ALGORITHMIZATION OF MANAGERIAL DECISION-MAKING BASED ON PREDICTIVE AND OPTIMIZATION MODELS OF STRUCTURAL TRANSFORMATION

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Abstract: Modern possibilities of digital transformation in socio-economic systems increase the possibility of intensive interaction of objects of these systems. Moreover, their management should be based on the use of the principles of leadership strategies. An important role in management is assigned to the control center. It will use a leadership strategy to properly define management objectives. An algorithm for controlling the classification ordering of objects in the system has been developed. For it, a structural diagram of the management of the classification orderliness of the first and second order is built. An algorithm for managing the inter-object distribution of resource provision has been developed. For it, a block diagram is built for the implementation of the process rank transformation. The results of the paper can be useful in the management of a wide class of socio-economic systems..

Key words: intellectualization, management decision-making, territorially connected systems.

1. INTRODUCTION

For the current stage, the transitions to be managed on the basis of leadership strategies during the development of social and economic systems can be considered. Such approaches were widespread in the case of an association of homogeneous objects of education, the banking sector, the tourism industry, trade in network organizational systems [1]. At the same time, the network manager determines the goals of management in accordance with the adopted leadership strategy and stimulates their execution of the system objects by allocating targeted resource provision. With a limited resource on the implementation of development programs, the distribution of resource support is synchronized with the choice of objects that potentially correspond to the leading positions in the fulfillment of the terms of the manager. This kind of synchronization requires orientation for predictive assessments and optimizing [2] management decisions.

The paper is associated with a modern trend in increasing the efficiency of managing network organizational systems based on the leadership strategy and the need to develop models and optimization algorithms focused on making management decisions in the conditions of a structural transformation.

2. ALGORITHM FOR MANAGING CLASSIFICATION ORDER

This algorithm is aimed at solving optimization tasks. For making management decisions, the following data are used:

$y_{im_1 j}(t)$ - temporary rows of values of objects of objects, offered by the control center for inclusion in the top classes,

$$i_{m_1} = \overline{1, I_{m_1}}, m_1 = \overline{1, M_1}, j = \overline{1, J}, t = \overline{1, T} \quad (1)$$

$F_{im_1}(t)$ – time series of values of integral assessment of the effectiveness of the operation of top classes,

$$i \in \overline{1, I}, i \not\subset \bigcup_{m_1}^{M_1} i_{m_1}, t = \overline{1, T} \quad (2)$$

$F_i(t)$ – time series of values of integral assessment of the effectiveness of the operation of top classes,

$$i \in \overline{1, I}, i \not\subset \bigcup_{m_1}^{M_1} i_{m_1}, t = \overline{1, T} \quad (3)$$

Based on this data, consider the steps to solve the optimization [3] model of Boolean programming.

Step 1. Using time series (1) experts of the Managing Center establish: 1) The number and category of top classes: $m_1 = \overline{1, M_1}$. 2) The list of key indicators for each top-class: $j_{m_1} = \overline{1, J_{m_1}} \in \overline{1, J}$. 3) A preliminary list of objects included in the top classes; 4) Boundary values of indicators for $m_1 = 1$; 5) Gradations of boundary values of the indicators $y^{bou}_{jm_1 l}, l = \overline{1, L}$ for classes $m_1 = \overline{1, M_1}$. 6)The volume of resource provision required to maintain the values of the indicators $j_{m_1} = \overline{1, J^{bou}_{Jm_1 l}}$ within the interval between their boundary values [4].

Step 2. Transition to a randomized formulation and solving the following task:

Randomization of Boolean variables:

$$p_{x_{jm_1j}} = (x_{jm_1j} = 1), q_{x_{jm_1j}} = P(\widetilde{x}_{jm_1j} = 0)$$
$$p_{x_{jm_1j}} + q_{x_{jm_1j}} = 1; \tag{4}$$

Installation of initial probability values on the first iteration k = 1:

$$p^1_{x_{jm_1l}} = 0{,}5, j_{m_1} = \overline{1, J_{m_1}}, l = \overline{1, L}, p^1_{l_{m_1}} = \frac{1}{L_{m_1}}, l = \overline{1, L_{m_1}};$$

Calculating the variations of the optimized function $\widetilde{\Delta}^k \varphi$:

$$\varphi(x_{jm_1l}) = \sum_{j(m_1-1)=1}^{J_{m_1}} (y^{bou}_{j(m_1-1)} - y^{bou}_{j_{m_1}}(x_{jm_1l})) + \lambda(v^C_{m_1} - \sum_{j(m_1-1)=1}^{J_{m_1}} v^C_{ijm_1} x_{jm_1l}), \tag{5}$$

Installation of initial probability values on the first iteration k = 1: $\lambda > 0 -$ fine coefficient installed on the first iteration, and checking the limit of $\sum_{j_{m_1}=1}^{J_{m_1}} x_{jm_1l} = 1$. The number of objects included in the $m_1 - th$ class is limited to the dedicated volume [5] of the target resource provision $V^C_{m_1}$ to support a sustainable development trend, correction of probability values (4) on $(k+1)$-th iterations in accordance with the variation (5); stop iterative process.

Step 3. Transition to the use of a genetic algorithm [6]:

Stop iterative randomized process at a given number of iterations $k \le k_1^0, k_1 \le k_2$; inclusion of the parameters X_{r_1} of those variables for which the stop rules are not performed at $k \le k_1$; inclusion in the number of individuals X_{r_2} of those variables for which the stop rule is not performed at $k \le k_2$; accept as values of the function of the adaptability of the value of the optimized [7] function for the x_Z variables $\mu(x_r) = \varphi(x_Z)$; calculate the values of random variables $r = \overline{1, R}$, $p_r = \frac{\mu(x_r)}{\sum_{r=1}^{R} \mu(x_r)}, \sum_{r=1}^{R} p_r = 1$; Carry out a positive assertive crossing and get r with a new set of x_r values; Stop crossing process after $k_1 - th$ counting.

Step 4. Selecting the final version of the management solution [8] based on expert assessment:

Combining the solutions of the problem obtained during a randomized search with $k \le k_1$ for variables for which the stop condition is satisfied with the values of variables for which the stop condition obtained after the stopping process is not satisfied [9]; formation based on the opinions of a group of experts $d = \overline{1, D}$ for rank ordering management decisions; selecting a final solution with the best value in rank sequence.

The structural scheme of the algorithm for controlling the classification ordering is shown in Figure 1.

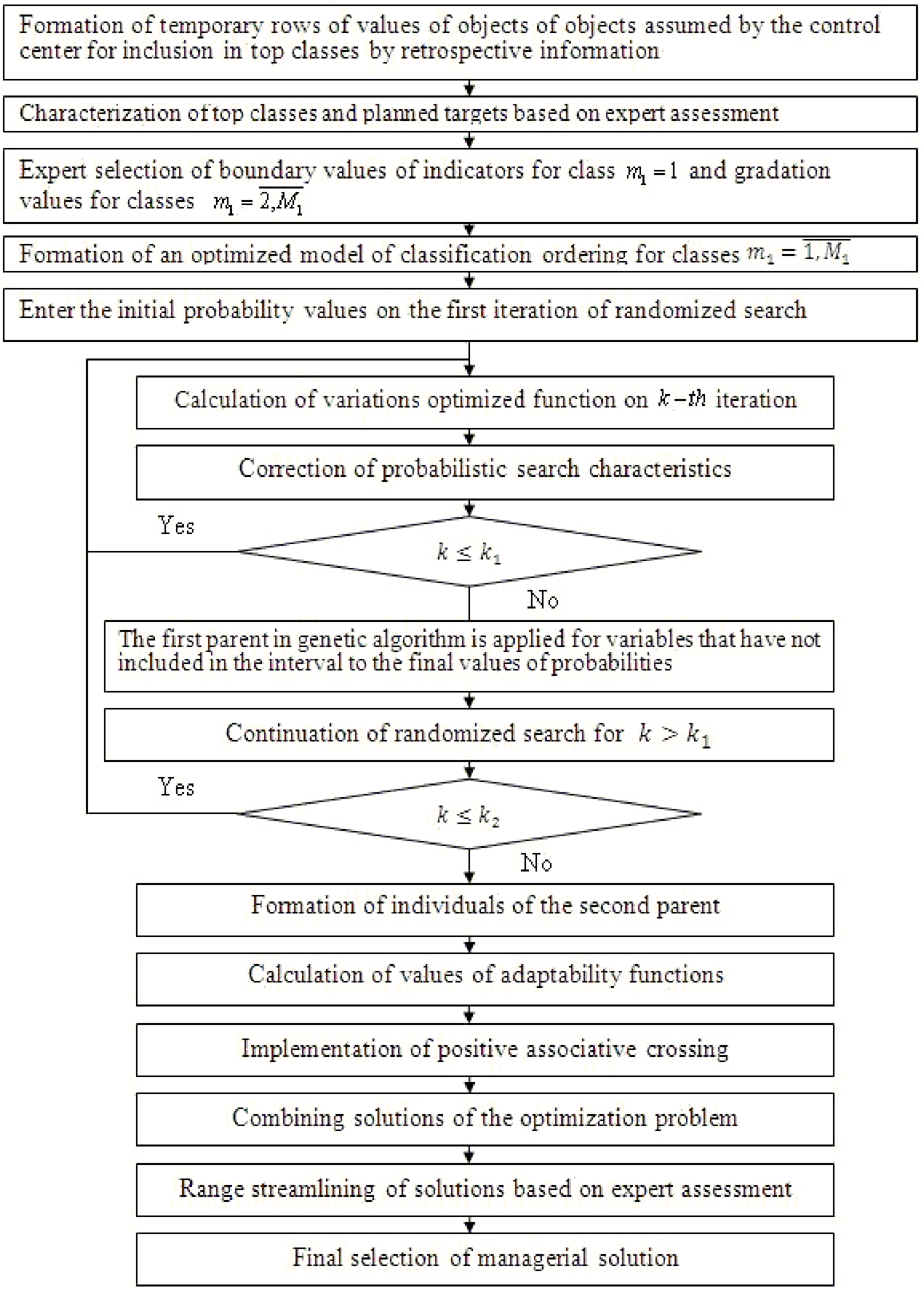

Fig. 1. Structural diagram of the classification control algorithm order of the first level

The solution to the optimization problem, taking into account the limitation of only one graduation in the integral assessment, will be carried out by analogy with the above task.

Step 1. Using the solution [10] to the above task, including:

- numbering set of top classes $m_1 = \overline{1, M_1}$;
- numbering key indicators;
- the structure and parameters of the integral estimation model are formed;
- by experts we select the boundary values of indicators for the class $m_1 = 1$, the gradation of values for the classes $m_1 = \overline{2, M_1}$ and the amount of resource provision $\varphi(x_Z)$.

Step 2. Transition to a randomized formulation and solution of the problem:

- randomization of Boolean variables (6):

$$x_l = \begin{cases} 1, if\ we\ select\ l-th\ variant\ of\ gradation\ for\ integral\ estimation \\ F^{bou}_{m_1}, m_1 = \overline{1, M_1} \\ 0, in\ other\ case\ l = \overline{1, L}. \end{cases} \tag{6}$$

$$p_{x_l} = P(x_l = 1), q_{x_l} = P(x_l = 0), p_{x_l} + q_{x_l} = 1; \tag{7}$$

- establishing the initial values of the probabilities at the first iteration $k = 1$;

$$p^1_{xlm_1} = 0{,}5, l_{m_1} = \overline{1, L_{m_1}}, m_1 = \overline{1, M_1}; p^1_{lm_1} = \frac{1}{L_{m_1}}, l = \overline{1, L_{m_1}};$$

- calculation of variations of the optimized function $\widetilde{\Delta}^k \varphi$, where

$$\varphi(x_{lm_1}) = (F^{bou}_{m-1} - F^{bou}_m(x_{lm_1})) - \lambda(V^C_{m_1} - V^0_{m_1}(x_{lm_1})), \tag{8}$$

and checking the fulfillment of the constraint

$$\sum_{lm_1}^{L_{m_1}} x_{lm_1} = 1, \tag{9}$$

in case of failure (9), a new value (8) is calculated before executing (8);

- correction of the values of probabilities (7) at the $(k+1)-th$ iteration in accordance with the variation (8);
- stop the iterative process.

Step 3. Since the dimension of this optimization problem is within times less than the dimension of the problem considered above, the further clarification of the many values of the Boolean variables included in the optimal solution [11], with the use of the genetic algorithm, are not required, immediately move to the expert selection of the final managerial solution.

Similarly, form an algorithm for managing the classification ordering of the second level using the optimization model that is listed below.

Step 1. Formation of information necessary to build an optimization model [12]: Expert analysis of temporary series (3) and establishing a numbering multiple orderly classes $m=\overline{M_1+1,M}$; $m_1=\overline{1,M_1}$;

- range ordering of objects that have not included in the top classes based on the values of the integral estimate for the $T-th$ calendar period and the introduction of the new numbering of objects; $i^{'}=\overline{1,I^{'}}$;
- graphic visualization of the dependence of the integral assessment from the new numbering of objects;
- analysis of hopping changes in the integral assessment and fixation of the numbering set of jumps;
- expert assessment of accessories of jumps to the classes in the form of Boolean variables.

Step 2. Transition to a randomized solution of the optimization problem;

- randomization of Boolean variables

$$p_{x_{j^{'}m}}=P(x_{j^{'}m}=1),q_{x_{j^{'}m}}=P(x_{j^{'}m}=0),p_{x_{j^{'}m}}+q_{x_{j^{'}m}}=1;$$

- randomization of discrete variables $(j^{'},m)$, determining the assignment of $j-th$ jump into $m-th$ secondary ordering class

$$p_{j'}=P(\widetilde{j}'=j'),\sum_{j'=1}^{J'}p_{j'}=1, \tag{10}$$

$$p_m=P(\widetilde{m}=m),\sum_{m=1}^{M-M_1}p_m=1; \tag{11}$$

- establishing initial probability values on the first iteration

$$p^1_{j^1}=1/J',j^1=\overline{1,J'};p_m=1/(M-M_1),m=\overline{M_1+1,M};$$

- calculating the variation of the target function $\Delta^k\psi$.

$$\varphi(x_{j'm})=-\sum_{j=1}^{J}\sum_{m=M_{1+1}}^{M}x_{j'm}-\sum_{m=M_{1+1}}^{M}\lambda_m(1-\sum_{j'=1}^{J'}b_{j'm}x_{j'm}), \tag{12}$$

- $\lambda_m\ge 0,m=\overline{M_1+1,M}$ are set by expert on the first iteration $k=1$;
- correction of probability values (9) - (11) on $(k+1)-th$ iterations in accordance with the variation (12);
- stop iterative process.

Stages 3, 4 are similar to steps 3, 4, shown on the structural scheme Figure 1. The structural diagram of the algorithm for the control of the classification ordering of the second order is shown in Figure 2.

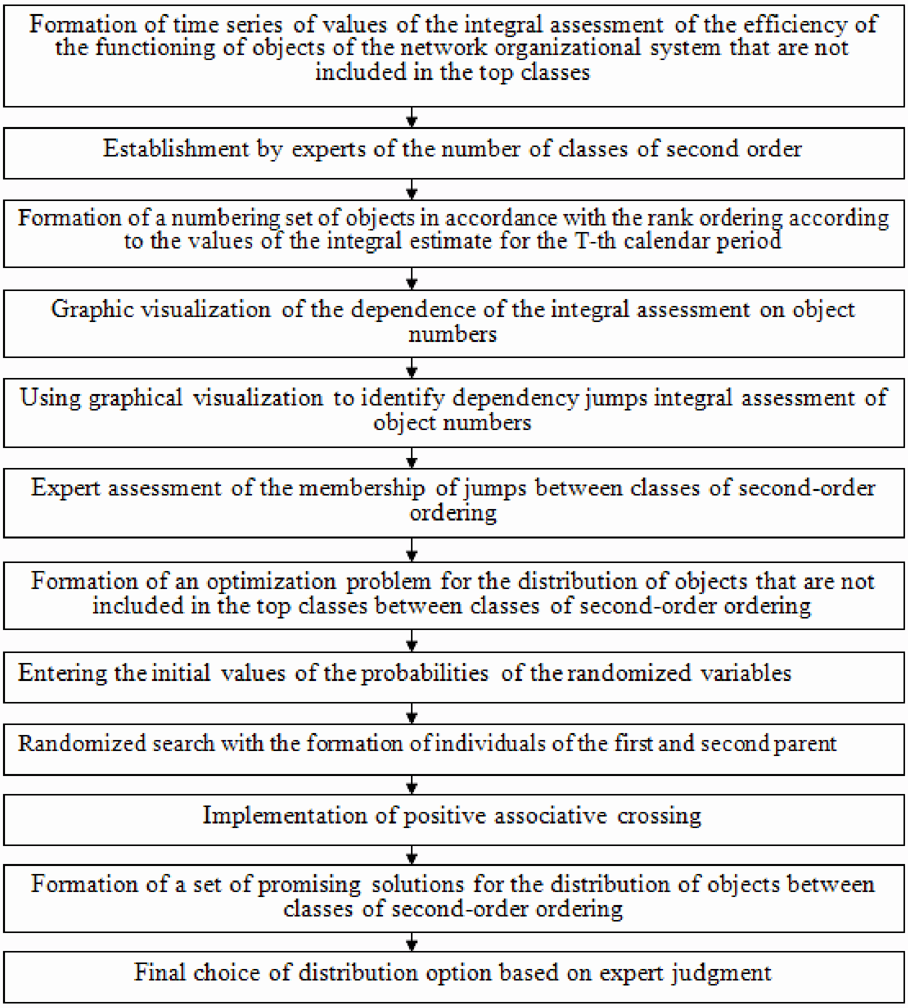

Fig. 2. The algorithm for the management of the classification ordering of the second order

3. ALGORITHM FOR MANAGING THE INTER-FACILITY DISTRIBUTION OF RESOURCE PROVISION

We construct an algorithm for managing the inter-object distribution of resource provision taking into account the optimization modeling of the mechanism for moving objects between classes and within classes in the process of rank and reduction transformation.

Let's start with a multi-stage control of the movement of objects from classes $m > M_1$ to top classes $m_1 = \overline{1, M_1}$ based on the classification ordering.

Step 1. Formation, based on expert assessments, of a numbering set of candidate objects from classes $m > M_1$ moved to classes $m_1 = \overline{1, M_1}$:

- structuring information for a training sample when building a model of an object classifier, according to the available data [13] for a calendar period about the relationship of each object included in the top classes and a sample set of objects that are not included in the top classes

$$y_{ijm_1}(T), i_{m_1} = \overline{1, I_{m_1}}, j_{m_1} = \overline{1, J_{m_1}}, m_1 = \overline{1, M_1},$$

$$y_{ij(M_1+1)}(T), i_{(M_1+1)} = \overline{1, I_{(M_1+1)}}, j_{(M+1)} = \overline{1, J_{(m+1)}},$$

- selection of the training algorithm for the classifier according to the values of the indicators of objects and their belonging to a certain class;
- training a classifier model based on machine learning;
- structuring of time series of values of indicators of objects, determined by the managing center, for the transition to top classes;
- construction of predictive estimates of the indicators [14] of these objects for the calendar period $t_1 = T + 1$;
- forecasting using a trained classification model and predictive estimates of indicators of an object's ability to enter the top class;
- the final formation of numbering sets $i_{1m_1} = \overline{1, I_{m_1}}$ for the implementation of the rank transformation process;
- expert assessment of the volume of targeted resource provision for moving objects to top classes $V'^{0}_{i_1 m_1}, i_{1m_1} = \overline{1, I_{1m_1}}, m_1 = \overline{1, M_1}$.

Step 2. Formation of additional data for building an optimization model of the rank transformation process by transferring objects to the number of leaders:

Average level of indicators of top classes for a calendar period $t = T$:

$$\bar{y}_{jm_1} = \frac{\sum_{j_{m_1}}^{J_{m_1}} y_{jm_1}(T)}{J_{m_1}}, j_{m_1} = \overline{1, J_{m_1}};$$

Coefficients of correspondence of indicators of moved objects to the average level of indicators of classes $m_1 = \overline{1, M_1}$ by calculating $a_{i_1 jm_1}$:

$$a_{i_1 j_{m_1}} = \begin{cases} 0, if\,(y_{i_1 jm_1}(t_1) - \bar{y}_{jm_1}) \le 0 \\ \min\limits_{m_1 = \overline{1, M_1}} (y_{i_1 jm_1}(t_1) - \bar{y}_{jm_1}) / \bar{y}_{jm_1}, otherwise \end{cases} \tag{13}$$

The amount of resource provision planned by the management center for the distribution of a set of leader objects – V^L.

Step 3. Transition to a randomized formulation [15] and solution of the optimization problem:

- randomization of Boolean variables

$$p_{x_{i_1m_1}} = P(x_{i_1m_1} = 1), q_{x_{i_1m_1}} = P(x_{i_1m_1} = 0),$$
$$p_{x_{i_1m_1}} + q_{x_{i_1m_1}} = 1; \tag{14}$$

- randomization of discrete variables for coordinate search

$$p_{i_1m_1} = P(\widetilde{i}_{1m_1} = i_{1m_1}), \sum_{i_{1m_1}=1}^{I_{1m_1}} p_{i_1m_1} = 1; \tag{15}$$

- setting the initial values of the probabilities at the first iteration step $k = 1$:

$$p^1_{x_{i_1m_1}} = 0{,}5, p^1_{i_1m_1} = \frac{1}{I_{1m_1}}, i_{1m_1} = \overline{1, I_{1m_1}};$$

- calculating the variation of the optimized [16] function $\widetilde{\Delta}^k\varphi$, where

$$\varphi(x_{i_1m_1}) = \sum\nolimits_{m_1=1}^{M_1} \sum\nolimits_{i_1m_1=1}^{I_{1m_1}} \sum\nolimits_{j_{m_1}}^{J_{m_1}} a_{1jm_1} x_{i_1m_1} +$$
$$\lambda(V^{Л} - \sum\nolimits_{m_1=1}^{M_1} \sum\nolimits_{i_1m_1=1}^{I_{1m_1}} V^0_{i_1m_1=1} x_{i_1m_1}); \tag{16}$$

Correction of the values of probabilities (14), (15) at $(k+1)-th$ iteration in accordance with variation (16).

Step 4. Application of the genetic algorithm:
- the formation of many [17] individuals;
- construction of a reduction group of individuals according to the condition $\mu(X_r) \geq \overline{\mu}$, where $\overline{\mu} -$ is the average fitness $\overline{\mu} = \frac{1}{R}\sum\nolimits_{r=1}^{R} \mu(X_r)$;
- random selection from the reproductive group of the parent couple X_{r_1}, X_{r_2};
- implementation of positive assortative crossing.

Step 5. Expert selection of the final management decision based on the rank ordering of daughter individuals by a group of experts [18].

The block diagram of the control algorithm for the inter-object distribution of resource provision during the implementation [19] of the rank transformation process is shown in Figure 3.

5. CONCLUSION

Predictive and optimization modeling of the system mechanism of classification ordering, the resource management algorithm is aimed at choosing a set of gradations of gradation indicators of indicators or their integral assessment of such that satisfy extreme and boundary requirements. Algorithmization of managerial decision-making in the inter-object distribution of target resource provision in network organizational systems is associated with the nature of predictive and optimization modeling of rank transformation processes. At the same time, the sequence of control stages is aimed at the optimal movement of objects between classes and within classes with taking higher positions with limited resources.

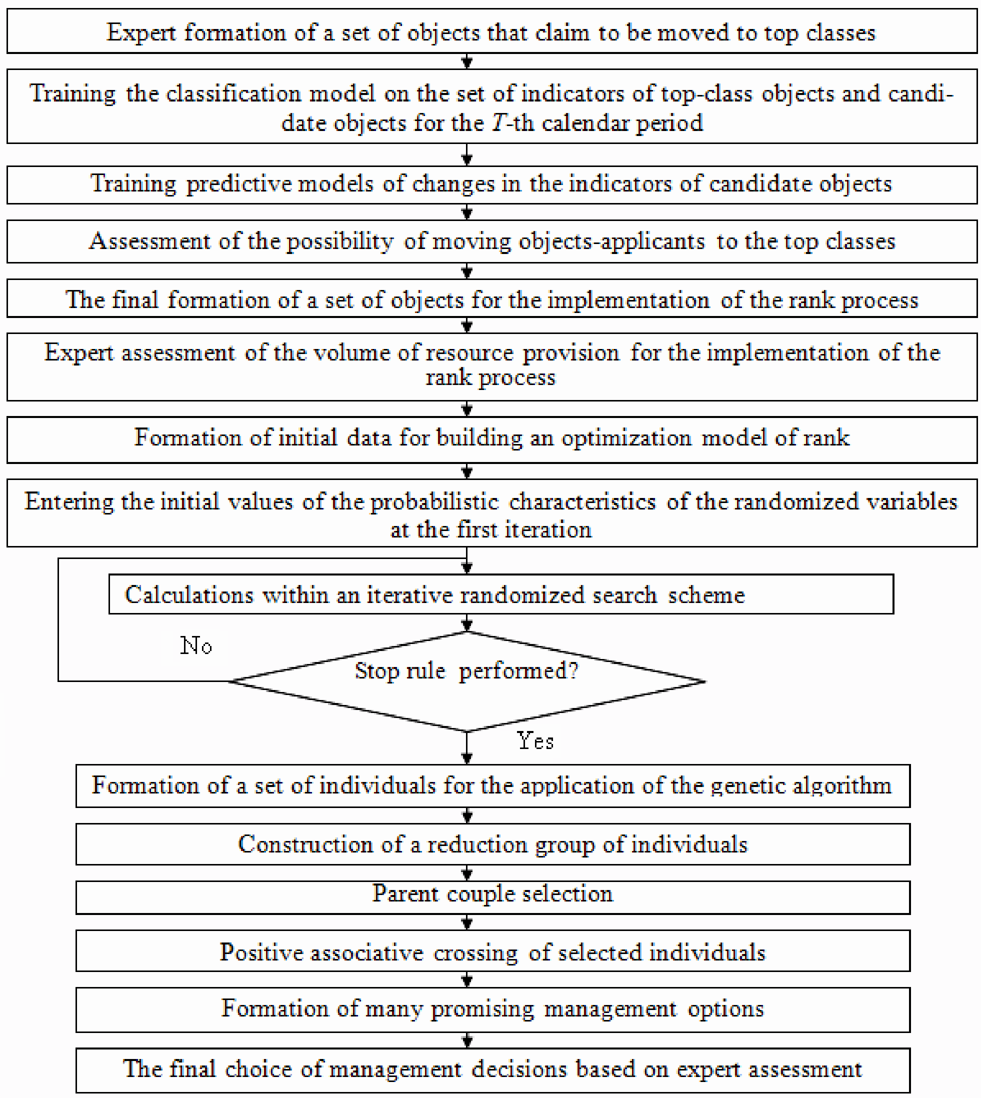

Fig. 3. Block diagram of the control algorithm for the inter-object distribution of resource provision during the implementation of the process rank transformation

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