Journal of Theoretical and Applied Information Technology
10th October 2015. Vol.80. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

SWARM-INTELLIGENCE-BASED ALGORITHM OF CONNECTIONS PERMUTATION BETWEEN PINS

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ABSTRACT

From a mathematical point of view routing is the most complicated problem of selection from a vast number of optimal solution choices. Development of methods and algorithms for solving the routing problem is carried out for many years though the issue is still relevant. This is due to the fact that, first of all, this is a nondeterministic polynomial time complete problem (so called NP-complete problem), and thus to develop a universal algorithm for finding the exact optimal solution within a reasonable time is quite a challenging task. The emergence of new, more sophisticated computer equipment, giving powerful computing resources, as well as exclusive standards of the projected devices is the driving force behind the development of new algorithms for solving the routing problem. There are several approaches to solve NP-complete problems. The first class of algorithms includes methods, which explicitly or implicitly provide for the exponential running time of the algorithm. These include full enumeration method, linear and nonlinear programming, etc. The second class includes the so-called heuristic algorithms allowing one to get reasonably good solutions within an acceptable time. A comparative analysis of the methods and algorithms for the first two classes showed that these algorithms do not guarantee the global result. The operation of such algorithms is completed or after a local optimum, or after an implementation of a predetermined number of steps. The third class includes algorithms of randomly directed search, based on the concepts of modeling [1]. They allow you to obtain a set of alternative solutions, and as a result of their analysis to obtain optimal and quasi-optimal results. These algorithms use a simulation of evolution and natural selection methods, observed among living organisms in nature to select the strongest. These methods allow you to create extremely flexible, fast and efficient data analysis tools. In this regard, in the paper we use the developments based on these technologies. For the study we proposed to use swarm algorithm of the redistribution of connections between terminals on the basis of integration of models of adaptive behavior of an ant colony and collective alternative adaptation. We propose the swarm algorithm of connection permutation between pins based on the integration of two models: an adaptive behavior of ant colony and collective alternative adaptation. The essence of the integration of these models is that in the course of performing the search procedure the certain procedures of the ant colony algorithm are alternating with collective alternative adaptation. The conducted experimental studies have confirmed the effectiveness of the proposed paradigm.

Keywords: *Swarm Intelligence, Ant Colony, Adaptive Behavior, Collective Alternative Adaptation, Connections Permutation, The Optimization.*

1. INTRODUCTION.

Now due to the development of manufacturing technologies of VLSI, a number of new trends in their design appear. Due to the reduction the elements' size and the time delay of the signal in which more than 60% of the total time delay accounts for the delay in interconnects. The increase of the area for the interconnections outstripping the growth of the size of the area intended for the active elements. Another new trend is the use of above-cell areas (AA), i.e. areas above the active elements. These trends lead to an increase in the value of the trace in the construction engineering, require the development of new methods for better decisions at this stage. In connection with the new technologies and trends in the design and manufacture of VLSI the development and research methods and means of their design that will improve the speed, quality

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and degree of automation of the design process becomes relevant. The analysis of technological problems of nanometer VLSI design shows the increased importance of tracing interconnections compared with submicron technologies.

Due to the high complexity and dimensionality of the routing problem, design engineering is usually based on employment of a hierarchical approach. There are two basic routing levels: global and detailed routings. The goal of the global routing is to distribute connections over subareas. Detailed routing consists in implementing of connections in each subarea. Usually detailed routing is divided into the channel routing and the routing of the switchboxes. It is noted that the end result of the routing depends to a large extent on the initial reservation of connections for pins. Consequently, the routing problem is preceded by the task of pins permutation [2, 3, 4].

The connection permutation between pins is possible in case where the pins are functionally equivalent. Two pins (or terminal row) are called functionally equivalent, if the switching of corresponding connected circuits does not change the logical function of the circuit [5]. The goal of permutation is to reduce the density of the routing areas, decrease the length of the connections, reduce the number of crossings, improve the integration density, etc.

The connections permutation phase is usually performed after the global routing phase. The main purpose of connections permutation between the pins is to increase the routability index for the next step of a detailed routing. The criteria based on the length of the conductors (the total length of communications, the length of the longest communication) have acquired widespread acceptance [6]. The length l_t of half the perimeter of a rectangle, contouring the pins of the circuit, is used to estimate the total length of the circuit. Although these criteria are easily computable and can be integrated into an optimization tool, they roughly simulate the routability index of the circuit. In the work of [4], instead of using the criterion of the total length of conductors, based on the simulation of routing that does not depend on the topology, i.e. is TP-free, a target function, which allows more accurate assessment of the conductors' concentration, is used. Switchboard is split into an ordered set of areas $\Theta=<\Theta_k|\Theta_{k+1}\subset\Theta_k, k=1,2,\ldots,N>$. Each area is included into the next area with the proper order of magnitude. The formal criterion is written as:

$$Q^1 = \sum_{k=0}^{N} Q(\Theta_k)$$

where $Q(\Theta k)$ is the number of circuits crossing the area border.

In the works of [7], as well as [8], usually the reference grid $X \times Y$ is superimposed on the circuit area at routing simulation. Routing biddings are simulated for each edge of the grid. To account for the close connection between the allocation and routing tasks the special local criteria are proposed. These criteria are based on the topology simulation, i.e. TP-based, providing building of the routing trees on the routing grid.

Recently, the methods based on the application of artificial intelligence techniques are used increasingly for solving various "complicated" problems, which include also the problems of distribution (or binding) of the circuits with pins. Especially, the rapid growth of interest is observed in the development of algorithms inspired by natural systems [9, 5, 8, 11, 12, 13]. One of the latest trend of such approaches are multi-agent methods of intelligent optimization, based on the simulation of collective intelligence [14, 15].

The architecture and operation framework of biological control systems that ensure the ability of animals to specialize and adapt to the constantly changing conditions of the external environment are the subject of active research in the leading scientific centers. Among them, the swarm intelligence methods are developing most actively [16, 17, 18], in which a set of relatively simple agents develop a strategy of their behavior without the global governance. The idea of applying ant colony (AC) algorithm is based on simulating the behavior of ants, associated with their ability to quickly find the shortest path from the anthill to the food source [16]. When moving, the ant marks the path by pheromone, and this information is used by other ants to choose the path. The ant colony algorithm is based on a simulation of ants' movement on the problem-solving graph. Distance covered by the ant is displayed as soon as the ant visits all the nodes of the graph. The process of finding solutions by ant-based algorithm is iterative. As for bees, the basic mechanisms of their behavior are as follows. First, some "scout" bees fly out of the hive in a random direction to seek out sources of nectar. After that other bees are sent to found nectar sources. At that, the number of bees flying to the source depends on the amount of available nectar; the more nectar is supposed to be found in the source, the more bees fly to this

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

source, while the "scout" bees fly again to look for other sources, and the process repeats. The current article proposes modifications and methodology for the representation of combinatorial problems in the form of swarm algorithms in accordance with the mathematical models of bees and ants behavior [19].

The work [9] outlines a method for solving the problem of the connections distribution between the pins based on the simulation of adaptive behavior of ant colony.

The advantage of the ant colony algorithm is guaranteed convergence to the optimal solution, as well as a higher rate of finding optimal solution as compared to traditional methods. The disadvantages include the fact that the proposed algorithm is quite dependent on the initial search parameters, which are chosen experimentally, as well as the lack of a detailed study of the search space. The work [20] outlines a method for solving the problem of connections distribution between the pins, based on the simulation of collective alternative adaptation. The experimental studies have shown that the use of this algorithm gives a significant reduction in the initial density of the channel, as well as the total length of the horizontal fragments and the total number of nonremovable connection intersections with each other [21].

To enhance the strengths and mitigate the weaknesses of the considered methods we propose a paradigm of swarm algorithm based on integration of the two models: an adaptive behavior of ant colony and collective alternative adaptation.

2. METHODOLOGY.

The problem of connections permutation between the pins of a special class is of principal interest. This concerns the problem on connections permutation in the channel or switching unit. Connections permutation is produced before the detailed routing phase and it aims at reducing the length of the connections inside the channel, as well as the density of the channel that facilitates the routing process [22].

Problem statement. Let the set of pins $V=<v_i|\ i=1,2,\ldots,n>$ are respectively connected to the set of terminal server connections $T^0 = <t_i|\ i=1,2,\ldots,n>$. A terminal is an endpoint of a connection linking it to the pin. Preliminarily, based on the analysis of the circuit, a set A of the equivalent pins group called terminal row is formed: $A=\{A_e|\ e=1,2,\ldots,n_e\}$. Where $A_e=\{a_{ej}|j=1,2,\ldots,n_{ej}\}$ is the terminal row; T^*_e - is a group of terminals connected to a terminal row A_e. One must find a valid permutation of terminals T^* at which the criterion has a better value. In turn, a valid permutation of terminals T^* is the set of admissible permutations of terminals T^*_e, either of which defines the connection of terminals to the appropriate terminal row A_e. $T^*=\cup T^*_e$, $T^*_i \cap T^*_j=\varnothing$.

The organization of the search procedures based on the simulation of adaptive behavior of an ant colony.

The ant colony method can be applied to any combinatorial problem, which is consistent with the following requirements [3].

Problem Representation:

- the solution space must be represented as a graph with a set of nodes and edges between the nodes;
- the correspondence should be set up between the solution of the combinatorial problem and the route in the graph.

It is necessary to develop the rules (methods) for:

- initial distribution of ants in the nodes of the graph;
- building a valid alternative solutions (route in a graph);
- determining the probability of movement of an ant from one node to another;
- updating pheromones on the edges (nodes) of the graph;
- pheromone evaporation.

The search for solutions is carried out on the family of complete subgraphs G={Ge|e=1,2,…,ne}, Ge=(Xe,Ue). The nodes of the Xe set correspond to the terminals of a T*e set, connected to the terminal row Ae.

In general, the search for a valid permutation of the terminals T* is carried out by the community of ants cluster Z={ze|e=1,2,…,ne}. The number of ants is equal to the number of terminal rows Ae. At each iteration, each ant ze of Z cluster builds on a corresponding graph Ge=(Xe,Ue) its particular solution, i.e. valid permutation of terminals T*e.

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The general solution, i.e. a valid permutation of terminals T^*, is determined by a set of admissible permutations of terminals T^*_e, built by ants of a single cluster. In other words, the number of solutions, generated by the ants at each iteration is equal to the number of ant clusters.

Simulating the behavior of ants in a problem of finding the permutation of terminals T^* is associated with the distribution of pheromone on the edges of the G graphs family. Initially, the same (small) amount of pheromone Φ/v is laid at all the edges of the G graphs family, where $v=|\cup U_e|$. The parameter Φ is specified a priori. The problem-solving process is iterative. Each iteration l consists of three phases. The number of solutions n_k, which will be formed by the ants at each iteration, are given. This serves basis to form n_k clusters of Z_k . At the first stage, each ant z_{ek} of each cluster Z_k builds a concrete solution, i.e. M_{ek} route on the corresponding graph $G_e=(X_e,U_e)$. In other words, the ants of Z_k cluster build cluster of routes $M_k=\{M_{ek}|e=1,2,\dots,n_e\}$. The sequence of X_e nodes set in the route M_{ek} corresponds to the permutation of terminals T^*_{ek}. For a set (cluster) of routes, built by the ants of a single cluster Z_k and corresponding to the k-th solution, we determine the value of the optimization criterion F_k.

In the second stage, each ant $z_{ek}\in Z_k$ lays pheromone on the edges of the built route in the graph G_e in amount proportional to the criterion F_k. We use ant-cycle method of ant systems. In this case pheromone is laid by all ants of all clusters simultaneously. The third step refers to the total evaporation of pheromone on the edges of the family of solution-searching graphs G. After performing all of the steps at the iteration we find the cluster with the best solution, which is saved. Then we proceed to the next iteration.

The ant colony algorithm

1. A set of terminal rows $A=\{A_e|e=1,2,\dots,n_e\}$ is formed in accordance with the original data, based on the circuit analysis. Then the value of n_e is determined.

$A_e=\{a_{ej}|j=1,2,\dots,n_{ej}\}$ - is a terminal row.

2. The solution-searching graphs $G=\{G_e|e=1,2,\dots,n_e\}$, $G_e=(X_e,U_e)$ are generated. At that, the nodes of set X_e correspond to the terminals of the set $T^*_{e,}$ connected to a terminal row A_e. $|A_e|=|X_e$

3. The initial amount of pheromone Φ/v, is laid on all edges (or nodes) of the graph G_e, where $v=|\cup U_e|$. Next the values of the parameters Q_i, α, and ρ are set.

4. The number of clusters n_k is set to form n_k clusters of ants.

The number of iterations n_l is set.

$l=0$ (l is the number of iterations).

5. $l=l+1$ (the next iteration is selected).

$k=0$ (k is the cluster number).

6. $k= k+1$ (the next cluster is selected).

$e=1$ (e - is the index of a subset of equivalent pins A_e).

7. The rout M_{ek} is constructed employing the ant colony algorithm.

8. If $e< n_e$, than $e= e+1$. Another ant in the cluster is selected and we go to the step 7 to build the next route, otherwise due to the fact that all routes of Z_k cluster are built, we go to step 9.

9. The objective function $F_k(l)$ is calculated for a set of routes, built by the ants of a single cluster Z_k on l-th iteration. If $k< n_k$, we go to step 6, otherwise, due to the fact that all the routes for all clusters Z_k are built, we go to step 10.

10. The solution with the best value of the optimization criterion F^*_k and the set of routes, built by the ants of the single Z_k cluster, are determined. $k=0$.

11. $k=k+1$. The same amount of pheromone is laid at all edges of all the routes, built by ants of a single cluster Z_k at the l-th iteration,

$h_k(l)= \lambda / F_k(l)$.

12. If $k< n_k$, we go to step 11, otherwise we go to step 13.

13. After each agent has formed a solution and laid the pheromone, the total evaporation of pheromone on the edges of the G graphs takes place at the 3rd stage in accordance with formula (5).

$h_{ij}(t+1) = h_{ij}(t) \cdot(1- \rho)+ \varphi_{ij}(l)$,

where $h_{ij}(t)$ - is the pheromone level on the edge (i,j), ρ - is the coefficient of renewal.

14. If $l< n_l$, we go to step 5, otherwise we go to step 15.

15. The end of the algorithm.

The ant colony algorithm

1. Choose (randomly) a node x_0 in the graph $G_e=(X_e,U_e)$ for the initial distribution of an ant $z_{ek}\in Z_{k}$..

2. $t=1$, t is is the $M_{ek}(t)$ routing step in the G_e graph.

The node x_0 is included in the route $M_{ek}(t)$.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$x_p(t)= x_0$.

($x_p(t)$- is the last node of the $M_{ek}(t)$ route.

3. A set of nodes $X_{ek}(t) \in X_e$ neighboring to $x_p(t)$, are formed. At that each of the nodes $x_i \in X_{ek}(t)$ can be added to the $M_{ek}(t)$ route under formation.

4. For each node $x_i \in X_{ek}(t)$ parameter h_{iek} is calculated, indicating the total level of pheromone laid on the edge of the G_e graph, which connects x_i with the node $x_p(t)$.

5. The probability $P_{iek}(t)$ of the inclusion of the node $x_i \in X_{ek}(t)$ in the route $M_{ek}(t)$ under formation is defined as the ratio $P_{iek}(t) = h_{iek} / \sum_i h_{iek}$

6. The agent with probability $P_{iek}(t)$ selects one of the nodes $x_i \in X_{ek}(t)$, which is included in the route $M_{ek}(t)$.

7. $x_p(t)= x_i$.

8. If the route $M_{ek}(t)$ is fully formed ($X_{ek}(t)= \varnothing$), we go to step 10, otherwise we go to step 8.

9. $t=t+1$. Go to step 3.

10. The end of the algorithm.

Time complexity of this algorithm depends on the lifetime of the colony l (number of iterations), number of graph nodes n, and the number of ants m. It is defined as $O(l*n^2*m)$.

The organization of the search procedures based on the simulation of collective alternative adaptation. Adaptation is the ability of a living organism or a technical system to change its state and behavior (parameters, structure, algorithm and performance) depending on changes in external environment conditions through the collection and use of information about the environment [23].

As a rule, the adaptive system is understood as a system, which operates under expected uncertainty and changing external conditions, while the information about these conditions, obtained in the course of operation, is used to improve the efficiency of the system's performance.

Adaptation is a special case of control with stable targets. The main goals of adaptation are associated with extreme requirements for an adaptation object in the form of maximizing the efficiency of its performance.

The adapting exposure may be of diverse nature. One can change the parameters of adaptation object, as well as its structure. In the first case we have parametric adaptation, while in the second case - structural adaptation. Depending on the type of variable parameters, parametric adaptation can be continuous, discrete and binary. It is obvious that structural adaptation is a deeper and more radical, as the relevant changes affect the most hidden part - the structure of the adaptable object. Structural adaptation is usually accompanied by parametric adaptation, since each structure has its own parameters, which also require adaptation.

Adaptation of a structure is possible, first, by its slight changes having the evolutionary nature - evolutionary adaptation, and secondly, by choosing one of the alternative structures of an object - an alternative adaptation.

The process of exploratory adaptation has sequential multistep nature, at which adapting impact on the object that increases its efficiency and optimizes quality criteria, is determined at each stage. In our case the initial commutation of the connections to the pins is given. At each iteration, under adapting impact, group switching of connections is fulfilled without changing the logical function of the circuit. As a model of a trainable system, M. Tsetlin proposed probabilistic trainable automatic machine, called the adaptation automatic machine. The state of the adaptation automatic machine corresponds to a specific alternative of adapting impact on the object. In the adaptation process, based on feedback from the external environment, the automatic machine turns to a state that corresponds to the best alternative of the adapting impact on the object [24].

For each circuit, at the points of location of the connected pins we introduce the attractive interaction forces, acting on the connected terminals. The magnitude and direction of these forces characterize the expectation of the connection to the switch. Then the force $F_{ij} = \alpha r_{ij}$ is applied from the terminal connection, attached to the pin v_j, towards the terminal connection, attached to the pin v_i, whereas the force $F_{ji} = -\alpha r_{ij}$ is applied from the terminal connection of the same circuit, attached to the pin v_j, where r_{ij} - is the distance between the terminals, α - is the coefficient. Note that F_{ij} is a vector. Since the circuit is connected to several pins, the terminal connection attached to the pin v_i experiences action of the total force defined as $F_i = \sum_j F_{ij}$. The terminals t_k connected to the pins v_i are the adaptation objects. In our case we used three types of adaptation impacts: switching to the left, switching to the right; and no switch. The attractive interaction forces, acting at the terminal, change due to switching. The local goal of a specific object t_k is to reach the state at which the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

attraction force, acting in the v_i, would be equal to 0. The global goal of the set of objects is to reach the state of the environment, providing favorable conditions for the subsequent routing (minimizing the density of the switchboard and the number of intersections). At the each iteration in some selected pairs of equivalent pins a reciprocal switching of terminals is carried out based on the analysis of the current situation.

When switching terminals, the following combinations of the states of corresponding pair *AA* are evident: $\rightarrow\leftarrow$; $\rightarrow 0$; $0\leftarrow$. Here $\rightarrow$ and $\leftarrow$ means tendency of *AA* to switch to the pin, located in the route from the right, or from the left, respectively, while 0 means neutral state.

Integrating the models of adaptive behavior of ant colony and collective alternative adaptation. The main goal when developing a new paradigm of swarm algorithm is to integrate the metaheuristic algorithm, embedded in the collective alternative adaptation, and the ant colony algorithm.

The searching process begins with the construction of solutions searching graphs $G=\{G_e|e=1,2,\ldots,n_e\}$, $G_e=(X_e,U_e)$ in accordance with the paradigm of the ant colony algorithm. At the initial stage on all edges of each graph G_e the same (small) amount of pheromone Φ/v, is laid, where $v=|U|$.

The solutions searching process is iterative. Each iteration consists of 3 steps. At the first stage of each iteration the set of $M^*(l)=\cup M_{ek}^*(l)$ routes is formed on the G_e graphs. The construction of each route $M_{ek}^*(l)\in M^*(l)$ is carried out in two steps. The first step deals with the procedures of ant colony algorithm. Each ant $z_{ek}\in Z_k$ forms at the edges of the G_e graph its own route $M_{ek}(l)$. Then the solution $R_k(l)$, corresponding to the cluster of routes $M_k(l)=\{M_{ek}(l)|e=1,2,\ldots,n_e\}$, constructed by the ants of Z_k cluster, is determined, and assessment of the solution $F_k(l)$ is carried out. At the second stage the solution $R_k(l)$ is treated as an initial solution, and the solution $R^*_k(l)$ is formed with an assessment of $F^*_k(l)$ using collective alternative adaptation algorithm. After constructing the aggregates of routes $M_k(l)$ by all the ants and building solutions $R^*k(l)$ on the basis of each aggregate using the algorithm of collective alternative adaptation of solutions $R^*_k(l)$, each solution $R^*_k(l)$ is represented into an aggregate of routes $M^*_k(l)$ on the solutions searching graphs G_e. At this stage, pheromone is laid on the edges of each set of routes $M^*_k(l)\in M^*(l)$, built on the solutions searching graphs G_e in accordance with assessments of the routes $F^*_k(l)$. The third step corresponds to the evaporation of pheromone on the edges of the set of *G* graphs. The best solution, found after performing *l* iterations, is saved.

3. RESULTS AND DISCUSSION

The analysis of existing approaches for solving the routing problem revealed the following: mathematical models of the problem were obtained and subjected to the standard methods of optimization, such as linear programming techniques, dynamic programming method, etc. Within this formulation it is possible in theory to obtain a global result. However, since no one standard method does not exclude the possibility of cycling in locally optimal regions, these methods turn out to be unacceptable for solving real-dimensionality problems [25, 26]. Comparative analysis with other algorithms for solving problems of this class was carried out using standard test examples and schemes (the benchmarks). The majority of global routing programs use various versions of greedy heuristics, or time-consuming methods of linear integer programming. To solve this problem, authors of the work [27, 28](Lee and Wang, 2003; Cho and Pan, 2006) propose an algorithm that first generates the circuits routing order, based on the result of a single-layer routing, and then solves the problem of distribution across layers (one circuit is selected at each step) using dynamic programming. Weak point of these approaches is the sequencing problem of traceable circuits.

In this regard, the developers of the algorithms had to devise algorithms based on intelligent optimization methods.

To enhance the convergence and provide the ability to exit from the local optima, we propose to base the search procedures on simulation of collective adaptation. The priority of criteria may be changed by simple modifications of the environment response. The developed search engine, which integrates alternative adaptation heuristics and ant colony algorithm, allows the use of a hierarchical control strategy. The article presents the technology of converting the population during the transition from one generation to another that allows us to secure the best solutions. The main advantages of these algorithms are: positive feedback that lets you quickly find good solutions; distributed calculation, preventing of early algorithm; the use of a greedy heuristic for finding good solutions in the early stages of the search process. The original formulation of the problem is presented in the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

form of an adaptive system based on the ideas of collective behavior. The system reaches a global goal as a result of low-level local agent interaction through the use of dynamic mechanisms. The proposed approach has shown high efficiency in solving optimization combinatorial problems.

Experimental studies were carried out on IBM PC. In general, the solutions obtained using hybrid algorithm, were better by 3% than those known previously. Under the new approach, the probability of obtaining the optimal solution was 0.9. The total estimation of time complexity lies within the limits of $O(n^2)$-$O(n^3)$. As a result of follow-up studies, it is assumed to speed up the process of complex systems synthesis by 10-15%, as well as to increase the routability index for the next step of a detailed routing by 10% as compared to the existing analogues, through the use of an integrated approach to solving the problem.

4. CONCLUSIONS

Based on the self-organization and self-learning ideas, the search adaptation methods are considered using trainable automatic machines, simulating the behavior of design objects in a random environment.

The article considers adaptation structures, their architecture and transition mechanisms.

The article highlights key issues and tasks to be solved in the course of original formulation of design engineering problems in the form of adaptive search processes that allows formalizing and streamlining the research and development of adaptive search mechanisms in relation to the current task.

In the article new mechanisms for solving the problem of tracing, using mathematical methods, in which lays down the principles of the natural mechanisms of decision-making are proposed. A distinctive feature of the proposed tracer is that it is fully applicable to the "girdles" trace connections of different widths. There is the time complexity of the algorithm ICA ≈ O (n2). In comparison with the existing algorithms there is an improvement in the results in 2-3%.

The use of the more complex modified selection policies for routing alternatives in the tracking, more appropriate selection of the cost function of the fragments, selection of the order of the above-cell areas and a method of their separating to the upper and lower parts, which can reduce the total density of the channels can be the source of the proposed algorithms improvement.

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