БАГАТОМОДАЛЬНОЇ ОПТИМІЗАЦІЇ

Purpose. Genetic algorithm is a kind of random search method evolved from the genetic mechanism, it has strong robustness and optimization ability. However, a large number of researches indicated that the traditional genetic algorithms have many deficiencies and limitations in global multimodal optimization, such as they are prone to premature convergence, high computational cost and weak local search abilities. The purpose is to overcome these disadvantages through the creation of a new algorithm for solving global multimodal optimization problems, which is self-adaptive dynamic niche genetic algorithm (SDNGA).

Methodology. By studying the GA optimization and niche theory, we combine multi-groups and niche method to traditional genetic algorithm, which is used in the solution of global multimodal optimization problems. The proposed algorithm is applied to test functions to demonstrate its effectiveness and applicability.

Findings. We adopted the niche technology to divide each generation of a group into several subgroups. Then, we choosed the best individual from each subgroup as the representative of such a subgroup, and then carried out the hybridization and mutation to produce a new generation within the population and between populations, thus enhancing the global optimization ability of the algorithm, and improving the convergence speed.

Originality. We made a study of genetic algorithm and niche theory to apply in the global multimodal optimization problem. We discussed the ideas and the steps of proposed algorithm, made the qualitative analysis on the searching ability and the convergence speed. The research on this aspect has not been found at present.

Practical value. We proposed a self-adaptive dynamic niche genetic algorithm, which can be used in global multimodal optimization problems. The test experimental results have shown that SDNGA has good searching ability, good performance and very strong robustness, which allows for solutions of higher quality.

Keywords: *niche theory, genetic algorithm, multimodal optimization problem, self-adaptive, dynamic, convergence speed, high quality solution*

Introduction. Genetic Algorithm (GA) is a random search method that evolves from and draws on the experience of the survival of the fittest. GA has the features of self-organizing, self-learning, self-adapting, parallelism and the strong fault-tolerant ability [1]. The choice, cross, and variation of GA are all operated randomly, instead of a certain precise rule. It needs no derivation or other auxiliary knowledge and it only needs the objective function and the corresponding fitness function that can affect the search direction. These features of the genetic algorithm have been broadly applied in the fields of the optimization problem, the self-adaption control, picture processing and machine learning, etc. It is one of the key technologies of modern intelligent computing [2].

The genetic algorithm is a global optimization algorithm derived from the thought of evolution and its basic idea is built on the evolution theory of Darwin and the theory of heredity of Mendel. The genetic algorithm is mainly formed in the relatively complete theory and method from the research of John Holland of the University of Michigan in America, who has proposed the Schema Theorem later [3]. De Jong has tried to apply the genetic algorithm in the function optimization and has proposed five test functions to test the optimal performance of the genetic algorithm. Schaffer has presented the multi-population genetic algorithm. Goldberg has published a book named "Genetic Algorithm in Search, Optimization, and Machine learning", which has been of major significance for subsequent researches on the algorithm. Another book named "Genetic Algorithm + Data Structure = Evolutionary Programming", published by Michalewicz is also considerably influential [4]. In recent years, a number of scholars have conducted abundant researches and improvements on the fitness function, genetic operators, preferences and convergence analyses of the genetic algorithm as well as the parallel genetic algorithm. At the present work, GA is not sufficient for solving the large-scale optimization and is easy to be involved in "prematurity". The mixed genetic algorithm and the cooperative evolutionary algorithm are often used as substitutes, which are derivative algorithms of GA [5]. This paper combines niche with the genetic algorithm to solve the global optimization of the multi-modal function.

Firstly, this paper introduces the description of the optimization problem and the rationale of the genetic algorithm, and then analyzes the niche. Based on the above-mentioned researches, the authors put forward a self-adaptive dynamic niche genetic algorithm to apply in the solution to the global optimization problem, which has achieved a relatively satisfactory result. The simulation experiment described in the paper proved that this method is effective.

Genetic algorithm and function optimization problem. ***Description of the function optimization problem.*** Recently, in theory and practice, with the growth of the optimization problems complexity, traditional optimization methods, for example, the iterative method, show their limitations and defects in the solutions of such problems. The intelligent evolutionary algorithm has a series of advantages such as the high optimization precision and easiness to implement etc., in solving the complex function optimization. According to different forms of the objective function and constraint function, the optimization problem can be divided into the unconstrained optimization, equality constraint optimization, and inequality constraint optimization; it also can be divided into the linear programming and nonlinear programming, single objective programming and multi-objective programming. Intelligent evolutionary algorithm plays a certain role in solving the complex function optimization [6]. General function optimization problem can be described as follows

$$P=\begin{cases}\min f(x)\\ s.t. x\in\Omega\end{cases}. \quad (1)$$

Where, $\Omega \subset R^n$ is a feasible set, f is the objective function defined in Ω. If there exists $y\in\Omega$ to make $\forall x\in\Omega$ and $f(y)\le f(x)$, y is referred to as the globally optimal soluteon to the optimization problem (1), and $f = f(y)$ is the globally optimal value.The optimization seeking for the globally opti-mal solution is named the global optimal problem [7].

Function optimization is a classic application of genetic algorithm, and also the commonly used numerical example in the performance evaluation of the genetic algorithm.

The principle of the genetic algorithm. The genetic algorithm can directly operate on the structural object with the search direction to be guided by the transition rule of the probability instead of the certainty search rule. This process makes the offspring population more adaptable to the environment than the parental population and the optimal individuals in the last population can be the approximate optimal soluteons to the problem after decoding. The flowchart of the basic genetic algorithm is shown in Fig. 1. Three operations executed on genetic population based on the principle of the genetic algorithm are selection, crossover and mutation [8, 9].

Selection: It refers to the operation of selecting several individuals from the population at a certain probability. In general, the selection process is the survival of the fittest based on the fitness. The reason is that during the selection of the individuals used to reproduce the next generation, its reproductive output is determined according to the fitness of the individual to the environment.

Crossover: It is also called genetic recombination, the offspring of which is commonly known as "hybrid". This process is about the genes exchange in same positions of two different individuals to produce new individuals among selected individuals used to reproduce next generation. DNA at one same position of two chromosomes is cut off, and two strings front and back are respectively crossover and combined to form two new chromosomes.

Mutation: This operation is to execute the transformation on certain genes among selected individuals. If one gene is 0, it is turned into 1 during the mutation. Some replication errors can be generated at small probability in the cell reproduction, thus resulting in some mutations in the DNA to produce new chromosomes.

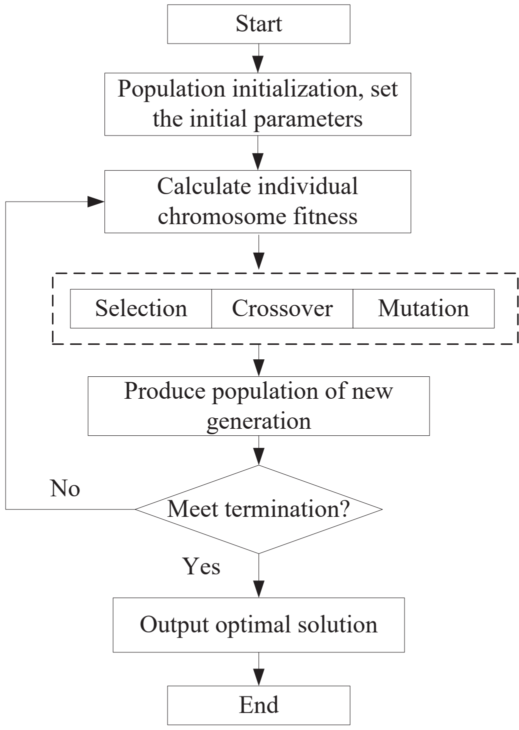

Fig. 1. The flowchart of basic genetic algorithm

Niche technology. In biology, niche refers to an organization structure in a particular environment. In nature, species with similar features and shapes often meet together and copulate among same species to reproduce next generations. By mainly referring to the diversity characteristic of the population's living environment, niche technology has the advantage of making the general evolutionary algorithm seek multiple optimal solutions. The purpose of introducing the niche technology is to use the niche technology based on the restrict competition selection strategy to make each sub-population dynamically form the independent search space and suppress the homoplasy resulted from the group synergy, and then carry out hybridization and mutation within the population and between populations to produce a new generation. The deficiency of species diversity is exactly the main cause why global search ability of the genetic algorithm is not strong. In order to prevent the diversity of population being damaged, the niche technology is introduced, and the preliminary selection mechanism, crowing-out mechanism or sharing mechanism are adopted to complete the task, thus better maintaining the diversity of population, and also having very high global search ability and convergence speed, which specially fits complexed puzzles with little priori knowledge [10].

Niche sharing method operation aims to decrease the replication of similar individuals to keep the diversity of population possibly, to achieve the aim of searching multiple regions at the same time. Divide fitness values by a niche count sum to gain Sharing Function. Niche count sum is the estimation of individual neighbor set intensity, and Sharing Function is the function expressing close relationship degree between two individuals in the group, and in which, $S(d)$ expresses the relationship between individual i and j.

$$sum = \sum S\{d[i, j]\} \quad . \tag{2}$$

In the above formula, $d[i, j]$ is the distance between individual i and j, $S[0]$ is sharing function which is decreasing function related to $d[i, j]$. When $S[d] = 0, d > \lambda_{share}$, here, λ_{share} is the radius of a niche. The intimacy degree between two individuals is mainly embodied in individual genotype similarity or individual's type similarity. When two individuals are extremely similar, its sharing function value is large; on the contrary, when two individuals are not extremely similar, its sharing function value is small. The flow process chart of the niche algorithm is shown in Fig. 2.

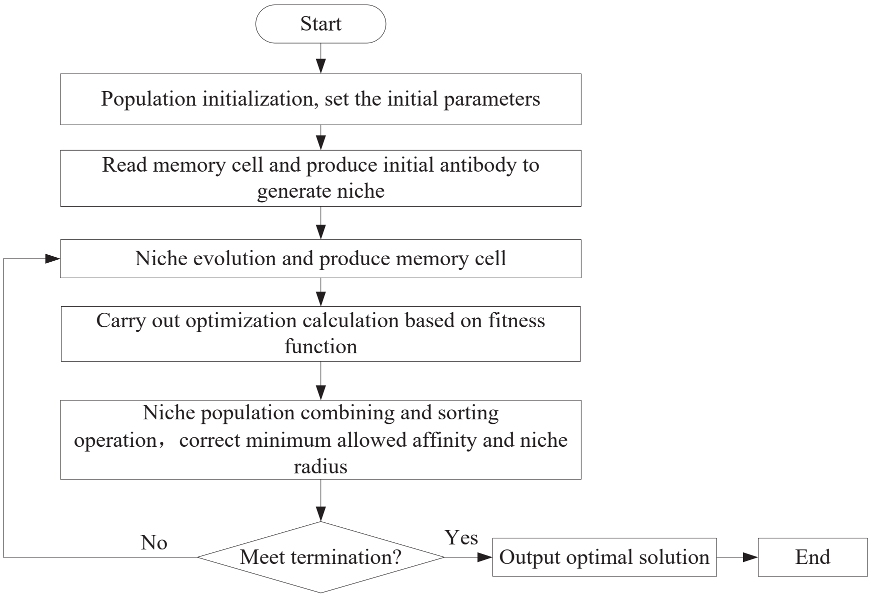

Fig. 2. The flow chart of niche algorithm

Self-adaptive genetic algorithm with niche topological structure. The basic idea of SDNGA algorithm is to adjust the fitness of each individual in the group by the Sharing Function (2) reflecting the similarity degree between individuals. Compare the distance between each individual two by two, if such distance is within the predetermined distance d, and then compare the fitness between these two. Conduct selection and calculation based on the adjusted new fitness. Within the distance d, there will exist only a good individual, so as to maintain the population diversity, and but also keep a certain distance between each individual, and also enable the individual to spread out in the whole constrained space, thus keeping the diversity of solutions, improving the global search ability, and fitting complex multimodal function optimization. Specific steps are as follows.

Step 1: generate number m population $P(s_i)$ by random initialization and determine each individual's fitness $F(i = 1,2,...m)$. Define one fitness functio $f(x)$, crossover rate p_c and mutation rate p_m in the search space W.

Step 2: randomly generate number m individual s_1, s_2, ..., s_m in W to form initial population $S(1) = \{s_1, s_2, ..., s_m\}$. Order the individual according to each individual's fitness by the descending order and memorize the front number n individual $(n < m)$.

Step 3: calculate the fitness function of each individual s_i among S, i.e. $f_i = f(s_i)$, and take the individual with the largest fitness among S as the required result.

Step 4: conduct the proportional selection algorithm on population $P(s_i)$ according to the following selection probability distribution formula.

$$P(s_i) = f_i / \sum_{i=1}^{m} f_i \quad i = 1, 2, ..., m \; . \tag{3}$$

Combine generated number m individuals and memorized number n individuals to gain one new population containing number $m + n$ individuals. Contrast number $m + n$ individuals according to function (2) to gain the distance between individual x_1 and x_2. When $\|x_1 - x_2\| < d$, compare the fitness of individual x_1 and x_2, and conduct the elimination algorithm to form one new niche, and such individual becomes the center of a new niche. When $\|x_1 - x_2\| > d$, such individual becomes an independent one.

Step 5: conduct crossover algorithm towards selected individual set $P(s_i)$ and randomly determine number c chromosome from S_1 based on the crossover rate p_c. Conduct the crossover operation in pair and replace former chromosomes with generated new ones.

Step 6: conduct the uniform mutation algorithm towards $P(s_i)$ and determine number m chromosomes from S_2 at the mutation rate p_m, and respectively conduct the mutation operation and replace former chromosomes with the generated new ones.

Step 7: estimate whether the terminal conditions are met, if not, take front number m individuals in Step 6 as next new generation population $P(s_{i+1})$, and then return to Step 3. If the terminal conditions are met, output calculated result. The algorithm ends.

Experiment and simulation test. *Test function.*

1. Schaffer function

$$\min f(x_1, x_2) = 0.5 + \frac{(\sin\sqrt{x_1^2 + x_2^2})^2 - 0.5}{(1 + 0.001(x_1^2 + x_2^2))^2},$$

of which $-10.0 \le x_1,\ x_2 \le 10.0$.

This function is a two-dimensional complicated function with countless minimal points. The minimum value of 0 can be obtained at the position of (0, 0). It is that the size of the potential maxima that need to be overcome to get to a minimum increases the closer one gets to the global minimum.

2. Griewank function

$$\min f(x_i) = \sum_{i=1}^{N} \frac{x_i^2}{4000} - \prod_{i=1}^{N} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1,$$

of which, $x_i \in [-600, 600]$.

This function is multimodal and non-separable, with several local optima within the search region. It is similar to the Rastrigin function, but the number of local optima is larger in this case. The global minimum of 0 can be obtained at the position of $(x_1, x_2, \cdots, x_n) = (0, 0, \cdots 0)$. This function is a typical non-linear multi-modal function, which is difficult to settle.

3. Rastrigin function

$$\min f(x_i) = \sum_{i=1}^{D} [x_i^2 - 10\cos(2\pi x_i) + 10],$$

of which, $x_i \in [-5.12, 5.12]$.

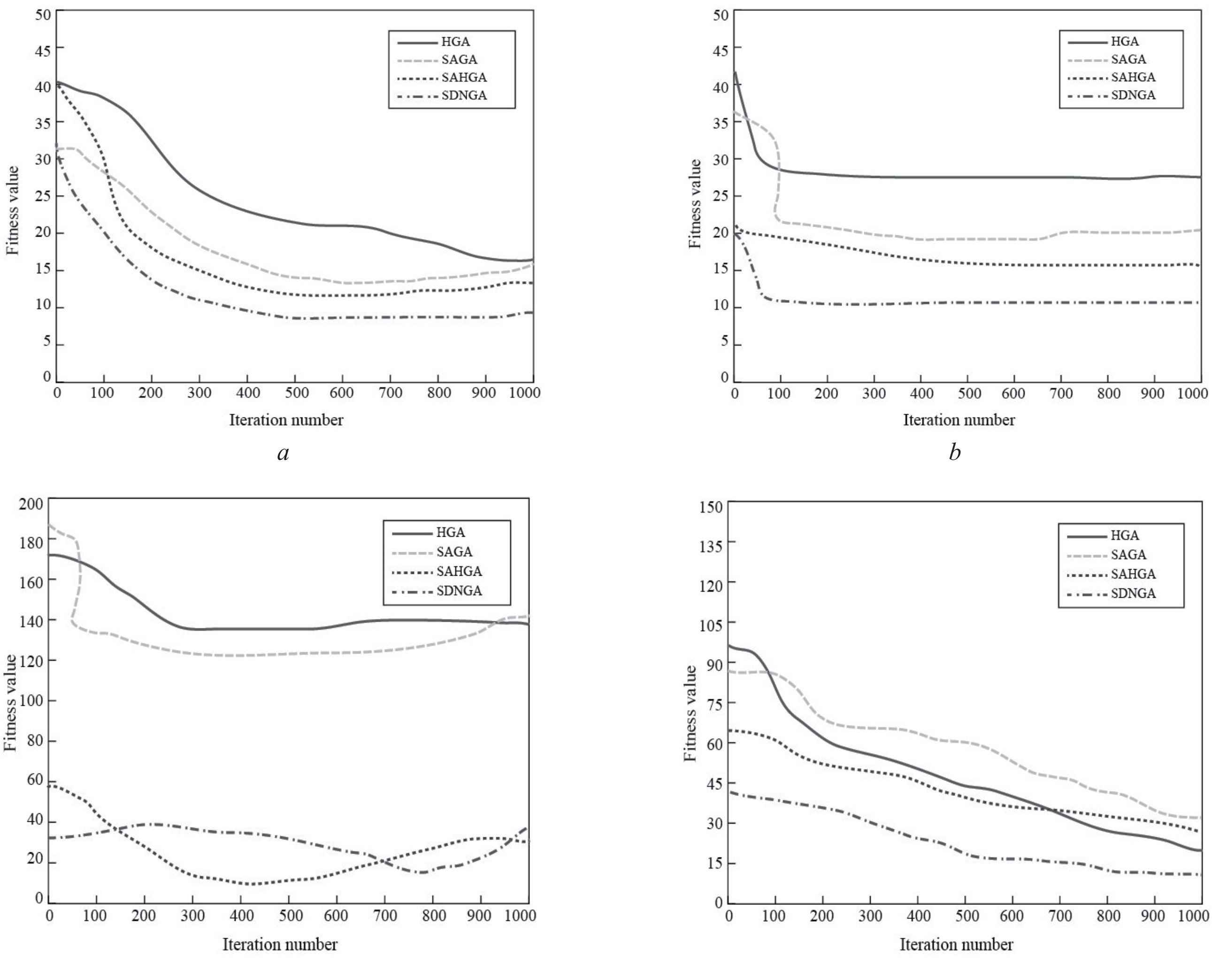

Fig. 3. Average evolution comparison curve of on the test functions: a − schaffer function; b − griewank function; c − rastrigin function; d − rosenbrock function

This function is a multi-modal function, and the minimum value can be obtained at the position of $(x_1, x_2, \cdots, x_n) = = (0, 0, \cdots 0)$. It is a difficult problem due to its large search space and its large number of local minima.

4. Rosenbrock function

$$\min f(x_i) = \sum_{i=1}^{D-1} \left[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2 \right],$$

of which $x_i \in [-2.048, 2.048]$.

This function is non-convex, unimodal and non-separable and known as Rosenbrock's valley. It is difficult to identify the search direction, converge to the global minimum and to find the optimal solution. The minimum value of 0 of the function can be found at the position of $(x_1, x_2, \cdots, x_n) = = (1, 1, \cdots 1)$, however, is difficult.

Experimental simulation testing. In recent researches, there have existed some algorithms, the optimization performance of which is good. Between them, the better ones in-clude Hierarchic Genetic Algorithm (HGA), Simulated Annealing Genetic Algorithm (SAGA) and Simulated Annealing Hierarchic Genetic Algorithm (SAHGA). This paper compares SDNGA and HGA, SAGA and SAHGA, sets crossover probability of the genetic algorithm $p_c = 0.7$, the mutation probability $p_m = 0.1$, the number of iterations $Gen = 1000$, the population size $m = 100$. Fig. 3 allows us to compare the fitness change with the increase of dimension. It shows the average fitness evolutionary curve of the four testing functions mentioned above under the condition of 30 dimension and test of 20 times.

As seen in the Fig. 3, the SDNGA algorithm approached the optimal value. When compared with other three algorithms, no matter in terms of the quality of the solution and the evaluation number of the used functions, SDNGA algorithm is better than the other three. In this research, all the four functions have found the approximate optimal solution 0 by such algorithm. It shows that the mixed algorithm's robustness is better than the same of the others is, and that SDNGA algorithm has better optimization performance for high-dimensional space, and decreases the replication of similar individuals possibly to keep the diversity of population, thus achieving the purpose of exploring multiple regions at the same time.

Conclusions. Genetic algorithm is a kind of random search method based on the natural selection and genetic evolutionary mechanism. Because of the inability of the traditional genetic algorithm to balance the fast convergence and maintain the diversity of the population, the authors proposed a self-adaptive dynamic genetic algorithm using niche technology (SDNGA). The experimental results have proved that for the global optimization problem, the suggested algorithm shows good performance and has very strong robustness, which allows for solutions of higher quality.

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Мета. Генетичний алгоритм – це, свого роду, метод випадкового пошуку, створений на основі механізмів генетики, він має хорошу стійкість та оптимізаційну здатність. Проте багато вчених вказує на те, що стандартні генетичні алгоритми мають безліч недоліків і обмежень при використанні у глобальній багатомодальній оптимізації, оскільки вони схильні до передчасної конвергенції, мають високу складність обчислення та слабкі можливості локального пошуку. Метою роботи є подолання вказаних недоліків шляхом створення нового алгоритму вирішення завдань глобальної мультимодальної оптимізації – самоналагоджувального динамічного генетичного алгоритму з використанням нішевої технології (SDNGA).

Методика. У ході вивчення оптимізації за допомогою генетичного алгоритму й теорії ніш, у традиційному генетичному алгоритмі, що використовується у глобальній мультимодальній оптимізації, були об'єднані мульти-групи та метод ніш. Запропонований алгоритм перевірявся на тестових функціях з метою підтвердження його ефективності та доцільності використання.

Результати. Нішева технологія була застосована для розділення генерації (покоління) однієї групи на декілька підгруп, із подальшим вибором кращого індивіда від кожної підгрупи в якості її представника. Потім проводилася гібридизація й мутація задля здобуття нових генерацій (поколінь) усередині однієї популяції та між різними популяціями, завдяки чому досягалося покращення оптимізаційної здатності алгоритму та підвищення швидкості конвергенції.

Наукова новизна. Вивчені можливості застосування генетичного алгоритму й теорії ніш задля вирішення завдань глобальної мультимодальної оптимізації. Розглянуті ідея й кроки (етапи виконання) запропонованого алгоритму, проведений якісний аналіз його пошукової здатності й швидкості конвергенції. Дослідження даного аспекту раніше не проводилися.

Практична значимість. Запропоновано самоналагоджувальний динамічний генетичний алгоритм з використанням нішевої технології, що може застосовуватися в завданнях глобальної мультимодальної оптимізації. Результати експериментального тестування показали, що SDNGA-алгоритм має хороші пошукові здібності, високу продуктивність і стійкість, що дозволяє знаходити кращі рішення.

Ключові слова: *нішева теорія, генетичний алгоритм, задача багатомодальної оптимізації, самоналагоджувальний, динамічний, швидкість конвергенції, якісне рішення*

Цель. Генетический алгоритм – это, своего рода, метод случайного поиска, созданный на основе механизмов генетики, он обладает хорошей устойчивостью и оптимизационной способностью. Однако многие ученые указывают на то, что стандартные генетические алгоритмы имеют множество недостатков и ограничений при использовании в глобальной многомодальной оптимизации, поскольку они подвержены преждевременной конвергенции, имеют высокую сложность вычисления и слабые возможности локального поиска. Целью работы является преодоление указанных недостатков путем создания нового алгоритма решения задач глобальной мультимодальной оптимизации – самонастраивающегося динамического генетического алгоритма с использованием нишевой технологии (SDNGA).

Методика. В ходе изучения оптимизации посредством генетического алгоритма и теории ниш, в традиционном генетическом алгоритме, используемом в глобальной мультимодальной оптимизации, были объединены мульти-группы и метод ниш. Предложенный алгоритм проверялся на тестовых функциях с целью подтверждения его эффективности и целесообразности применения.

Результаты. Нишевая технология была применена для разделения генерации (поколения) одной группы на несколько подгрупп, с последующим выбором лучшего индивида от каждой подгруппы в качестве ее представителя. Затем проводилась гибридизация и мутация для получения новых генераций (поколений) внутри одной популяции и между разными популяциями, благодаря чему достигалось улучшение оптимизационной способности алгоритма и повышение скорости конвергенции.

Научная новизна. Изучены возможности применения генетического алгоритма и теории ниш для решения задач глобальной мультимодальной оптимизации. Рассмотрены идея и шаги (этапы выполнения) предложенного алгоритма, проведен качественный анализ его поисковой способности и скорости конвергенции. Исследования данного аспекта ранее не проводились.

Практическая значимость. Предложен самонастраивающийся динамический генетический алгоритм с использованием нишевой технологии, который может применяться в задачах глобальной мультимодальной оптимизации. Результаты экспериментального тестирования показали, что SDNGA-алгоритм имеет хорошие поисковые способности, высокую производительность и устойчивость, что позволяет находить лучшие решения.

Ключевые слова: *нишевая теория, генетический алгоритм, задача многомодальной оптимизации, самонастраивающийся, динамический, скорость конвергенции, качественное решение*

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