НЕЙРОІНФОРМАТИКА
ТА ІНТЕЛЕКТУАЛЬНІ СИСТЕМИ

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OPTIMIZATION METHOD BASED ON THE SYNTHESIS OF CLONAL SELECTION AND ANNEALING SIMULATION ALGORITHMS

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ABSTRACT

Context. The problem of increasing the efficiency of optimization methods by synthesizing metaheuristics is considered. The object of the research is the process of finding a solution to optimization problems.

Objective. The goal of the work is to increase the efficiency of searching for a quasi-optimal solution at the expense of a metaheuristic method based on the synthesis of clonal selection and annealing simulation algorithms.

Method. The proposed optimization method improves the clonal selection algorithm by dynamically changing based on the annealing simulation algorithm of the mutation step, the mutation probability, the number of potential solutions to be replaced. This reduces the risk of hitting the local optimum through extensive exploration of the search space at the initial iterations and guarantees convergence due to the focus of the search at the final iterations. The proposed optimization method makes it possible to find a conditional minimum through a dynamic penalty function, the value of which increases with increasing iteration number. The proposed optimization method admits non-binary potential solutions in the mutation operator by using the standard normal distribution instead of the uniform distribution.

Results. The proposed optimization method was programmatically implemented using the CUDA parallel processing technology and studied for the problem of finding the conditional minimum of a function, the optimal separation problem of a discrete set, the traveling salesman problem, the backpack problem on their corresponding problem-oriented databases. The results obtained allowed to investigate the dependence of the parameter values on the probability of mutation.

Conclusions. The conducted experiments have confirmed the performance of the proposed method and allow us to recommend it for use in practice in solving optimization problems. Prospects for further research are to create intelligent parallel and distributed computer systems for general and special purposes, which use the proposed method for problems of numerical and combinatorial optimization, machine learning and pattern recognition, forecast.

KEYWORDS: metaheuristics, clonal selection, annealing simulation, optimization, technology of information parallel processing.

ABBREVIATIONS

CLONALG is a clonal selection algorithm;
SA is an algorithm for simulating annealing;
MSE is a mean square error;
CUDA is the compute unified device architecture.

NOMENCLATURE

A^{mt} is the mutation operator;

A^{cl} is the cloning operator;

A^{rd} is the reduction operator;

A^{rp} is the replacement operator;

x is a solution (antibody);

x^* is a (quasi) optimal solution (antibody);

$F(\cdot)$ is the fitness function;

$f(\cdot)$ is the function for which the conditional minimum should be found;

$F_w(\cdot)$ is the penalty function;

$\Phi(\cdot)$ is an affinity;

$X^{(n)}$ is a population at iteration n;

μ is population and intermediate population power;

C is a set of antibody clones;

q is a number of clones for each antibody;

$\hat{C}$ is a set of mutated antibodies clones;

λ is a power of the set mutated clones;

M is the intermediate population;

α is the cloning parameter;

$p(\cdot)$ is the mutation probability;

$round()$ is the function, rounding the number to the nearest integer;

$U(0,1)$ is the function that returns a uniformly distributed random number in the range $[0,1]$;

$N(0,1)$ is the function that returns a standard normally distributed random number;

d is a number of replaced antibodies;

$d^{\max}$ is the maximum number of replaced antibodies;

n is an iteration number;

$n^{\max}$ is the maximum number of iterations;

$x_i^{\min}$, $x_i^{\max}$ are the minimum and maximum values of the i th component of the antibody respectively;

Δ_i is a mutation step for the i th component of the clone;

δ is the mutation parameter, $0 < \delta < 1$;

$T(n)$ is the annealing temperature at iteration n;

T_0 is an initial annealing temperature;

β is a cooling ratio;

$h_z(\cdot)$ is the z th equality constraint;

$g_z(\cdot)$ is the z th inequality constraint;

Z_1 is a number of equality constraints;

Z_2 is a number of inequality constraints;

X_w is the subset of the current population containing antibodies that satisfy all constraints;

I_1 is a number of arguments of the function for which the conditional minimum should be found;

S is the partitionable set;

s_k is a vector, one-to-one corresponding to the k th element of the partitionable set;

J is a number of features of the element partitionable set;

K is the power of the partitionable set;

I_2 is a number of classes into the partitionable set;

d_{x_i, x_j} is the distance between points of the route x_i, x_j;

I_3 is a number of points of the route;

W is a load capacity;

w_i is a weight of i th cargo;

v_i is a value of the i th cargo;

I_4 is a number of cargo.

INTRODUCTION

Today, the development of methods aimed at solving problems of numerical and combinatorial optimization, machine learning, etc., which are used in general and special-purpose intelligent computer systems, is an urgent task.

Existing optimization methods that find the exact solution have high computational complexity. Optimization and machine learning methods that find an approximate solution through directional search have a high probability of falling into a local extremum. Random search methods do not guarantee convergence. In this connection, the problem of insufficient efficiency of optimization methods, which needs to be solved, arises.

The object of study is the process of finding solutions to optimization problems.

The subject of study is the methods for finding a quasi-optimal solution based on metaheuristics.

The purpose of the work is to increase the efficiency of searching for a quasi-optimal solution at the expense of a metaheuristic method based on the synthesis of clonal selection and annealing simulation algorithms.

To achieve this goal, it is necessary to solve the following tasks:

1) to create a quasi-optimal method based on the synthesis of clonal selection and annealing simulation algorithms;

2) to adapt the proposed method to the problem of finding the conditional minimum of functions;

3) to adapt the proposed method to the problem of optimal partitioning of a discrete set;

4) to adapt the proposed method to the traveling salesman problem;

5) to adapt the proposed method to the knapsack problem;

6) to conduct a numerical study of the proposed optimization method.

1 PROBLEM STATEMENT

The problem of increasing the efficiency of searching a solution to an optimization problem based on clonal selection is represented as the problem of finding such an ordered set of operators $\{A^{mt}, A^{cl}, A^{rd}, A^{rp}\}$, the iterative application of which provides finding such a solution x^* in which $F(x^*) \to \min$ and $T \to \min$, moreover, the solution structure x, fitness function $F(\cdot)$ and mutation operator A^{mt} depend on the problem to be

solved, and the structures of the cloning A^{cl}, reduction A^{rd} and replacement A^{rp} operators are independent.

2 REVIEW OF THE LITERATURE

To accelerate a quasi-optimal solution of optimization and machine learning problems and reduce the likelihood of falling into a local extremum, metaheuristics (or advanced heuristics) are used [1–5]. Metaheuristics expands the capabilities of heuristics by combining heuristic methods based on a high-level strategy [6–10].

However, modern metaheuristics have one or more of the following disadvantages:

– there is only an abstract description of the method or the description of the method is focused on solving only a specific task [1];

– the influence of the iteration number on the solution search process [2] is not taken into account;

– the convergence of the method [11] is not guaranteed;

– there is no possibility of using non-binary potential solutions [12];

– the procedure for determining the values of parameters [13] is not automated;

– there is no possibility to solve the problems of conditional optimization [14];

– insufficient accuracy of the method [15].

Therefore, the efficiency of the method for the search of quasi-optimal solution is of paramount importance.

The clonal selection algorithm, proposed by Castro and von Zuben [16–17], developed in [18–21] and programmatically implemented in [22], is one of the popular metaheuristics.

3 MATERIALS AND METHODS

The optimization method based on the synthesis of clonal selection and annealing simulation algorithms is developed.

The sequence of procedures of the proposed optimization method based on the synthesis of clonal selection and annealing simulation algorithms is shown in Fig. 1.

In block 1, an initial population $X^{(1)} = \{x\}$ with power μ is created, and each antibody of this population corresponds to a potential solution of the problem.

In block 2, the current annealing temperature at iteration n is calculated

$$T(n) = \beta^n T_0 , \; T_0 > 0 , \; 0 < \beta < 1 .$$

In block 3, the value of the fitness function $F(x)$ for each antibody x, which is determined by the specificity of the particular optimization problem, is calculated.

In block 4, the affinity value for each antibody x is calculated.

Affinity is a function that determines the proximity of antibody x to the best antibody in the current population and is calculated based on the utility function. The affinity value is calculated as

$$\Phi(x) = \frac{\max\limits_{x \in X^{(n)}} F(x) - F(x)}{\max\limits_{x \in X^{(n)}} F(x) - \min\limits_{x \in X^{(n)}} F(x)} .$$

If $\Phi(x) = 1$, then the antibody is the best.

If $\Phi(x) = 0$, then the antibody is the worst.

In block 5, the mutation probability for each antibody x which depends on the affinity value $\Phi(x)$ and the annealing temperature $T(n)$ is calculated

$$p(x) = \exp(-\Phi(x)) \exp(-1/T(n)).$$

In block 6, the cloning operator for each antibody x is executed.

The cloning operator A^{cl} plays a role similar to the operator of genetic algorithm reproduction.

The number of clones q for each antibody x is determined as

$$q = round(\alpha \cdot \mu), \; \alpha \in (0, 1] .$$

As a result of applying the cloning operator A^{cl} to the current population $X^{(n)} = \{x\}$, a set of antibody clones $C = \{c\}$ are formed.

In block 7, the mutation operator for each clone c is executed.

The mutation operator A^{mt} allows to obtain new antibodies from antibody clones with sharply different properties.

The mutation based on the annealing simulation over each component of each clone c is executed when $p(x) < U(0, 1)$.

The features of the proposed variant of the mutation operator are the following:

– there is an inverse relationship between the mutation probability and the affinity value, i.e. the best (in terms of affinity) clones change less often than the worst (in terms of affinity) clones;

– there is an inverse relationship between the mutation probability and the iteration number, i.e. at the initial iterations the entire search space is explored and at the final iterations the search becomes directional.

As a result of applying the mutation operator A^{mt} to a set of antibody clones $C = \{c\}$, a set of mutated clones $\hat{C} = \{\hat{c}\}$ is formed.

In block 8, the reduction operator is executed.

As the reduction operator A^{rd}, the scheme $(\mu + \lambda)$ [9] is used, which provides the direction of the search (the best antibodies are preserved) and
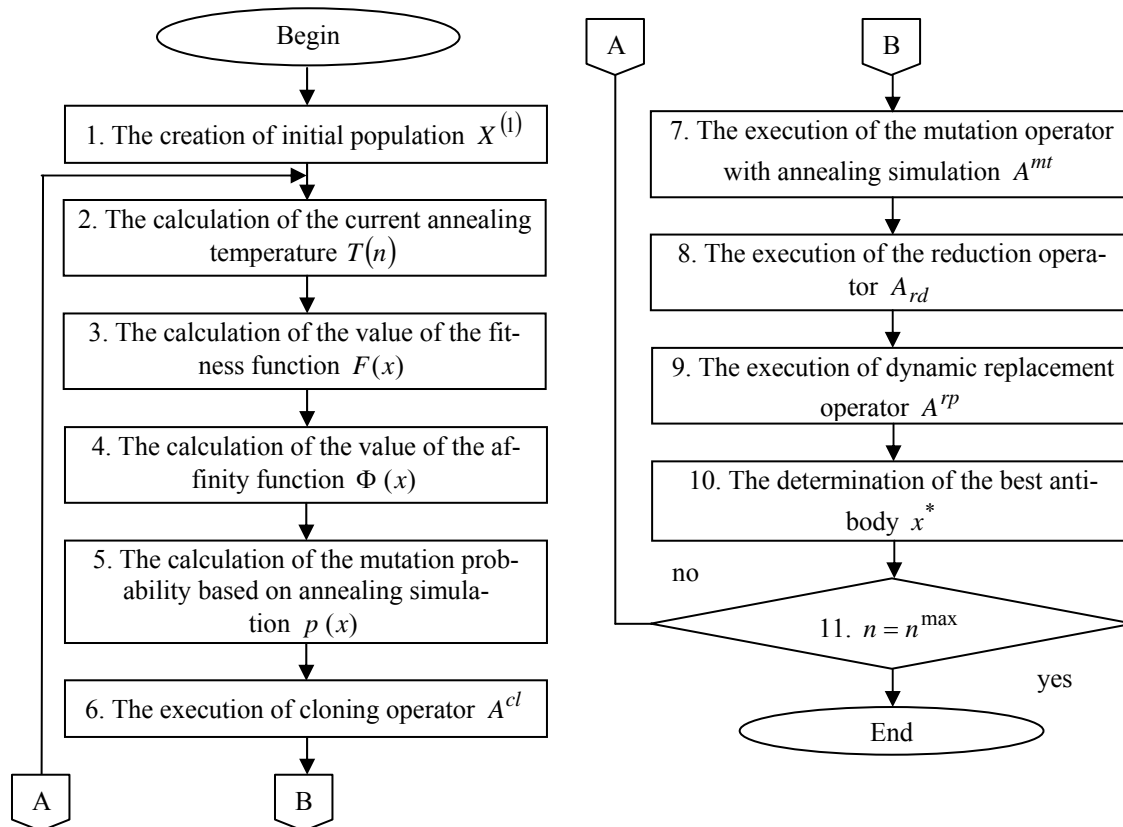
Figure 1 – The sequence of procedures of the optimization method based on clonal selection and annealing simulation

consists in the following. The current population $X^{(n)} = \{x\}$ of power μ and the set of mutated clones $\hat{C} = \{\hat{c}\}$ of power $\lambda = q \cdot \mu$ are combined and ordered by affinity value $\Phi(x)$. The first μ (best in affinity) individuals of the intermediate population are selected for the intermediate population $M = \{m\}$.

In block 9, a dynamic replacement operator is executed.

For a broader study of the search space an operator A^{rp}, which replaces the last (the worst by affinity) antibodies of the intermediate population with new antibodies, is used.

The number of replaced antibodies d is determined as

$$d = round\left(d^{\max}\left(\frac{n^{\max} - n}{n^{\max}} \right) \right), \ d^{\max} \in [0, \mu).$$

A peculiarity of the proposed dynamic replacement operator is the following – there is an inverse relationship between new antibodies number and the iteration number, i.e. at the initial iterations the entire search space is explored and at the final iterations the search becomes directional.

As a result of the application of the replacement operator A^{rp} to the intermediate population $M = \{m\}$, a new population $X^{(n+1)} = \{x\}$ is formed.

In block 10, the best antibody by the value of the fitness function $x^* = \arg \min_{x \in X^{(n+1)}} F(x)$ is determined.

In block 11, the condition for completing the solution search is checked.

If $n = n^{\max}$, then a quasi-optimal solution x^* is obtained.

The adaptation of the optimization method based on the synthesis of clonal selection and annealing simulation algorithms for the problem of finding the conditional minimum of the function is given.

The proposed method is used to minimize the function, taking into account equality constraints and inequality constraints. For this task, each antibody is a collection of function arguments, and blocks 1, 3, 7, 9 have the following features.

In block 1 and block 9, each component x_i of each antibody x is initialized as

$$x_i = (x_i^{\max} - x_i^{\min}) U(0, 1) + x_i^{\min}, i \in \{ 1, \dots, I_1 \}.$$

In block 3, the value of the fitness function $F(x)$ for each antibody x is calculated as

$$F_w(x) = n \left(\frac{|X_w| - \mu}{\mu} \right) \left(\sum_{z=1}^{Z_1} |h_z(x)| + \sum_{z=1}^{Z_2} (\max\{0, g_z(x)\}) \right),$$

$$F(x) = f(x) + F_w(x).$$

In block 7, a mutation based on annealing simulation algorithm over each component c_i of each clone c is executed as

$$r_i = U(0,1),$$

$$\Delta_i = \begin{cases} \delta (x_i^{\max} - x_i^{\min}) \left(\dfrac{n^{\max} - n}{n^{\max}} \right) \exp(-\Phi(x)) N(0,1), & r_i \leq p, \\ 0, & r_i > p \end{cases}$$

$$\widehat{c}_i = \begin{cases} x_i^{\min}, & (c_i + \Delta_i) \leq x_i^{\min} \\ (c_i + \Delta_i), & x_i^{\min} < (c_i + \Delta_i) < x_i^{\max} \\ x_i^{\max}, & (c_i + \Delta_i) \geq x_i^{\max} \end{cases}.$$

For this task, the mutation operator, besides the features indicated in the description of the developed method, has the following additional features:

– the value of each component $\widehat{c}_i$ is always in the allowable range $[x_i^{\min}, x_i^{\max}]$;

– there is an inverse relationship between the magnitude of the mutation step and the affinity value, i.e. the best (in terms of affinity) clones change less than the worst (in terms of affinity) clones;

– there is an inverse relationship between the magnitude of the mutation step and the iteration number, i.e. at the initial iterations the entire search space is explored and at the final iterations the search becomes directional;

– it does not require the use of binary potential solutions, i.e. there is no need to convert real potential solutions into binary ones before the mutation and to convert binary potential solutions into real ones after the mutation, which reduces the computational complexity of the mutation operator and speeds up the search for a solution.

The adaptation of the optimization method based on the synthesis of clonal selection and annealing simulation algorithms to the problem of optimal discrete set partitioning is given.

The proposed method is used to minimize the root-mean-square error of the partition of a finite discrete set into a given number of classes. For this task, each antibody is a set of class centers, and blocks 1, 3, 7, 9 have the following features.

In block 1 and block 9, each component x_{ij} of each antibody x is initialized as

$$x_{ij} = (x_j^{\max} - x_j^{\min}) U(0,1) + x_j^{\min},$$

$$i \in \{1, \dots, I_2\}, \quad j \in \{1, \dots, J\}.$$

In block 3, the value of the fitness function $F(x)$ for each antibody x is calculated as

$$j_k = \arg \min_{i \in 1, I_2} \| s_k - x_i \|^2,$$

$$s_k \in S, \quad k \in \{1, \dots, K\},$$

$$F(x) = \sum_{k=1}^{K} \| s_k - x_{j_k} \|^2.$$

In block 7, a mutation based on the annealing simulation algorithm over each component c_{ij} of each clone c is executed as

$$r_{ij} = U(0,1),$$

$$\Delta_j = \begin{cases} \delta (x_j^{\max} - x_j^{\min}) \left(\dfrac{n^{\max} - n}{n^{\max}} \right) \exp(-\Phi(x)) N(0,1), & r_{ij} \leq p(x), \\ 0, & r_{ij} > p(x) \end{cases}$$

$$\widehat{c}_{ij} = \begin{cases} x_j^{\min}, & (c_{ij} + \Delta_{ij}) \leq x_j^{\min} \\ (c_{ij} + \Delta_{ij}), & x_j^{\min} < (c_{ij} + \Delta_{ij}) < x_j^{\max} \\ x_j^{\max}, & (c_{ij} + \Delta_{ij}) \geq x_j^{\max} \end{cases}.$$

For this task, the mutation operator, besides the features indicated in the description of the developed method, has the following additional features:

– the value of each component $\widehat{c}_{ij}$ is always in the allowable range $[x_j^{\min}, x_j^{\max}]$;

– there is an inverse relationship between the magnitude of the mutation step and the affinity value, i.e. the best (in terms of affinity) clones change less than the worst (in terms of affinity) clones;

– there is an inverse relationship between the magnitude of the mutation step and the iteration number, i.e. at the initial iterations the entire search space is explored and at the final iterations the search becomes directional;

– it does not require the use of binary potential solutions, i.e. there is no need to convert real potential solutions into binary ones before the mutation and convert binary potential solutions into real ones after the mutation, which reduces the computational complexity of the mutation operator and speeds up the search for a solution.

The adaptation of the optimization method based on the synthesis of clonal selection and annealing simulation algorithms for the traveling salesman problem is given.

The proposed method is used to minimize the length of the route, passing only once through all points. For this

task, each antibody is a collection of route points, and blocks 1, 3, 7, 9 have the following features.

In block 1 and block 9, each component x_i of each antibody x is initialized with a randomly selected route point number, and the point numbers should not be duplicated.

In block 3, the value of the fitness function $F(x)$ for each antibody x is calculated as

$$F(x) = d_{x_I, x_1} + \sum_{i=1}^{I_3-1} d_{x_i, x_{i+1}} .$$

In block 7, the mutation based on an annealing simulation algorithm over each component c_i and a randomly selected component c_k of each clone is executed as

$$r_i = U(0,1) ,$$
$$k = round\ ((I_3 - 1)\ U\ (0,1) + 1) ,$$
$$\widehat{c}_i = \begin{cases} c_k, & r_i \le p(x) \\ c_i, & r_i > p(x) \end{cases} ,$$
$$\widehat{c}_k = \begin{cases} c_i, & r_i \le p(x) \\ c_k, & r_i > p(x) \end{cases} .$$

For this task, the mutation operator, besides the features indicated in the description of the developed method, has the following additional features:

– the value of each component always belongs to an admissible set $\{1,...,I_3\}$;

– it does not require the use of binary potential solutions, i.e. there is no need to convert integer potential solutions into binary ones before the mutation and to convert binary potential solutions into real ones after mutation, which reduces the computational complexity of the mutation operator and speeds up the search for a solution.

The adaptation of the optimization method based on the synthesis of clonal selection and annealing simulation algorithms for the knapsack problem is given.

The proposed method is used to select from a given set of objects with the properties "cost" and "weight" the subset with the maximum cost, while observing the limit on the total weight. For this task, each antibody is a collection of weights, and blocks 1, 3, 7, 9 have the following features.

In block 1 and block 9, each component x_i of each antibody x is initialized as

$$x_i = round\ (U(0,1)),\ \ i \in \left\{1, ..., I_4\right\} .$$

In block 3, the value of the fitness function $F(x)$ for each antibody x is calculated as

$$f(x) = \frac{\sum_{i=1}^{I_4} v_i}{\sum_{i=1}^{I_4} v_i x_i} ,$$
$$F_w(x) = n \left(\frac{|X_w| - \mu}{\mu} \right) \left(\max \left\{ 0, \sum_{i=1}^{I_4} w_i x_i - W \right\} \right) ,$$
$$F(x) = f(x) + F_w(x) .$$

In block 7, the mutation based on an annealing simulation algorithm over each component c_i of each clone c is executed as

$$r_i = rand\ () ,$$
$$\widehat{c}_i = \begin{cases} 1, & (r_i \ge p\ (x) \wedge (c_i = 1)) \vee ((r_i < p\ (x)) \wedge (c_i = 0)) \\ 0, & (r_i \ge p\ (x) \wedge (c_i = 0)) \vee ((r_i < p\ (x)) \wedge (c_i = 1)) \end{cases} .$$

For this problem, the mutation operator has the features indicated in the description of the developed method.

4 EXPERIMENTS

A numerical study of the proposed optimization method was carried out using the CUDA technology of information parallel processing, the number of threads in the block corresponded to the population size, the population was sorted based on the paired-disparity sorting algorithm, the antibody with the lowest value of the fitness function was searched.

Let the size of the population $\mu = 100$, the maximum number of iterations $n^{\max} = 100$, the initial temperature $T_0 = 106$, the cooling ratio $\beta = 0.94$, the cloning parameter $\alpha = 0.1$, the maximum number of antibodies replaced $d^{\max} = 0.2\ \mu$.

For the task of:

– finding the conditional minimum of the function, the search for a solution was carried out on Rosenbrock test function $f(x, y) = (1 - x)^2 + 100(y - x^2)^2$ with constraints $(x-1)^3 - y + 1 \le 0$ and $x + y - 2 \le 0$, and, moreover, $-1.5 \le x \le 1.5$, $-0.5 \le x \le 2.5$;

– optimal partitioning of a discrete set, the search for a solution was carried out on the standard BSDS500 database;

– "the traveling salesman", the search for a solution was conducted on the standard berlin52 database;

– "the knapsack", the search for a solution was carried out on the standard KNAPSACK_01 database.

The study leads to the conclusion that the proposed method provides a high accuracy of finding a solution.

5 RESULTS

The function of the annealing temperature decrease is determined by the formula $T(n) = \beta^n\ T_0$ and is shown in Fig. 2.
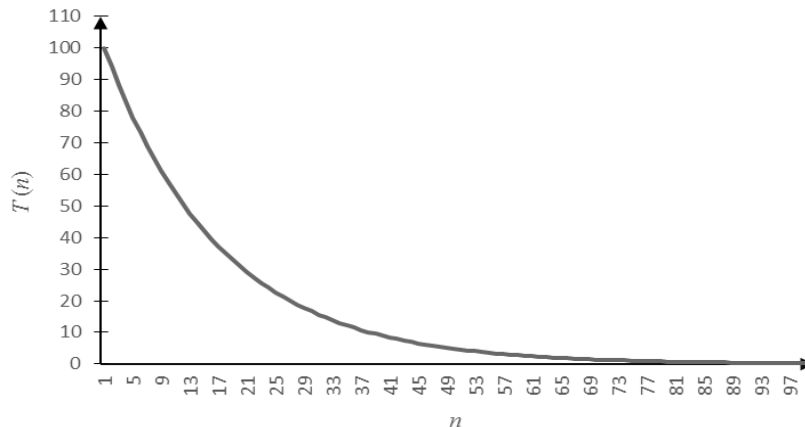
Figure 2 – The function of the annealing temperature decrease

The dependence (Fig. 2) of the annealing temperature on the iteration number shows that the annealing temperature decreases with increasing of the iteration number.

The mutation probability in the case for the worst antibody $(\Phi(x) = 0)$ is determined by the formula $p(x) = \exp(-1/T(n))$ and is shown in Fig. 3.

The dependence (Fig. 3) of the mutation probability on the annealing temperature shows that the mutation probability decreases with temperature decreasing.

The results of the comparison of the proposed method with the method based on the theory of clonal selection and described in [16–22] are presented in Table 1.

6 DISCUSSION

The selected values of the parameters of the proposed optimization method provide a high probability of mutation at the initial iterations and a low probability of mutation at the final iterations. For example, for the worst antibody with the maximum probability of mutation, the mutation occurs with a probability of no less than 0.9 for the first 40% iterations and with a probability below 0.1 for the last 10% iterations (Fig. 3).

Method based on clonal selection theory [16–22]:

– does not take into account the iteration number in the operator of mutation and replacement, which reduces the accuracy of the search for a solution (Table 1);

– does not allow real potential solutions in the mutation operator, which increases the computational complexity of the mutation operator and slows down the search for a solution. This is due to the need to convert non-binary potential solutions into binary before the mutation and binary potential solutions into non-binary after mutation (Table 1);

– does not allow to find the conditional extremum.

The proposed method allows to eliminate these drawbacks.

CONCLUSIONS

In this paper, the actual scientific and technical problem of increasing the efficiency of optimization methods was solved by dint of creates the method of finding a quasi-optimal solution by a metaheuristic.

The scientific novelty of obtained results is that the optimization method based on the synthesis of clonal selection and annealing simulation algorithms is proposed. It allows to increase the search accuracy through the application of the principle of organizing the study of the entire search space at the initial iterations and focusing of the search on the final iterations.

The adaptation of the proposed method both for the problem of finding the conditional minimum of functions and for the problem of optimal partitioning of a discrete set:

– allows real potential solutions in the mutation operator, which reduces the computational complexity of the mutation operator and speeds up the search for a solution;

– uses a dynamic mutation step, which allows to investigate the entire search space at the initial iterations and to make the search directional at the final iterations, that ensures high accuracy of the search.

The solution of finding the problem of conditional minimum of functions and the knapsack problem by the proposed method uses a penalty function, which allows to find a conditional extremum.

In addition, the application of the proposed method for solving the traveling salesman problem allows integer potential solutions in the mutation operator, which reduces the computational complexity of the mutation operator and speeds up the search for a solution.

The practical significance of the obtained results lies in the fact that the scope of application of metaheuristics is expanding on the basis of the theory of clonal selection by adapting the proposed method for the indicated optimization problems. This contributes to the effectiveness of intelligent computer systems for general and special purposes.

Prospects for further research are the study of the proposed method for a wide class of artificial intelligence tasks.
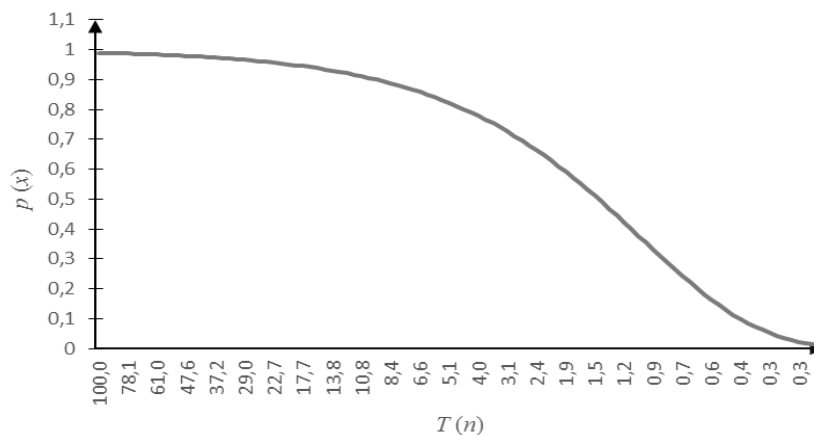
Figure 3 – The mutation probability

Table 1 – The comparison of the proposed optimization method with the existing one for solving optimization problems

No.	Problem of	Root-mean-square error of the method		Conversion time of antibody clones of the method	
		proposed	existing	proposed	existing
1	finding the conditional minimum of the function	0.02	0.07	–	proportionally $\mu q I_1$
2	optimal partitioning of a discrete set	0.02	0.06	–	proportionally $\mu q I_2$
3	"the traveling salesman"	0.03	0.08	–	proportionally $\mu q I_3$
4	"the knapsack"	0.04	0.1	–	–

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МЕТОД ОПТИМІЗАЦІЇ НА ОСНОВІ СИНТЕЗУ АЛГОРИТМІВ КЛОНАЛЬНОГО ВІДБОРУ ТА ІМІТАЦІЇ ВІДПАЛУ

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АНОТАЦІЯ

Актуальність. Розглянута задача підвищення ефективності методів оптимізації шляхом синтезу метаевристик. Об'єктом дослідження є процес пошуку рішення оптимізаційних задач.

Метою роботи є підвищення ефективності пошуку квазіоптимального рішення за рахунок метаевристичного методу на основі синтезу алгоритмів клонального відбору та імітації відпалу.

Метод. Запропонований метод оптимізації удосконалює алгоритм клонального відбору за рахунок динамічної зміни на основі алгоритму імітації відпалу кроку мутації, ймовірності мутації, кількості замінних потенційних рішень. Це зменшує ризик потрапляння в локальний оптимум завдяки широкому дослідженню простору пошуку на початкових ітераціях й гарантує збіжність через спрямованість пошуку на заключних ітераціях. Запропонований метод оптимізації дозволяє знаходити умовний мінімум за рахунок динамічної штрафної функції, значення якої зростає зі збільшенням номера ітерації. Запропонований метод оптимізації допускає небінарні потенційні рішення в операторі мутації завдяки використанню стандартного нормального розподілу замість рівномірного розподілу.

Результати. Запропонований метод оптимізації був програмно реалізований за допомогою технології паралельної обробки інформації CUDA і досліджений для задачі знаходження умовного мінімуму функції, задачі оптимального розбиття дискретної множини, задачі комівояжера, задачі про рюкзак на відповідних їм проблемно-орієнтованих базах даних. Отримані результати дозволили досліджувати залежність значень параметрів на ймовірність мутації.

Висновки. Проведені експерименти підтвердили працездатність запропонованого методу та дозволяють рекомендувати його для використання на практиці при вирішенні задач оптимізації. Перспективи подальших досліджень полягають у створенні інтелектуальних паралельних й розподілених комп'ютерних систем загального і спеціального призначення, які використовують запропонований метод для задач чисельної та комбінаторної оптимізації, машинного навчання й розпізнавання образів, прогнозу.

КЛЮЧОВІ СЛОВА: метаевристика, клональний відбір, імітація відпалу, оптимізація, технологія паралельної обробки інформації.

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МЕТОД ОПТИМИЗАЦИИ НА ОСНОВЕ СИНТЕЗА АЛГОРИТМОВ КЛОНАЛЬНОГО ОТБОРА И ИМИТАЦИИ ОТЖИГА

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АННОТАЦИЯ

Актуальность. Рассмотрена задача повышения эффективности методов оптимизации путем синтеза метаэвристик. Объектом исследования является процесс поиска решения оптимизационных задач.

Целью работы является повышение эффективности поиска квазиоптимального решения за счет метаэвристического метода на основе синтеза алгоритмов клонального отбора и имитации отжига.

Метод. Предложенный метод оптимизации усовершенствует алгоритм клонального отбора за счет динамического изменения на основе алгоритма имитации отжига шага мутации, вероятности мутации, количества заменяемых потенциальных решений. Это уменьшает риск попадания в локальный оптимум благодаря широкому исследованию пространства поиска на начальных итерациях и гарантирует сходимость из-за направленности поиска на заключительных итерациях. Предложенный метод оптимизации позволяет находить условный минимум за счет динамической штрафной функции, значение которой возрастает с увеличением номера итерации. Предложенный метод оптимизации допускает небинарные потенциальные решения в операторе мутации благодаря использованию стандартного нормального распределения вместо равномерного распределения.

Результаты. Предложенный метод оптимизации был программно реализован посредством технологии параллельной обработки информации CUDA и исследован для задачи нахождения условного минимума функции, задачи оптимального разбиения дискретного множества, задачи коммивояжера, задачи о рюкзаке на соответствующих им проблемно-ориентированных базах данных. Полученные результаты позволили исследовать зависимость значений параметров на вероятность мутации.

Выводы. Проведенные эксперименты подтвердили работоспособность предложенного метода и позволяют рекомендовать его для использования на практике при решении задач оптимизации. Перспективы дальнейших исследований заключаются в создании интеллектуальных параллельных и распределенных компьютерных систем общего и специального назначения, которые используют предложенный метод для задач численной и комбинаторной оптимизации, машинного обучения и распознавания образов, прогноза.

КЛЮЧЕВЫЕ СЛОВА: метаэвристика, клональный отбор, имитация отжига, оптимизация, технология параллельной обработки информации.

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