Development of the Genetic Algorithm for Technical Diagnostics of Aircraft

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Abstract

The problem of developing a method of technical diagnostics on the basis of data for the study of the structural strength of the blades is considered. Methods and software tools for technical diagnostics based on the evolutionary approach have been developed. The proposed methods and tools can be used to predict the state of critical load points in the diagnosis of gas turbine blades of aircraft engines during operation.

A modification of the general genetic algorithm proposed by the mechanism of the genetic search mechanism to increase the darkness of predicting random processes has been developed, and the procedure for forming the initial message processing has been determined.

An evolutionary selection operator is proposed as in the generation of the first generation of indicators of the output coefficient of the threshold depending on the values of the objective function, and on the next iterations of the production rate of new production directions of the environment of the production production. The operators of mutation and inversion in the proposed modification are set up in such a way that the search is carried out in unexplored areas. This makes it possible to increase the rate of convergence of evolutionary optimization for small generations and small population sizes.

In the process of testing the developed method on unimodal and multimodal functions, the genetic algorithm parameters should be used in each case to increase the rate of convergence of evolutionary optimization at small numbers of generations and small populations are determined. The parameters of the method, in particular, the size of the population, the number of generations, the bit rate and the type of crossover, are selected in such a way as to minimize the time required to work. The results of the experiments showed the feasibility of using the developed program to find the optimal values of multidimensional functions.

Keywords

Evolutionary method, genetic algorithm, optimization, technical diagnostics, software, forecasting

1. Introduction

Methods of technical diagnostics have become widely used in the diagnosis of aircraft engine parts. Today's gas turbines, thanks to such qualities as low specific metal content and labor-intensive production, high degree of automation of management [1] – [8]. Increasing the specific power and efficiency of cumulative chazoturbine octane are inextricably linked with the intensification of energy conversion processes and lowering the level of exploitation of loads on them.

The blades are one of the most important elements and the most expensive elements in gas turbine engines, which are exposed to direct action, which affects the gas flow temperature, significant stress from centrifugal forces and aerodynamic. The main indicator that determines the efficiency of the

IT&I-2020 Information Technology and Interactions, December 02–03, 2020, KNU Taras Shevchenko, Kyiv, Ukraine

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blades during long-term operation is their characteristic of fatigue resistance, which changes in the future. Fatigue resistance of turbine blades can vary significantly due to the influence of design, technological and operational factors. An aerodynamic profile is characteristic for each blade [9].

As a rule, the details of aircraft engines are quite expensive, so diagnosing them with the help of destructive diagnostic methods is not very effective. This necessitates the development of methods, models and software tools for technical diagnostics of aircraft engine components based on.

The relevance of the research topic lies in the presence of the need for accurate and fast methods of searching for critical points of functions of different complexity, especially multimodal and multifunctional. Even in such cases, the application of standard search methods complicates the search, makes it more costly and increases the time of information processing. Such a problem is especially acute in areas where diagnostic processes are critical to time and high accuracy, such as aircraft construction.

2. Analysis of literature data and problem statement

Despite the constant development of methods and algorithms for solving technical diagnostics, this task is relevant. This is due to the fact that it is impossible to create a universal method, because the task of technical diagnosis is divided into subtasks. Such tasks include preventive technical diagnostics, technical diagnostics of failures, diagnostics of maintenance of the current state of the object, etc. These subtasks can also be divided by the nature of the diagnosis. It can be a diagnosis by one or more parameters, and so on. The described reasons are the basis for the creation of new methods of technical diagnosis.

The authors of [9], to solve the problem of technical diagnosis, propose the use of a hybrid Bayesian image recognition classifier, which uses statistical and fuzzy paradigms and expresses information about the values of parameters by four types of features (discrete, pseudo-discrete, multi-normal and independent-continuous). It uses frequency and subjective information to identify unknown parameters of density functions for each technical condition. The proposed classifier has such advantages as simplicity of algorithm and speed. However, with large amounts of data, the accuracy of the classifier decreases.

In [10], an extension of the Bayesian fault detection algorithm is proposed. The algorithm is implemented on a reference model. Fault probability estimation is performed using a one-step calculation, which thus confuses the complexity of the algorithm. Fault identification is performed using the recursive method of the named square. The advantage of the algorithm is its low complexity and accuracy of results, but the time used for calculations is relatively large.

To solve the problem of technical diagnostics in [11] a general diagnostic model based on two probability matrices is presented: a confidence matrix showing the probability of detecting faults and a diagnostic matrix representing the individual result of each stochastic method of detecting faults based on the distribution. and Poisson and the gamma distribution. Then, using the Bayesian decision-making model, the technical condition is assessed and a decision on maintenance is made. The test results showed that the proposed diagnostic model has a significant disadvantage due to the high uncertainty of the levels of reliability at the beginning of the algorithm. The more the model is updated, the better the accuracy of the results, but the use of such a model takes a long time.

In [12], a method of pattern recognition for a technical diagnostic problem based on the linear discriminant algorithm with extended trace coefficient (ETR-LDA) is proposed. This is an extension of TR-LDA, which maximizes class spacing and minimizes intra-class lag. Because TR-LDA focuses on the overall distance between classes and ignores local features, this can lead to shortcomings in the classification of specific patterns / classes. To overcome this limitation, the proposed ETR-LDA reviews the relationship between the overall class distance and global certainty. The new target function is obtained in ETR-LDA taking into account the smallest distance between classes. The advantage of the method is its convergence to the global optimum. However, time costs are unacceptable.

[13] describes a new approach to technical diagnostics, in which the short-term Fourier transform (STFT) is first used to obtain the frequency-time characteristics of the object being diagnosed. Next, the optimal clustering numbers are estimated using the Bayesian information criterion (BIC) theory,

which has the ability to estimate simultaneously. Then, NMF (negative matrix factorization)-based clustering methods perform classification results, after which the results are determined using a gradient rise strategy to obtain reliable diagnostic results. The accuracy of this method is high, and time costs are 10% less compared to classical methods. However, the algorithm demonstrates good results on small amounts of data, if the amount of data is increased, the accuracy of the method will decrease.

In addition to the described methods [9] - [13], evolutionary methods [14]- [19] are also effective methods of computational intelligence that can be used to construct diagnostic models.

In [14], the diagnostic model is based on the use of a combination of GA (genetic algorithm) and neural network. However, classical GA is usually characterized by premature convergence and reaching the local minimum. To solve these problems, a multiple mutation operator is added to the GA. The neural network in the proposed model has a radial-basis function.

The advantage of this method is to use the method of simple extraction of traits and an improved genetic algorithm to optimize the threshold and weights of the neural network. In the results of experimental analysis, the proposed method showed good results of convergence, high accuracy and reliability. The disadvantages of this method include the time spent on calculations.

In [15], to solve the problem of technical diagnosis, it is proposed to introduce subgroups of the population into the GA in accordance with the migration model, to preserve useful genetic diversity among individuals from generation to generation. The migration model divides people into several subgroups. These groups develop independently of each other over a period of time. After that, individuals, based on the values of the objective function, are distributed among subpopulations.

The introduction of migration into the algorithm improves the efficiency of GA and reduces the time for its execution. The application of this approach showed that GA finds the global optimum more often with fewer generations than classical GA. The disadvantage of the algorithm is the decrease in the accuracy of the results with increasing experimental data.

In [16], an optimized GA is proposed to solve the problem of technical diagnosis, namely to describe the behavior of fatigue in terms of the number of cycles to failure for different sets of parameters of the laser hardening process of medium carbon steel AISI 1040. To solve this problem crossover and mutation operators run in parallel. This study adopts coding of real value, in which each chromosome is represented as a set of real values.

The advantage of using this method is the gain in time and efficiency, due to the simultaneous use of operators, the avoidance of any intermediate encoding and decoding, which is achieved by using real value encoding. Testing of the algorithm has shown that it reaches convergence to a global minimum in less than 15 generations.

In [17], GA was used as an optimized artificial intelligence method that uses the first three relative modal parameters, such as natural frequencies, as input data. This technique was found to be sufficiently reliable for diagnosis by monitoring changes in relative natural frequencies. In this work, the method of mutation of the binary coding was taken as the mutation operator. with such a mutation, bit 1 is converted to bit 0, thus reducing the numerical values associated with the chromosomes, and is called an ascending mutation. The method has sufficient accuracy with the number of generations equal to thirty, otherwise the method spends more time on calculations, which leads to reduced performance and erroneous results.

In [18], a GA with valid coding is proposed, which contains a new fitness function and the process of choosing a crossover. The fitness function proposed in the work uses the relationship between the peaks of the frequency of damage and the maximum peak. The process of choosing a crossover uses a triangular series of methods of dividing people based on the score obtained using the fitness function. The algorithm showed fast convergence, but has a relatively long time.

The authors of [19] propose a model of technical diagnosis based on the ensemble of the empirical method of decomposition and the machine of reference vectors. In this model, the improved GA is aimed at filtering the component of the internal mode function (FVR). GA, in this case, was improved by using a dynamic weight function. The results showed that the choice of the FVR component as an object vector is much higher. Therefore, the use of improved GA is effective for this task.

The test results showed that the model is effective and reaches the global optimum. A significant disadvantage of this model is its use on small data samples, and the information about the data of the diagnostic object should be as complete as possible and the data should be strongly correlated.

3. The purpose and objectives of the study

The purpose of the research is to develop methods and software tools to solve the problem of studying the structural strength of aircraft engine blades.

To achieve the goal of the study it was necessary to solve the following tasks:

• to solve the problem of diagnostics of aircraft engine blades in the process of operation on the basis of sets of values of the spectra of damping oscillations of the blades after impact;

• present an analysis of the mathematical model taking into account the requirements for the quality of technical diagnostics, in particular the prediction of critical load points at any part of the load function of aircraft engine blades at any complexity of this function;

• to present the analysis of functioning of the formed mathematical model by calculations of various operating modes of system.

4. Development of an algorithm for technical diagnosis

Diagnostic models based on classical methods are characterized by the following main disadvantages: good accuracy is manifested with a fairly small set of input data, but the time spent on the necessary calculations is unacceptable. The disadvantages of such models are significant. Thus, the existing models of technical diagnosis based on evolutionary methods, namely the genetic algorithm, were analyzed. Genetic algorithms are characterized by greater speed and accuracy of problem solving. However, since there is no universal method for solving any technical problem, it is necessary to upgrade the existing GA to solve the problem of technical diagnostics of aircraft engine blades.

After analyzing the work [9] – [23], it was found that in the genetic method with increasing number of individuals, the efficiency and operating time of the method increase in direct proportion. In addition, in small populations, genes spread too quickly. All individuals become similar even before the solution of the problem is found. To solve this problem, it was decided to develop a modified method "GA with selection of the fittest" based on GA with decreasing population size. The modification is that the selection will involve the next individual and the resulting, obtained during the execution of crossover operators and mutations. The proposed modification will increase the productivity of the method and maintain the accuracy of execution, and the proposed method will be more flexible to choose the type of crossing.

In the proposed modification of the evolutionary method "GA with selection of the fittest" in the generation of the first generation, the selection is based on the threshold depending on the value of the goal. In the following iterations, the selection is carried out with the representatives of the current generation and their descendants in such a way that only the devices adapted to the new generation will be included. To do this, first calculate the suitability of each individual fi. Then the individuals of the population are sorted by increasing the population, and for each individual the value of Rp (i) is calculated by formula (1):

$$R_p(i) = \frac{1}{N}\left(\mu_{\max} - \left(\mu_{\max} - \mu_{\min}\right)\frac{i-1}{N-1}\right) \tag{1}$$

where $\mu_{\max} \in [1; 2]$, $\mu_{\min} = 2 - \mu\max$, N is a count of chromosomes. If the value of $R_p(i) > 0.5$, the chromosome is allowed to cross [19] – [21].

Next, mutation and inversion operators are performed, which are configured in such a way that the search is performed in unexplored areas.

The implementation of the crossover operator is to cross the information chains of the genetic material of all parent pairs and the formation of child decisions that inherit the characteristics of both "parents". In the proposed algorithm during crossing, preference is given to individuals (parents) with genetically dissimilar coding x_n^h, x_m^h, which satisfies condition (2):

$$\gamma \le \left(x_n^h, x_m^h\right) \le K \tag{2}$$

where

$$\gamma\left(x_n^h, x_m^h\right) = \sum_{k=1}^{K} x_k\left(b_n^h\right) \otimes x_k\left(b_m^h\right) \tag{3}$$

where γ is a parameter that regulates the degree of dissimilarity of individuals in pairs; K – is a length of encodings of individuals; b_n^h, b_m^h are genes in individuals [22] – [23].

The obtained degenerate population is used as a criterion for stopping the method and the threshold of the coefficient of improvement of the fitness function of the best chromosome φ is used. Initially, for each chromosome from a degenerate population, the value of the target function is found and the best indicator is selected from these values. Then look for the best value of the objective function in previous generations and calculate the improvement factor φ by formula (4):

$$\varphi = \frac{f_{best_p} - f_{best_{p-1}}}{f_{best_{p-1}}}. \tag{4}$$

If the value of the improvement factor φ found is less than that obtained in previous generations, the stop criterion is considered reached, otherwise the next cycle of genetic search is performed.

Algorithm of the modernized GA with leader method based on GA with decreasing population size.

In different literature sources there are completely different views on the choice of population size, but, everywhere, the size of the population remains unchanged during evolution. As a result of observations of the work of GA, it was noticed that if you add to the randomly formed initial population a consciously known good solution the so-called artificial leader, you can see that in the course of evolution in each new population the best quality criteria will be contained in individuals of this leader or his descendants. And in general, obtaining a new absolute leader in the population is most likely from individuals with the highest value of the quality criterion, and accordingly the production of offspring from individuals with low quality in the population is less promising, because the probability of a good solution in this case is much lower. Therefore, it was decided to develop a modified method "GA with leader" based on GA with population reduction, which proposes to change the population size depending on the number of most adapted individuals in the population, thus reducing the amount of computation to obtain the optimal solution [24].

In the proposed method for generating a new set of solutions from the input data, the number of individuals corresponding to the size of the population, the most adapted to the analysis, is selected. Then, when selecting the parent pair from the current generation, a certain number of pairs is selected by the probable rank. In each iteration (in each generation) this number is different. Each pair is selected taking into account the values of the objective functions of the most adapted and least adapted individual in the population:

$$e^{-\frac{f_j - f^t_{worst}}{f^t_{tbest} - f^t_{worst}}} < rand(e^{-1};1),\ j = \overline{1;N} \tag{5}$$

where N is the size of the current population; f_i is a the value of the fitness function of the j-th individual; f^t_{best} is a the best value of the fitness function of the current population t; f^t_{worst} is a the worst value of the fitness function of the current population t; rand (e^{-1};1) is a random number from e^{-1} to 1 [25].

During crossing, a descendant G_i is created, which is located at some distance from the ancestor with the best values of the fitness function G_1 in the direction from the ancestor with the worst value of the fitness function G_2. Determining the value of the i-th gene of the gi chromosome-offspring is determined by the formula:

$$g_i = k\left(g_{1i} - g_{2i}\right) + g_{1i} \tag{6}$$

where $k \in [0; 1]$ a is the actual coefficient specified by the user at the stage of initialization of genetic search.

At the stage of mutation, starting from the first chromosome, the whole population is reviewed, and for each chromosome H_j, drop numbers x_i from the interval [0; 1) are assigned. If this number is less than the probability of mutation, then the current chromosome H_i is mutated. In the selected chromosome there is a mutation of genes by some value (7):

$$g^*_{ij} = g_{ij} + \Delta g_{ij}, \tag{7}$$

where i is the gene number in the chromosome; j is a chromosome number; g_{ij} is a gene for mutation; g_{ij}* is a gene after mutation [26].

The values of the i-th gene gij of the chromosome G_j after mutation can be calculated by formula (8):

$$g_{ij}^{*}=\begin{cases} g_{ij}+\Delta\left(p,\max_i-g_{ij}\right), if\ 1\le i\le w \\ g_{ij}+\Delta\left(p,g_{ij}-\min_i\right), if\ w<i\le K \end{cases}, \tag{8}$$

where

$$\Delta\left(p,y\right)=y\left(1-c^{\left(1-p/P\right)^{v}}\right), \tag{9}$$

where c is a randomly generated number in the interval [0; 1]; p is the number of the current iteration; P is the maximum number of iterations; v is a parameter that determines the degree of homogeneity (uniformity); $\min_i$ and $\max_i$ are the minimum and maximum value of the i-th parameter in the solution with the help of the genetic method of the problem; w is a number equal to | K / 2 |; K is the number of genes in the chromosome [27] – [30].

After that, the nature of the connections between the components of the chromosome changes with the help of the inversion operator. To do this, two breakpoints are randomly selected on the chromosome, between which the chromosome genes are arranged in reverse order [31] – [34].

The new generation is formed from the existing set of solutions obtained as a result of the application of crossing, mutation and inversion operators [34] – [39]. The probability of an individual to be selected for a new generation is calculated by formula (10):

$$P\left(X^{i}\right)=\frac{-fitness\left(X^{i}\right)+D}{N\cdot D-\sum_{j=1}^{N} fitness\left(X^{j}\right)} \tag{10}$$

After that, the criteria for stopping the evolutionary search are checked (achievement of an acceptable value of the objective function, absence of significant improvements of the values of the objective function during a certain number of iterations, exceeding the maximum possible search time, etc.). In case of non-satisfaction of the stopping criteria, the stages of crossing, mutation and inversion are repeated [39] – [45].

5. The results of the algorithm

In the developed software various models of evolutionary search are realized, in addition to the canonical model, in addition to the canonical model, the Genitor model, the CHC (Cross-population selection, Heterogenous recombination and Cataclysmic mutation) model, Island model, Bidirectional GA (DAGA2), GA with a decrease in population size.

The most important thing in the process of development of software for technical diagnostics is the company, which implements the process of developing diagnostic models, practical implementation of which is responsible for the optimal joke of the most significant and valuable functions, At this work, there was a lot of respect for the realizable methods and models of revolutionary joke with the optimization of multimodal and multimodal functions.

For correct adjustment of parameters the complex research taking into account influence of adjacent parameters one on one, and on accuracy, and speed was carried out.

The dismantled modifications have a revolutionary vidbury operator, which, with the first generation of generals, stays at the base of the vidbury at the thresholds of its central function, a At the coming iterations of the Vidbars to be held with the representatives of the stream generation i ih their naschadkiv so that in the new generation to spend only a few of the hired individuals. The operators of mutation and inversion in the proposed modification are set up in such a way that the search is carried out in unexplored areas. This makes it possible to increase the rate of convergence of evolutionary optimization for small generations and small population sizes.

As a result of the research, the genetic algorithm was refined and adjusted with a decrease in the size of the population by adjusting its parameters for speed.

For the possibility of comparing the obtained results with the indicators of already available optimization methods, the classical algorithm "Golden Cross" was chosen. All tests were performed on a single computer to reduce the impact of hardware on test results. The exceptions to all tests of GA in the acts of the world are stochastic (i.e. non-stochastic), so that the daily reading of the law on the acts of these types of jokes is optimal, then for the change of the immune influx of skin experiments were carried out 5 times the average result.

To study the work of GA in finding the minimum of unimodal functions, a function (11) was taken

$$f\left(x_1, x_2\right) = 1 - \left(\frac{\left(x_1+3\right)^2 + \left(x_2+3\right)^2}{200} - \cos\left(x_1+3\right) \cdot \cos\left(\frac{x_2+3}{\sqrt{2}}\right) + 2 \right). \quad (11)$$

For all the GA conducted a test to test the growth of the popularity for the accuracy and width of the algorithms (the results are shown in Table 1), Testing for the introduction of a generation of fuel for the accuracy of the i-switchiness of the robot algorithms (the results are shown in Table 2), testing for the introduction of a generation of fuel rozdryadnost GA on the accuracy of the i-switchiness of the robot algorithms (the results are shown in Table 3).

Tests were performed for 3 GA to determine the type of crossing on the accuracy and speed of the algorithms (the results of the study are given in Table 4).

The following crossing operators were implemented for testing:

• proportional crossover;
• crossover with a fixed point of intersection;
• crossing on the basis of logical I;
• crossing on the basis of logical OR;
• at the exit twins are prone to parental genes;
• at the exit twins are prone to maternal genes;
• two-point crossover with partial use of logic I;
• two-point cross with partial application of logical OR;
• crossing with the use of logical operators AND and OR;
• crossing with the use of logical operators XOR;
• crossing with probabilistic selection.

In the column "Minimum" of tables 1-4 the value of the minimum of the analyzed function received as a result of work of the tested algorithm at the set parameters is specified. In the column "Time" - the time spent by the tested GA to find the optimum of the function.

From the results shown in Table 1, we can see that the precision of all the methods is reflected in the growth of the population of 80 i more individuals, and is stably in the range of 160. It is important to note that the method of changing the size of the population shows a stable result in all values of the size of the population.

From the results, which are shown in Table 2, we can see that all the algorithms show the accuracy of 100% in the 5th generation, and at only 55 i generation - the bi-directional algorithms show a great number of noise, which can be increased to unacceptable results.

From the obtained results, which are shown in Table 3, the conclusion is made that all algorithms show the accuracy of 100% already with a bit rate of 4/1, and at 2048/512 and higher they are used. display the result correctly. Also, for the equilibrium model at bit rates 128/32 and 256/64, one-time noises were observed, which show a higher instability of the algorithm itself than any other bit.

Studies have shown that the most accurate for all three algorithms were proportional crossover and crossover with a fixed point of intersection. The selection of the type of crossover for each specific case requires an individual approach.

To study the work of GA in finding the minimum of multimodal functions was taken function:

$$y = \cos\left(\left(x^2 - 3\right) + tg\left(x\right) / \ln\left(x / 45\right)\right) \quad (12)$$

the minimum of which is: min (y = cos (x2-3) + tg (x) / ln (x / 45))) = - 1.

This function has many local optimums, as the main component is a sinusoid. Tangent and logarithm functions are added to shift the optimum by level, period, and amplitude. All these parameters contribute to the creation of the most appropriate conditions for testing genetic algorithms.

The task set in this way is to search for the optimum, first of all, of multimodal functions, and the results obtained in this test will be considered to be more important.

Table 1
Influence of population size on the accuracy and speed of algorithm operation during processing of unimodal functions (number of generations is 50, total discharge is 256, of them into a fractional part 16)

Population size	5	10	20	40	80	160	320	640	1280	2560	5120
Canonical											
Minimum	4	3,9867	4	4	3,7968	3	3	3	3	3	3
time, s	0,8548	0,8392	0,8299	0,8361	0,8392	0,8361	0,8486	0,8642	0,9110	0,9952	1,2292
Genitor											
Minimum	4	4	4	4	3	3	3	3	3	3	3
time, s	1,0077	0,9360	1,1481	1,0826	1,3260	1,5412	2,1122	3,1512	5,3040	9,7344	19,041
CHC											
Minimum	4	4	4	4	3	3	3	3	3	3	3
time, s	0,9453	0,9703	1,0358	1,0670	1,2417	1,4976	2,0716	3,1512	5,3383	9,7719	18,670
Island model											
Minimum	-	1.63e+137	2.07e+120	1.198e+51	3	3	3,2000	3	3	3	3
time, c	-	1,7752	1,7971	1,8751	1,9812	2,1590	2,5833	3,4320	5,4600	11,422	30,601
Bidirectional GA (DAGA2)											
Minimum	-	5,29e+122	6,549e+60	3,095e+53	1,47e+19	3	3	3	3	3	3
time, s	-	2,7268	2,6239	3,0544	3,7253	5,3071	8,6518	15,703	32,791	74,562	265,38
GA with a decrease in population size											
Minimum	-	3	3	3	3,2000	3	3	3,2000	3	3,2000	3
time, s	-	1,2261	1,3010	1,4664	1,8782	2,7175	4,3118	7,7064	14,139	27,992	60,394

Table 2
Influence of the number of generations on the accuracy and speed of operation of the algorithm during processing of unimodal functions (population size is100, total discharge is 256, of which 16 per hour).

Number of generations	5	15	25	35	45	55	65	75	85	95	105
Canonical											
Minimum	3	3	3	3	3	3	3	3	3,2000	3	3,1999
Time, c	0,7768	0,7893	0,7924	0,8174	0,8299	0,8611	0,8486	0,8798	0,8829	0,9016	0,9360
Genitor											
Minimum	3	3	3	3	3	3	3	3	3	3	3
Hour, c	0,8704	0,9640	1,0576	1,1949	1,2230	1,3291	1,4383	1,5280	1,5444	1,6692	1,7752
CHC											
Minimum	3	3	3	3	3	3	3	3	3	3	3
Time, c	0,8018	0,9328	0,9578	1,1325	1,1762	1,4289	1,3728	1,5069	1,5880	1,7191	1,8187
Island model											
Minimum	3	3	3	3	3	1,314e+33	6,674e+93	3,221e+59	4,949e+113	4,673e+120	2,976e+122
Time, c	1,6754	1,7596	1,8439	1,9063	1,9718	2,0748	2,1122	2,2089	2,2713	2,3462	2,4117
Bidirectional GA (DAGA2)											
Minimum	3	3	3	3	3	3	2,056e+61	1,107e+55	2,796e+65	1,972e+114	5,574e+98
Time, c	1,8626	2,4367	2,8984	3,3259	3,9187	4,4834	5,1074	5,7221	6,3554	6,7205	7,5317
GA with a decrease in population size											
Minimum	3	3	3	3	3	3	3	3	3	3	3
Time, c	0,9484	1,1820	1,4320	1,6660	1,9375	2,2183	2,4242	2,8610	2,9733	3,1699	3,4632

Table 3
Influence of GA bit rate on the accuracy and speed of algorithm operation during processing of unimodal functions (population size is100, number of generations is 50). The bit rate is specified in the R1 / R2 format, where R1 is the general bit rate of the algorithm, and R2 is the bit rate of the fractional part.

Number of generations	4/1	8/2	16/4	32/8	64/16	128/32	256/64	512/ 128	1024/ 256	2048/ 512	4096/ 1024
Canonical											
Minimum	3	3	3	3	3	3	3	3	3	NaN	NaN
Time, c	0,0436	0,0624	0,0748	0,1123	0,2152	0,4243	0,8486	1,8127	5,0263	11,297	23,265
Genitor											
Minimum	3	3	3	3	3	3	3	3	3	NaN	NaN
Time, c	0,1092	0,1435	0,1747	0,2745	0,4461	0,7425	1,2573	2,6052	6,4054	13,696	27,515
CHC											
Minimum	3	3	3	3	3	3	3	3	3	NaN	NaN
Time, c	0,0561	0,1092	0,1716	0,3057	0,4368	0,6988	1,2480	2,5646	6,3523	13,687	27,531
Island model											
Minimum	3	3	3	3	3	822,21	6,054e+24	3	3	NaN	NaN
Time, c	0,2059	0,2558	0,2995	0,4149	0,6614	1,1450	2,0217	4,0747	10,863	24,289	49,792
Bidirectional GA (DAGA2)											
Minimum	3	3	3	3	3	3	3	3	3	-	-
Time, c	1,5912	0,9235	1,2604	1,2885	1,8220	2,4928	4,3493	7,6159	17,325	-	-
GA with a decrease in population size											
Minimum	3	3	3	3	3	3	3	3	3	-	-
Time, c	0,3775	0,4992	0,4867	0,5990	0,8829	1,2480	2,0841	3,8594	8,5363	-	-

Table 4
Influence of the type of crossing on the accuracy and speed of the algorithm when processing unimodal functions (population size is 100, number of generations is 50, dimension 256/16)

Type of crossing	Proportional crossover	Crossover with fixed crossing point	Baptism on the basis of logical I	Crossing on the basis of logical OR	At the end, the twins are prone to maternal genes	At the end, the twins are prone to maternal genes	Two-point crossover with partial detection of logical I	Two-point crossover with partial logic or	Crossing with the use of logical operators I and OR	Crossing with the use of logical operators I and OR...	Crossbreeding with probable selection
Island model											
Minimum	3	3	2,866e+103	1,668e+93	5,265e+63	6,805e+37	2,722e+38	823,80	5,045e+116	4	5,892e+128
Time, c	2,2432	2,0124	2,2588	2,2651	1,9968	2,0061	3,4289	3,4476	2,2838	2,2682	2,0623
Bidirectional GA (DAGA2)											
Minimum	3	3	1,749e+99	1,482e78	838863	3,581e+12	6,189e+25	9,223e+19	4,718e+92	4	5,164e+119
Time, c	4,4616	4,1777	4,5021	4,3617	3,9593	4,2057	5,5754	5,6503	4,4397	4,0997	4,0560
GA with a decrease in population size											
Minimum	3	3,2000	3,2000	3	3,4000	3,078e+112	3	3	3,2000	4	3,9757
Time, c	2,1528	2,0904	2,1715	2,1902	2,0685	1,9968	2,8329	2,7549	2,1621	2,1746	2,0248

For all the GA conducted a test to test the growth of the popularity for the accuracy and width of the algorithms (the results are shown in Table 5), Testing for the replication of the popularity's image for the accuracy and width of the work of the algorithms (the results are shown in Table 6), testing for the replication of the popularity's image for the accuracy and width of the work of the algorithms (the results are shown in Table 7). Tests were performed for 3 GA to determine the type of crossing on the accuracy and speed of the algorithms (the results of the study are given in Table 8). The same crossing operators were implemented for testing as for the study of GA operation in finding the minimum of unimodal functions. In the column "Minimum" of tables 5-8 the value of the minimum of the analyzed function received as a result of work of the tested algorithm at the set pairs is specified. In the column "Time" - the time spent by the tested GA to find the optimum of the function.

Table 5

Influence of population size on the accuracy and speed of algorithm operation during processing of unimodal functions (y = cos (x2-3) + tg (x) / ln (x / 45)), number of generations is 50, number of times fractional part is 16).

Population size	5	10	20	40	80	160	320	640	1280	2560	5120
Canonical											
Minimum	-0,989	-0,881	-0,993	-0,997	-0,997	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	0,8923	0,9297	1,8486	2,8642	4,8923	5,8798	6,8673	7,8767	11,9111	12,0389	19,304
Genitor											
Minimum	-0,989	-0,989	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	0,8798	0,9110	0,9640	1,0421	1,2043	1,4913	1,9999	3,1075	5,2634	9,7126	18,673
CHC											
Minimum	-0,989	-0,989	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	1,2448	1,3634	1,5007	1,7128	2,1559	3,2978	5,6690	10,895	23,646	62,256	189,82
Island model											
Minimum	-	-0,895	-0,994	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	-	3,6660	3,7034	3,7533	3,8688	4,0841	4,4397	5,2946	7,3507	13,250	32,535
Bidirectional GA (DAGA2)											
Minimum	-	-0,977	-0,996	-0,998	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	-	4,6800	4,6113	5,1917	5,8843	7,6846	10,770	17,762	34,395	79,332	274,42
GA with a decrease in population size											
Minimum	-	-0,994	-0,996	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	-	0,1996	0,3212	0,6488	1,0326	1,9281	2,8001	2,9575	4,835	6,758	11,799

From the obtained results, which are shown in Table 5, the conclusion is made that the sufficient accuracy of all methods is manifested in the size of the population of 20 and more.

From the obtained results, which are shown in Table 6, the conclusion is made that all algorithms behave uniquely with respect to the change in the number of generations. No regularity was found between all methods, but all methods showed sufficient accuracy in the entire range of tests.

From the obtained results, which are shown in table 7, the conclusion is made that all algorithms show sufficient accuracy already with a bit rate of 4/1 and close to 100% - from 20 to 12 and from 20/48/16 All algorithms show too much noise, which leads to the impossibility to correctly display the results or to the impracticability of the method. Studies have shown that the values of the minimum for all types of crossbreeding are quite similar. The only type of crossover that has consistently shown the worst results is a crossover with the XOR logic operator. The selection of the type of crossover for each specific case requires an individual approach.

Table 6
Influence of population size on the accuracy and speed of algorithm operation during processing of unimodal functions (y = cos (x2-3) + tg (x) / ln (x / 45)), number of generations is 25, number of times fractional part is 16).

Number of generations	5	15	25	35	45	55	65	75	85	95	105
Canonical											
Minimum	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	0,8049	0,8080	0,8299	0,8361	0,8548	0,8923	0,9141	0,9734	0,9796	1,0670	0,9828
Genitor											
Minimum	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	0,8205	0,9079	0,9796	1,1263	1,1824	1,2760	1,3790	1,4664	1,6348	1,6754	1,7690
CHC											
Minimum	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	0,9422	1,3135	1,6972	2,0904	2,4710	2,8454	3,2198	3,6660	3,9873	4,4491	4,9202
Island model											
Minimum	-0,988	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,998	-0,992
Time, c	3,5630	3,6504	3,7346	3,8064	3,8501	3,9686	4,0341	4,0466	4,3025	4,3149	4,4897
Bidirectional GA (DAGA2)											
Minimum	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	3,7752	4,3243	4,8672	5,3882	5,9997	6,6425	7,4256	8,1588	9,1010	9,4162	10,018
GA with a decrease in population size											
Minimum	-0,994	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999
Time, c	1,9406	2,2526	2,5527	3,0420	3,3134	3,7315	3,8563	4,4054	4,7673	5,2197	6,0278

Table 7
Influence of population size on the accuracy and speed of the algorithm operation during processing of unimodal functions (y = cos (x2-3) + tg (x) / ln (x / 45)), number of generations is 50 times, number of times fractional part is 16).

Number of generations	4/1	8/2	16/4	32/8	64/16	128/32	256/64	512/ 128	1024/ 256	2048/ 512	4096/ 1024
Canonical											
Minimum	-0,989	-0,989	-0,995	-0,991	-0,999	-0,999	-0,999	-0,999	-0,998	NaN	NaN
Time, c	0,0436	0,0468	0,0740	0,1310	0,2433	0,4524	0,9048	1,9624	5,5973	12,214	25,499
Genitor											
Minimum	-0,989	-0,989	-0,989	-0,991	-0,999	-0,999	-0,999	-0,999	-0,999	NaN	NaN
Time, c	0,0530	0,0780	0,1216	0,2121	0,3712	0,6801	1,2698	2,5677	6,3742	13,731	27,502
CHC											
Minimum	-0,989	-0,989	-0,989	-0,989	-0,999	-0,999	-0,999	-0,999	-0,999	-	-
Time, c	0,7675	0,6489	0,6583	0,8299	1,0951	1,7066	2,7393	5,0263	10,860	-	-
Island model											
Minimum	-0,948	-0,956	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,033	-	-
Time, c	2,1528	2,1746	2,2183	2,3400	2,5740	3,0482	3,9062	6,0871	12,876	-	-
Bidirectional GA (DAGA2)											
Minimum	-0,951	-0,942	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,035	-	-
Time, c	2,9452	2,7112	2,9078	2,9889	3,7783	4,2182	6,1370	10,817	19,827	-	-
GA with a decrease in population size											
Minimum	-0,989	-0,944	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,035	-	-
Time, c	1,5412	1,4320	1,9718	1,8439	2,6052	2,4273	3,4418	5,4007	10,414	-	-

6. Discussion of work results

Analyzing the data obtained when testing the program, shown in tables 1-4 for unimodal function and tables 5-8 for multimodal function, we can draw the following conclusions:

1. when processing unimodal functions, it is advisable to use the following parameters:

• the number of individuals in the population should be in the range of 80 to 160 individuals. Increasing the number of individuals more than 160 only increases the operating time of the algorithm without improving the accuracy. Using a population size of less than 80 individuals results in a large error for most methods;

• the number of generations in the population should be in the range of 5-45 generations. The number of generations more than 45 leads to an increase in the amount of noise, leading to unacceptable results. The use of the number of generations less than 5, does not give the appropriate accuracy;

• acceptable bit rate for unimodal functions - from 4/1 to 1024/256 depending on how many signs to the comma and after it we need to encode;

• proportional crossover and crossover with a fixed crossing point proved to be the most accurate among all used;

Table 8

Influence of the type of crossing on the accuracy and speed of the algorithm during processing of multimodal functions (y = cos (x2-3) + tg (x) / ln (x / 45)),population size is 100, number 16).

Type of crossing	Proportional crossover	Crossover with fixed crossing point	Baptism on the basis of logical I	Crossing on the basis of logical OR	At the end, the twins are prone to maternal genes	At the end, the twins are prone to maternal genes	Two-point crossover with partial detection of	Two-point crossover with partial logic or	Crossing with the use of logical operators I and OR	Crossing with the use of logical operators I and	Crossbreeding with probable selection
Island model											
Minimum	-0,999	-0,995	-0,999	-0,998	-0,995	-0,998	-0,999	-0,995	-0,999	-0,994	-0,997
Time, c	4,2026	3,9125	4,1558	4,1059	4,0529	4,1153	5,5973	5,6690	4,3680	4,3337	4,1340
Bidirectional GA (DAGA2)											
Minimum	-0,999	-0,998	-0,999	-0,999	-0,999	-0,998	-0,999	-0,999	-0,999	-0,993	-0,999
Time, c	6,8172	6,4865	6,5551	6,6986	6,3773	6,3554	7,9997	7,9123	6,4147	5,9373	6,1058
GA with a decrease in population size											
Minimum	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,999	-0,990	-0,999
Time, c	3,5100	3,3852	3,7596	3,8532	3,5349	3,5162	4,3149	4,1745	3,5256	3,3665	3,2136

2. when processing multimodal functions, it is advisable to use the following parameters:

• the number of individuals in the population should be in the range from 20 to 160 individuals. Increasing the number of individuals more than 160 only increases the operating time of the algorithm. The use of a population size of less than 80 individuals leads to a large error for most methods, in addition, for three methods the value of a population size of less than 6 is generally unacceptable;

• the number of generations in the case of processing multimodal functions can be arbitrary;

• acceptable bit rate for multimodal functions is from 4/1 to 512/128, depending on how many characters to and from the comma we need to encode;

• the type of crossover can be any, but crossing with the XOR logic operator showed the worst result, so its use is not recommended.

7. Conclusions

It has been determined that technical diagnostics is a field of knowledge, that it consists of theory, methods and means for identifying the state of objects. It is noted that, as a rule, the state of an object is determined based on the available observations of it (measured values of input parameters) and a mathematical model that describes the relationship between the input and output parameters of the objects under study, and which is built on the basis of the training sample data. It has been determined that evolutionary methods, including genetic algorithms, are effective methods of computational intelligence that can be used to build diagnostic models.

As a result of the research, the genetic algorithm was refined and adjusted to reduce the proportion by adjusting its parameters to increase the speed of evolutionary optimization. Recommendations are given for tuning the initial parameters of the evolutionary search when using the proposed modification. The parameters of the method, in particular, the size of the population, the number of generations, the bit width and the type of crossover are selected in such a way as to minimize the operating time of the module being developed and to obtain an accuracy within acceptable limits.

As a result, a genetic algorithm with a decrease in the population size was investigated and adjusted by adjusting its parameters to increase the speed of evolutionary optimization. Recommendations are given for tuning the initial parameters of the evolutionary search when using the proposed modification. The parameters of the method, in particular, the size of the population, the number of generations, the bit width and the type of crossover are selected in such a way as to minimize the operating time of the module being developed and to obtain within acceptable limits.

Various models of evolutionary search have been implemented, in particular the canonical model, Genitor models, CHC, island model, DAGA2, GA with a decrease in population size. The implemented methods and models have been tested on unimodal and multimodal functions. Experiments were carried out to study the effectiveness of the application of the developed software, the results of which showed the locality of using the developed program to find the optimal values of multidimensional functions.

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