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The Choice of Structures of Heterogeneous Information-Computer Systems Based on the Apparatus of Genetic Algorithms

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Abstract. **Sufficiently adequate dynamic models of the functioning of complex systems are characterized by high computational complexity, which leads to a significant complexity of optimization procedures. Therefore, the solution of the problem of combinatorial optimization by a complete search of possible solutions in practice is unacceptable.**

The advantages of evolutionary search as a method of combinatorial optimization of the structure of the information and computing system is the possibility of various ways of setting the target function and types of optimization variables, as well as in the use of probabilistic, rather than deterministic rules for finding solutions. A method of formalizing the structure of a heterogeneous information and computing system is proposed, which takes into account its hierarchical-network structure.

The presented approach allows by selecting rational parameters of the genetic algorithm and using the stochastic fitness function with a variable coefficient of variation to achieve a satisfactory speed of its convergence with a large dimension of the task. Examples of application of this method to the search for a rational structure of the computing system are given.

Keywords: **computer system, evolution search, genetic algorithm, stochastic fitness-function.**

Introduction

Modern information-computer systems (ICS) have complex heterogeneous hierarchical-network structures, with a large number of elements, often reconfigurable. Given the large number of possible configurations of computer systems — structures, parameters of the functioning of their elements and the composition of the tasks they solve — a mathematical apparatus of structural and parametric synthesis of hierarchical ICS is necessary.

The presence of such an apparatus will allow on the basis of modeling of ICS to form a rational structure adapted to solve specific computational tasks in various conditions. Therefore, the issues of improving the structure of the ICS come to the fore. The fundamental features of the systems of this class require taking into account the diversity of elements, the variety of their possible states, the heterogeneity of the connections in the system, the conditions of functioning. At the same time, traditional approaches to solving problems of structural-parametric synthesis are often reduced to a consistent choice of system architecture based on a qualitative analysis of existing options, formalization of the selected type of structure and parametric synthesis of its components using known optimization methods. However, sufficiently adequate dynamic models of the functioning of complex ICS, as a rule, are characterized by high computational complexity, which leads to a significant complexity of optimization procedures. Therefore, the solution of the problem of combinatorial optimization by a complete search of possible solutions in practice is unacceptable, which is primarily due to the following circumstances:

– significant number of the set of solutions, depending on the allowable number of elements in the structure and the considered number of their types;

– the labor-intensity of accurate calculation of the objective function (OF) on the basis of simulation and analytical models;

– time spent on obtaining statistical estimates of the quality of the solution;

– the need to repeatedly solve the noted problem in practice when varying the initial data, which, as a rule, is required in applied problems in order to implement a scenario approach that removes uncertainties in the conditions of functioning.

The numerical method of setting the OF and the alleged presence of several local extremes leads to serious difficulties in using well-known mathematical methods and requires special approaches based on a significant limitation of the many solutions under consideration.

A powerful tool for the approximate solution of complex combinatorial optimization problems are the methods of evolutionary search, among which genetic algorithms (GA) stand out. They are ways to solve optimization problems on the basis of evolutionary modeling, based on the use of analogies with natural processes of natural selection [1–4]. The advantages of optimization methods based on GA in comparison with classical ones consist primarily in the possibility of various ways of specifying OF and types of optimization variables, as well as in the use of probabilistic, rather than deterministic rules for finding solutions [5].

The theory of GA is currently quite developed, but significant non-trivial issues in specific cases are, firstly, the construction of the so-called «fitness function» (FF) to assess the quality of solution options and the formalization of optimization variables in the space of possible solutions, which in this case requires taking into account the peculiarities of coding a hierarchical-network heterogeneous structure, and, secondly, the justification for adjusting the parameters of the GA that ensure obtaining satisfactory according to the specified criterion of the decision in a limited time [6–8].

The traditional approach involves adjusting the parameters of the algorithm to obtain a satisfactory result by its repeated implementation with a pre-built FF. In the case of limited time to solve the problem and its significant labor intensity, as noted above, such a path does not seem quite appropriate. Therefore, to solve the problem of stochastic combinatorial optimization, it is proposed to use a GA with a stochastic FF with a variable (changing in the search process) coefficient of variation, conducting a preliminary selection of rational parameters for adjusting the algorithm.

Formulation of the problem of choosing the structure of an inhomogeneous information-computer system

The essence of the task of choosing the structure of the ICS is as follows. There is a nomenclature of electronic component base (ECB), which can be used as elements of ICS. An imitation-analytical model of ICS is given, correlating its structure with the achieved indicator of the target effect, acting as a OF. It is necessary to find the structure of the ICS that provides the highest value of the mathematical expectation of the OF indicator. The time for solving the problem is limited, which is due to the laboriousness of obtaining estimates of the values of the OF by repeatedly implementing simulation modeling of the work of the ICS in the study of many solutions.

With a sufficiently general statement of the problem, we will assume that the:

1. Nomenclature of ECB for building ICS many available types of processor $\mathcal{B}^p = \{\mathscr{b}_i^{pr}\}$ and interface elements (modules) $\mathcal{B}^{if} = \{\mathscr{b}_i^{if}\}, \mathscr{b}_i =< \vec{f}_i^{fu}, \vec{f}_i^{re}, \vec{f}_i^{mg} >, \mathscr{b}_i \in \mathcal{B}, \mathcal{B} = \mathcal{B}^{pr} \cup \mathcal{B}^{if}$, having functional parameters $\vec{f}_i^{fu}$, resource parameters $\vec{f}_i^{re}$, weight and size parameters $\vec{f}_i^{mg}$, defining their particular quality indicators $\vec{d}(\mathscr{b}_i) =< d_j(\vec{f}_i^{fu}, \vec{f}_i^{re}, \vec{f}_i^{mg}) >$. Particular quality indicators are understood, for example, performance, failure rate, power consumption, etc.

2. A model of the functioning of the ICS, which allows to assess the value $\widehat{\Psi}(S)$ OF under conditions of deterministic and random internal and external factors, where S — hierarchically-the network structure of the ICS, given by the parameters of the elements and the matrix of their adjacency. The OF can be, for example, the productivity of the ICS at a given time interval for a given set of tasks.

3. Vector-function of technical and operational indicators of ICS quality: $W(S_i) =< w_j(S_i) >$.

Restrictions:

1. Set of permissible values of technical and operational indicators of ICS quality $\mathcal{W}^{dir}$.

2. Computational labor intensity of solving the problem, represented in the limit number Υ implementations of the OF $\widehat{\Psi}(S)$.

Find: On a variety of possible structures $\mathbb{S}$ ICS the structure S^*, providing the maximum expected target effect:

$$S^* = arg \max_{S_i \in \mathbb{S}} M[\widehat{\Psi}(S_i)], W(S_i) \in \mathcal{W}^{dir}, S_i \in \mathbb{S}.$$

Given the high complexity of solving the problem in practice, it is advisable to build an algorithm for finding its approximate solution. Let's assume that the value of the OF lies in the range $0 \le \widehat{\Psi} \le 1$, and the value of the OF equal to 1 corresponds to the ICS with the optimal structure.

The essence of GA is stated, for example, in [4, 5]. However, the effectiveness of GA searches ultimately depends on the «tuning» of the research-use ratio determined by the parameters of genetic operators.

Algorithm for choosing the structure of heterogeneous information-computer system

The developed method includes as the main stages: filtration of ECB and formalization of possible structures of ICS; adjustment of rational parameters of GA using the deterministic variant of FF; substantiation of the initial coefficient of variation of stochastic FF, taking into account the limit on the maximum number of OF implementations; implementation of the constructed GA. The implementation of this method can be described as a sequence of the following steps.

Step 1. Narrowing of the set of ECB is carried out according to the Pareto principle by allocating subsets $\mathcal{B}^{pr*}$ and $\mathcal{B}^{if*}$, containing respectively options for building computational (CM) and interface modules (IM) with non-improving characteristics.

Step 2. Formalization of the structure $S \to X$ (Fig. 1). Depending on the available element base, the characteristics of subscribers interacting with the ICS, the requirements for interfaces, etc., a structure template is formed that corresponds to the maximum possible composition of elements and a variety of connections within the capabilities of the implemented architecture: the number u of levels, the number m_k, $m_u = 1$ of blocks on each level; each block i-level combines l_i lower nodes: $m_k = l_k m_{k-1}$, herewith $n_{cm} \le m_0 \le n_{cm}^2$, here is n_{cm} — the maximum possible number CM in structure. Structure option S is encoded as a «chromosome»

$$X(S) =< x_j^{(k)}(S) | k = 0, \dots, u, \ j = 1, \dots, m_k > ,$$

here is «gene» $x_j^{(k)}(S)$ — processor module implementation number for $k = 0$ or implementing an interface module for $k = 1, \dots, u$; $x_j^{(k)}(S) = 0$ means the absence of an element at a given position of the structure.

Step 3. To build a FF $\widetilde{\Psi}_N(S_i)$ based on OF $\widehat{\Psi}$ the Bayes — Laplace criterion is used, taking into account the penalty function of constraints: $\widetilde{\Psi}_N(S_i) = M[\widehat{\Psi}] \times \varpi(S_i)$, here is $\varpi(S_i)$=0, $\vec{W}(S_i) \notin \mathcal{W}^{dir}$; $\varpi(S_i)$=1, $\vec{W}(S_i) \in \mathcal{W}^{dir}$; $M[\widehat{\Psi}] = \frac{\sum_{k=1}^{N} \widehat{\Psi}_i}{N}$, $\widehat{\Psi}_k$ — implementation of OF in k-th from N experiences.

In order to adjust the rational parameters of GA, a deterministic version of FF is built, which has low computational labor-intensity, heuristically or, for example, using estimates of mathematical expectation of parameters of random factors $\hat{Z}$: $\Phi(X_i) = \Psi(S_i | M[\hat{Z}])$. Based on $\Phi(X_i)$ a stochastic variant of FF is constructed, having a normal (Gauss) distribution and coefficient of variation V:

$$\Phi_V(X_i) = \left(1 + V \times \sqrt{-2 \ln \hat{\varrho}_1} \times \cos 2\pi \hat{\varrho}_2\right) \times \Phi(X_i) ,$$

where $\hat{\varrho}_1, \hat{\varrho}_2 \in [0; 1]$ — uniformly distributed random variables.

Step 4. For some similar structure of the ICS (typical structure, possible construction option, analogues of the desired ICS, etc.), an estimate of the coefficient of variation of the OF is determined:

$$V_0 = V[\widehat{\Psi}] = \frac{1}{\widetilde{\Psi}_N} \sqrt{\frac{\sum_{k=1}^{N} (\widehat{\Psi}_k - \widetilde{\Psi}_N)^2}{N}}, \ N > 10^5.$$

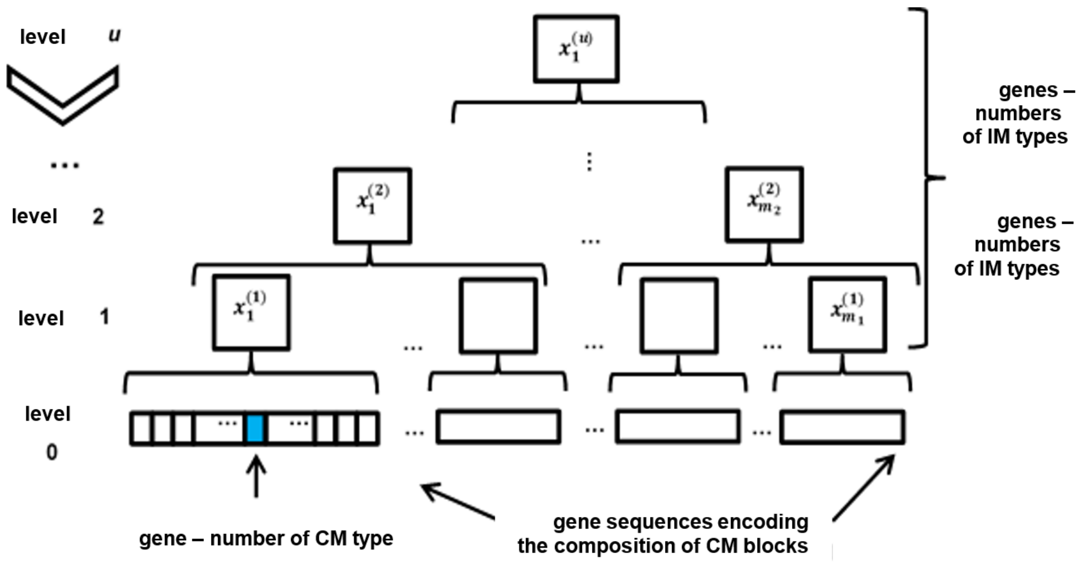

Fig. 1. Scheme of coding variants of the ICS structure

Step 5. Finding an option $X_0 = \arg\max_{X_i} \Phi(X_i)$, providing the maximum value of the deterministic FF, for example by enumeration, which is provided with low computational labor-intensity $\Phi(X_i)$.

Step 6. The initial (for the first generation) coefficient of variation V of the stochastic FF is selected from the range corresponding to $-3 \le \lg V \le -0.5$.

Step 7. GA parameters are selected $\mathcal{G} =< M, K_1, K_2 >$ (discussed below when describing GA operators, recommended ranges $M = 0.5, \dots, 0.05$; $K_1, K_2 = 0.1, \dots, 0.9$).

Step 8. Population size is selected Ω, $2 \le \Omega \le \Upsilon/2\,({}^{V}/_{V_0})^2$, and the number of generations is determined N_p, corresponding to the limit on the number of calculations of the OF Υ:

$$N_p(V,\Omega): \Upsilon \ge \sum_{i=1}^{N_p}\left(\frac{V_0}{V_i}\right)^2,$$

$$V_i = V - \frac{N_p}{i}(V - V_\Delta),$$

here is V_Δ — a given coefficient of variation of FF for the latest generation, which determines the accuracy of the solution.

Step 9. By series N_γ GA launches with selected parameters $\mathcal{G}, N_p$, Ω indicators are determined

$$\varphi = \frac{\sum_{j=1}^{N_\gamma}\Phi_{V_i}(X_j^*)}{n \times \Phi(X_0)},$$

here is $\Phi_{V_i}(X_j^*)$ — result *j-th* run GA for N_p generations, and

$$P_\gamma = \frac{N\{\Phi_{V_i}(X_j^*)/\Phi(X_0) \ge \gamma\}}{N_\gamma},$$

here is $N\{\Phi_{V_i}(X_j^*)/\Phi(X_0) \ge \gamma\}$ — number of «successful» launches, when $\Phi_{V_i}(X_j^*)/\Phi(X_0) \ge \gamma$. Meaning φ consists in the average relative proximity of the resulting solution to the optimal value of FF, a P_γ it makes sense to have the probability of «success» of the launch of the GA, when $\varphi \ge \gamma$, where is γ — the value of the acceptable deviation set in advance. Statistically expedient number of launches of GA to assess its effectiveness based on the variance of the binomial distribution and the «three sigma» rule we will count $N_\gamma \approx \frac{9P_\gamma(1-P_\gamma)}{(1-\alpha)^2}$, α — confidence probability. So, for example, $N_\gamma = 360 \dots 900$ for $\alpha = 0.05$, $P_\gamma = 0.5, \dots, 0.9$. From these considerations, we obtain an indicator of the relative effectiveness of the GA with the selected parameters $\psi = \varphi \times P_\gamma$.

Step 10. Repeating steps 8–9 and varying population size Ω, get the dependence of relative effectiveness ψ from Ω at fixed V and $\mathcal{G}$, which is easily interpolated, which allows you to find $\Omega^* = \arg\max_{\Omega} \psi(V,\mathcal{G},\Omega)$ and get $\psi^*(V,\mathcal{G}) = \psi(V,\mathcal{G},\Omega^*)$.

Step 11. By repeating steps 7–10 and varying the parameters $\mathcal{G}$ heuristically the selection is carried out

$$\mathcal{G}^* = \arg\max_{\mathcal{G}} \psi^*(V,\mathcal{G})$$

and receiving $\psi^{**}(V) = \psi^*(V,\mathcal{G}^*)$.

Step 12. Repeat steps 6–11 for different V and similar to the step10 is being sought $V_{opt} = \arg\max_{V} \psi^{**}(V)$.

Step 13. Define

$\mathcal{G}_{opt} = \arg\max_{\mathcal{G}} \psi^*(V_{opt},\mathcal{G})$,

$\Omega_{opt} = \arg\max_{\Omega} \psi(V_{opt},\mathcal{G}_{opt},\Omega)$.

Step 14. In the case of a low assessment of the performance of the GA, what should be considered $\psi(V_{opt},\mathcal{G}_{opt},\Omega_{opt}) < \gamma$, it is necessary, returning to step 1, to reduce the numbers of the sets $\mathcal{B}^{pr}, \mathcal{B}^{if}$ due to more strict filtering of the element base and (or), returning to step 2, facilitate structure parameters u, m_k, $k = 1, \dots u$ by reducing the permissible complexity and diversity of structures.

Step 15. Launch of GA with FF for *i*-th generation

$$\tilde{\Psi}_{N_i},\ N_i = \frac{V_0^2}{V_i^2},\ V_i = V_{opt} - \frac{N_p}{i}(V_{opt} - V_\Delta)$$

and parameters: mutations and crossing overs respectively $< M, K_1, K_2 >= \mathcal{G}_{opt}$, population volume Ω_{opt}, number of generations $N_p(V_{opt},\mathcal{G}_{opt},\Omega_{opt})$, which leads to the desired solution $X^* \to S^*$.

FEATURES OF THE FORMATION OF GENETIC OPERATORS IN THE OPTIMIZATION OF THE STRUCTURE OF INFORMATION-COMPUTER SYSTEM

Let denote through F some FF and describe the main operators of GA, justified as a result of the research.

Mutation operator $X' = \text{Mut}(X, M)$ assumes for mutating with probability M gene equally-likeable choice of alleles from the set of possible: with probability M

$$x_j'^{(0)} = [\hat{\varrho} \times \text{card}(\mathcal{B}^{pr*}) + 1)],\ j = 1, \dots, m_0;$$

$$x_j'^{(k)} = [\hat{\varrho} \times \text{card}(\mathcal{B}^{if*}) + 1)], j = 1, \dots, m_k, k = 1, \dots, u.$$

Here and below, the square brackets mean rounding to the integer at the bottom.

Selection operator assumes selection for the next generation (range Sel) chromosomes with a FF value not lower than the average in the generation:

$$Sel = \{i: F(X_i) \geq \bar{F}, i = 1 \dots \Omega\} =$$

$$= \{sel_k | k = 1, \dots, \text{card}(Sel)\},\ \bar{F} = \tfrac{1}{\Omega}\textstyle\sum_{i=1}^{\Omega} F(X_i);$$

$$\overline{Sel} = \{i: i \notin Sel, i = 1, \dots, \Omega\} = \{\overline{sel}_k | k = 1, \dots, \Omega - \text{card}(Sel)\},$$

here is Ω — number of chromosomes in generation.

Crossing over operator $X' = \text{Kross}(X, Y, K_1, K_2)$ involves the exchange of genes on the epymous positions of the parent chromosomes X, Y with probability K: if $F(X) \geq F(Y), \hat{\varrho} > K$; or $F(X) \leq F(Y), \hat{\varrho} < K$: $x_j'^{(k)} = y_j^{(k)}$, else $x_j'^{(k)} = x_j^{(k)}$, where is $\hat{\varrho} \in [0; 1]$ — played uniformly distributed random variable, $K = K_1 + (K_2 - K_1) \times {}^{k}/_{u}$, K_1, K_2 — crossing over parameters for 0-th и (u-1)-th hierarchical level respectively, $i, j = 1, \dots, m_k$, $k = 0, \dots, u$. This construction of the crossing over takes into account the expediency of different intensity of exchange of structural units of different levels of hierarchy between parent variants that shown by researches.

Implementation of the GA includes the following steps:

1. Formation of a random initial population

$$X(i) = \text{Mut}(X(i), 1), i = 1, \dots, \Omega.$$

2. Equally probable chromosome selection from the entire generation $i_k = [\Omega\hat{\varrho}] + 1$, equally likely choice of chromosome from among those selected for the next generation:

$$j_k = sel_{[card(Sel) \cdot \hat{\varrho}]+1}\,,$$

and the use of a crossing over operator for them

$$X(k) = \text{Kross}(X(i_k), X(j_k), K_1, K_2),\ k \in \overline{Sel}.$$

This method has the advantage that such an operator does not change the total number of chromosomes in the generation, forming a new one instead of the one being removed, and reduces the likelihood of losing successful search directions during selection, leaving the possibility of participation of «rejected» chromosomes in the formation of the next generation.

3. Application of the mutation operator for all chromosomes in the generation except the best FF value:

$$X(i) = \text{Mut}(X(i), M), i = 1, \dots \Omega, i \neq \arg \max_{i=1,\dots\Omega} F[X(i)]\,,$$

that ensures that the best possible solution is preserved.

4. Iterative execution of steps 2–3 and formation of the result $X^* = \arg \max_{i=1,\dots\Omega} F[X(i)]$ while achieve the number of generations N_p.

EXAMPLE OF SEARCH THE STRUCTURE OF INFORMATION-COMPUTER SYSTEM

Let us give an example of the application of the developed approach [9, 10] to the choice of the rational structure of a multi-module computing system. For this purpose, an appropriate software package was developed and used [11]. At the same time, the calculation time of a single implementation of the OF was about 300 ms for 100 integration steps (a PC based on Intel i5 with a clock frequency of 3 GHz in the MATLAB 7), the required standard deviation of the OF score of 1 %, which corresponds to 10^4 experiments (the initial coefficient of variation of the OF is close to 1). With the total allowable number of elements of the three-level structure $N = 22$, the estimate of the total number of its formalized variants of the structure was $1{,}9 \times 10^9$, taking into account the resource constraints on the composition of the elements - about 4.3×10^4.

On Figure 2 shows the experimental dependence of FF on the number of generations and the coefficient of variation with rational parameters justified by the above $KV = 0.95$; $KN = 0.8$; $M = 0.3$; $\Omega = 10$.

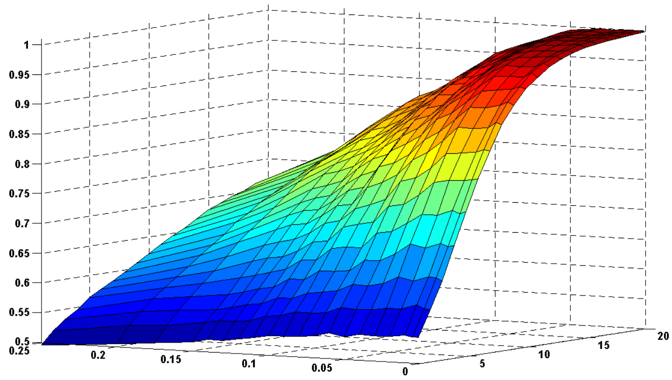

Fig. 2. Example of dependence of the objective function on the number of generations of GA and the coefficient of variation of FF

On Figure 3 shows the experimental dependence of the performance indicator ψ on the number of OF calculations for various methods of constructing the GA (heuristic «directional-random» setting corresponds to $KV = 0.9$; $KN = 0.6$; $M = 0.1$; $\Omega = 12$; «random-directional» — $KV = 0.6$; $KN = 0.5$; $M = 0.4$; $\Omega = 4$).

For example, a search time limit of 36 hours was set, which corresponds to the enumeration of 48 variants of structures in the traditional way. In this case, the use of the developed method made it possible to find a quasi-optimal solution that provides a value of the OF estimate of about 0.99. At the same time, for the traditional method of using GA (constant coefficient of variation of FF) with rational parameters, this value was 0.56, i. e. the increment of the OF was 77 %. On the other hand, fixing the required value of the OF assessment, it is possible to estimate the gain by the time of its achievement: about 8 times for the value of 0.95, 12 times — for 0.9.

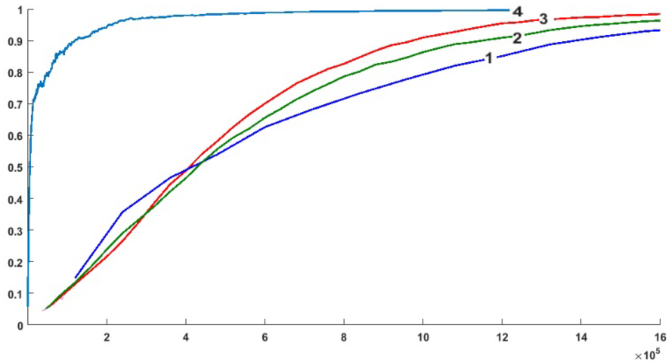

Fig. 3. Comparative analysis of the effectiveness of GA in the search for the optimal structure of the ICS
1 — heuristic «directional-random» setting;
2 — heuristic «random-directional» setting;
3 — setting with a constant coefficient of variation of FF;
4 — setting with variable coefficient of variation FF

In practice, the choice of the option of constructing a complex technical object is, as a rule, multi-criteria, and the final decision is made as an optimal compromise from some subset of possible solutions. The fact is that, firstly, a significant impact on the decision is exerted by difficult to formalize factors associated, for example, with the labor-intensity of the implementation of a particular option with existing developments, etc. Secondly, it is necessary to eliminate uncertainties in the formation of initial data, for example, sets of computational tasks. Therefore, the application of the developed method is most expedient in cases where it is required in a limited time to form a set of quasi-optimal solutions in the scope of possible structures, thereby providing a reasonable optimal-compromise choice of the desired structure.

Conclusion

A method of heuristic solution of a complex combinatorial optimization problem of large dimension with a stochastic target function through the use of an evolutionary modeling apparatus – genetic algorithms is proposed. The problem of structural-parametric optimization of complex heterogeneous hierarchical-network ICS fully belongs to this class. This is due, on the one hand, to the many possible options for their construction, taking into account the variety of types of elements and their places. in the structure, and on the other hand, the complexity of the models of functioning and the corresponding complexity of their computational implementation. Therefore, despite the capabilities of modern computer technology, the proposed method should be used to develop proposals for substantiating the technical appearance of complex ICS. Statistical research has shown the possibility of significantly reducing the time spent on finding rational options for building ICS.

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Выбор структур неоднородных информационно-вычислительных систем на основе аппарата генетических алгоритмов

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Аннотация. **Достаточно адекватные динамические модели функционирования сложных систем характеризуются высокой вычислительной сложностью, что ведет к существенной трудоемкости оптимизационных процедур. Поэтому решение задачи комбинаторной оптимизации путем полного перебора возможных решений на практике оказывается неприемлемым.**

Преимуществами эволюционного поиска как метода комбинаторной оптимизации структуры информационно-вычислительной системы является наличие возможности различных способов задания целевой функции и типов переменных оптимизации, а также в использовании вероятностных, а не детерминированных правил поиска решений. Предложен способ формализации структуры гетерогенной информационно-вычислительной системы, который учитывает ее иерархически-сетевую структуру.

Представленный подход позволяет посредством выбора рациональных параметров генетического алгоритма и использования стохастической фитнесс-функции с переменным коэффициентом вариации достигать удовлетворительной скорости его сходимости при большой размерности задачи. Приведены примеры приложения указанного метода к поиску рациональной структуры вычислительной системы.

Ключевые слова: **вычислительная система, эволюционный поиск, генетический алгоритм, стохастическая фитнесс-функция.**

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