Mathematical Support of the Task of Determining the Strategic Directions of Development and Priorities of the Organization

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Abstract

The situation of realization a strategic session in a medium or large system organization is considered. Up to 20 top managers-experts take part in the strategic session. In order to determine the most important directions of the organization's development and prioritize the directions of development, experts have the opportunity to add new directions to the generated base set, remove from the list those directions that are not up to date, and also rank the directions that are relevant from their point of view. A mathematical model of the process of collective selection of priority directions is proposed to justify and facilitate work with large data sets. For a small number of directions, on the order of ten, it is proposed to solve the problem of finding the resulting ranking of directions by direct sorting. If the experts have identified significantly more than ten important directions of the organization's development, it is proposed and substantiated to find the resulting ranking using algorithms of evolutionary calculations or the algorithm of the nearest search. For cases of incomplete rankings, appropriate algorithms focused on incomplete data can be applied. An additional task is to determine the relative competence coefficients of experts, which can be interpreted as the degree of satisfaction of the expert's wishes.

Keywords [1]

Strategic session, experts, directions of development, organization, median, alternative, resulting ranking

1. Introduction

In the activities of various organizations, situations often have accumulated in which the management of the company loses certain orientations. Such situations arise, for example, when a crisis occurs, radical changes in the organization's team occurs, owners or top managers change, a new product or service is launched, etc. Large system companies engage in strategic planning regularly, within specified time limits. The interaction of practical work experience of internal managers and special training of external consultants create a situation that allows to look at the organization's activities from different, often new, angles [1, 2].

Building a development strategy of any organization is a complex problem, so it is logical to use modern approaches and methods developed in the field of information technologies [3-5]. Therefore, the problem of creating mathematical support for the procedures of strategic development and determining the priority of strategic plans is extremely relevant today [6, 7].

2. Strategic session in the organization

A strategic session is a type of collective work in which the organization's team together with external consultants seek answers to strategically important questions for the organization and make important decisions that affect the organization's further development [8, 9].

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A strategic session is a creative tool and has significant differences for different fields of activity and different organizations [10, 11]. But, as a rule, important issues for the organization are resolved during this event:

- strategic goals are agreed;
- conditions for the generation of new opportunities for the organization in order to achieve new goals are created;
- assessment of development prospects and risks that arise when new strategic decisions are made;
- the organization's services are prioritized;
- new approaches to pricing are evaluated;
- the desired and possible marginality of the organization's services is determined;
- an audit of the organization's stakeholders is conducted;
- target audiences of the organization are clarified;
- planning of PR support for the main services of the organization is carried out; public relations;
- the conditions for improving the effectiveness of the organization's activities are considered;
- approaches to motivating managers and other employees of the organization in conditions of constant changes are developed;
- plans for the development of new products and services are discussed and generated, as well as opportunities to enter new customer segments;
- issues of adequate and optimal sales volumes by market segments, etc. are considered.

Top managers of the organization, that is, functional heads of the organization's activities, participate in the strategic session for medium and large organizations. At the same time, criteria for the importance of various aspects of the organization's activities are discussed and determined [12-14]. In addition, success factors and risk factors of the organization are determined, as well as their probability in the market conditions.

Let the number of participants is k, the set of strategic session participants denote through $I = \{1,...,k\}$, and refer to these participants as experts.

3. Directions of development and problems that are solved by the strategy session

Today, most of the systemically successful organizations recognize that the strategic session is an effective tool for determining the strategic goals of the organization and a good environment for developing tactical action plans for the realization of the set goals [15, 16],

For further formalization of the problem and the application of mathematical modeling and artificial intelligence methods, we will introduce a list of problems that are solved by a strategic session. It is clear that this list is a priori incomplete, and cannot be so, because a single recipe cannot be applied to different fields of activity, organizations with different corporate cultures, etc. The main issues that should be prioritized during the strategy session are [16, 17]:

$a_1 -$ clarifying the organization's strategic goals or formulating new strategic goals;

$a_2 -$ implementation of corporate culture and other related standards;

$a_3 -$ development of corporate values and competency models;

$a_4 -$ reforming the organizational structure;

$a_5 -$ optimization of the organization's management system;

$a_6 -$ determination of priority areas of development for the nearest periods;

$a_7 -$ opportunities and risks of entering new markets;

a_8 – terms of development and launch of new products;

a_9 – generation and implementation of ideas to increase the effectiveness of sales or the provision of services by the organization;

a_{10} – implementation of measures to intensify interaction between units;

a_{11} – development and implementation of a set of measures to increase the material and non-material motivation of the organization's employees;

a_{12} – generating ideas, developing a set of measures and a system of motivating the organization's personnel to reduce costs and find reserves for increasing the efficiency of the organization's activities;

a_{13} – implementation of measures for the development of the organization in the long term.

a_{14} – improvement of the state of reporting in all directions of the organization's activities.

In the future, we will call these and other problems discussed at the strategic session alternatives, and denote the initial set of these alternatives [18] by A^0 :

$$a_j \in A^0, j \in J = \{1,...,n_0\}.$$

where n_0 – is the total initial number of alternatives for which the resulting ranking should be determined, which reflects the priority of the alternatives for the strategic development of the organization.

4. The problem of determining the directions of development and priorities of the organization

The particularity of the task of determining the priorities of the development directions of the organization is that the majority of experts, who are the participants of the strategic session, that is, the heads of structural units and functional areas, do not defend corporate interests, not the goals of the organization, as a whole, but mainly take care of the goals of their functional areas and the interests of their subdivisions. Adequate models for such a situation can be multi-criteria optimization models [19, 20]. Moreover, among the criteria of the task, a large part is contradictory. In such cases, technologies of limited rational multi-criteria selection can be successfully applied [21].

We note that the relevance of determining the priorities of the organization's development directions is necessary, first of all, for the allocation of funding levels for the organization's development directions when building its strategy [17, 22]. In addition, the priority of the organization's development directions also affects the distribution of other resources (management technologies, organization personnel, material assets, production technologies, business processes, information resources, etc.) or determining the sequence of concentration of efforts of the organization's personnel and its management [22, 23].

4.1. Formulation of the problem

Let the k experts set ordering on set of n objects. Let set of indexes is $L = \{1,...,n\}, l \in L$. We denote by $R^i = (r_1^i,...,r_n^i)$ the ranking obtained from the i -th expert.

The most common method of finding the resulting ranking of alternatives is to calculate the median of the given rankings [4, 5, 24, 25]. One of the common metrics used in problems of this class is to determine the distances between ranks by the rank dissimilarity metric, also called Cook metric [26]:

$$d(R^i, R^j) = \sum_{l=1}^{n} \left| r_l^i - r_l^j \right| . \tag{1}$$

For the Cook metric, when using the additive criterion, the Cook-Sayford median is calculated [25, 26]:

$$R^{KS} \in \Omega^{KS} = Arg \sum_{R \in \Omega^n} \max_{l \in L} d\left(R, R^l\right). \tag{2}$$

And when applying the minimax criterion, there is a compromise median, which is also called the HV-median [25]:

$$R^{HV} \in \Omega^{HV} = Arg \min_{R \in \Omega^n} \max_{l \in L} d\left(R, R^l\right). \tag{3}$$

The symbols Ω^{KS} and Ω^{HV} denote the set of Cook-Sayford or compromise medians, i.e., rankings equivalent according to criterion (2) or according to criterion (3) because solutions of type (2) and type (3) may not be unique.

The problem of determining the median of given rankings in the space of all possible permutations of n objects is NP-hard [27-29]. Therefore, even with $n > 10$ objects, there are problems with direct sorting: the "curse of dimensionality" effect occurs. To determine the median of the form (2) when applying the distance of the form (1), in some studies, branch-and-bounds methods or schemes of sequential analysis of options are used [25, 30].

5. Heuristics for determining multiple directions of organizational development

Different heuristics can be used to determine the set of organization development directions for which priorities and the sequence of their solution or implementation should be established. Depending on the adopted heuristics, the set of problems on which the management of a high-level organization should focus changes significantly [30, 31]. We will denote the sets of alternatives that are relevant for each $i-$ th expert by $A^i, i \in I.$

Heuristics H1. (Heuristics of unanimity). The set of directions of the organization's development, for which priorities and the sequence of their solution or implementation should be established, is an intersection of the subsets of directions chosen by all experts, i.e.

$$A^0 = \bigcap_{i \in I} A^i.$$

In the case of applying the H1 heuristic, part of the alternatives is lost, because experts who excluded some alternatives from their consideration appeared.

Since the H1 heuristic is used, first of all, to reduce the dimension of the problem, in many practical situations, after applying such a heuristic, the resulting ranking of alternatives is calculated by direct enumeration.

Heuristics H2. (Heuristics of a stable set of alternatives). The procedure for selecting a set of alternatives is separated from the general procedure for determining the sequence of solving the organization's problems. After stabilization of the set A^0 during rounds of preliminary negotiations and final agreement of the set A^0, experts are prohibited from making changes to this set - neither removing alternatives nor adding new ones.

When applying an approach based on the H2 heuristic, the set of alternatives to be collectively ordered can be several dozen, so direct sorting methods cannot be applied to this type of problem due to the "curse of dimensionality". Therefore, the authors have developed approaches that allow the use of methods and algorithms of evolutionary computations considering the specifics of ranking problems. In addition, when there is a significant number of alternatives, the algorithms of the nearest ranking search, developed by the authors, can also be applied.

Next, the genetic algorithm for determining the ranking [25] and the algorithms for the nearest search of medians of individual expert rankings will be considered for illustration.

Heuristics H3. (Availability heuristics). The set of directions for the organization's development, for which priorities and the sequence of solving problems or implementing solutions should be established, is an union of subsets of directions selected by all experts - participants of the strategic session. That is, the united set of directions of the organization's development includes all directions, even if at least one expert spoke for its presence in the total set of directions, i.e.

$$A^0 = \bigcup_{i \in I} A^i.$$

Thus, when applying the H2 heuristic, each expert has an influence on the formation of the total set of alternatives, and the opportunity to include his unique alternatives in the total set of alternatives A^0. But in this case, the dimension of the problem increases significantly and the algorithms for its solution become more complicated due to the incompleteness of the data.

When applying the H3 heuristic, many uncertainties naturally arise, which were investigated by the authors in previous papers [25, 32]. Algorithms designed for incomplete rankings of alternatives can be used to calculate collective rankings when applying the H3 heuristic. Such algorithms are characterized by a significant number of features and require the involvement of additional heuristics.

As a result of conducting the next stage of the strategic session, regardless of the heuristics that were adopted, experts set their individual rankings for a set of alternatives A^0. We will mark these individual rankings of each of the k experts through

$$R^i = \left(a^i_{j_1}, ..., a^i_{j_n}\right), i = 1, ..., k;\ j = 1, ..., n, \tag{4}$$

Taking into account the fact that in the individual ranking of the form (4) each alternative has a corresponding rank, and thus each individual ranking of the form (4) corresponds to the vector of the ranks of the alternatives

$$r^i = \left(r^i_{j_1}, ..., r^i_{j_n}\right), i = 1, ..., k;\ j = 1, ..., n. \tag{5}$$

5.1. Unanimity heuristics

Heuristic H1 (unanimity) is convenient for reducing the computational complexity of the problem, but it is obvious that its application can lead to the loss of many directions of development that may turn out to be priorities. Moreover, the desire for unanimity, the introduction of the right of veto, and the consensus approach have not proven themselves very well in the modern world, for example, in the activities of the United Nations. At the same time, for compact organizations that have clearly defined main directions of development, the use of unanimity heuristics can be useful.

5.1.1. Features of direct selection of alternatives

If the organization carries out strategic planning within broad directions of development and the number of alternatives that should be prioritized is 10-12, a direct enumeration of all possible alternative rankings can be applied, when determining the resulting ranking. To do this, the generation of all possible transpositions is organized and the resulting ranking is determined by a complete search of transpositions of alternatives.

That is, all possible ranks of n objects are searched. Their total number is $j = 1, ... n!$

The peculiarity of the search for the resulting ranking in the space of all possible rankings of these alternatives is that the researcher needs to organize a search on the set of all possible permutations of n numbers, which are interpreted not as the numbers of alternatives in the ranking of the form (4), but as the ranks of these alternatives in each ranking (5). This is a very important aspect to keep in mind throughout your research. Denote throug

$$X^j = (x^j_1, ..., x^j_n),\ j = 1, ..., n! \tag{6}$$

next generated vector of ranks of alternatives. We denote the set of all possible rankings n of alternatives by Ω^n . We will indicate any ranking of n alternatives by $R^j,\ j=1,...,n!$ or without an index by R . Thus, $R^j \in \Omega^n,\ j=1,...,n!$ or $R \in \Omega^n$.

The vector of ranks corresponding to the ranking of alternatives R^i obtained from the i -th expert is denoted by

$$Y^i = (y_1^i,..., y_n^i)\ ,\ i \in I\ . \tag{7}$$

The distance between rankings from the set of all possible rankings of alternatives $R^j \in \Omega^n,\ j=1,...,n!$ and $R^i, i=1,...,k,$ is defined as the distance between vectors of the rank (6) and (7) according to the rank mismatch metric (Cook's metric) and is described by the formula

$$d\left(R^i, R\right) = d(Y^i, X^j) = \sum_{l=1}^{n} \left| y_l^i - x_l^j \right|, \tag{8}$$

for $j=1,...,n!$ or $R \in \Omega^n$, which is equivalent.

The problem consists in determining on the set of all possible $n!$ rankings of n alternatives to such a ranking (or equivalent rankings according to the ranking criterion) which according to the metric (8) provides a minimum to the additive criterion:

$$R^{KS} = \sum_{i=1}^{k} d(R^i, R) \to \min_{R \in \Omega^n}, \tag{9}$$

and was named the Cook-Sayford median.

Depending on the corporate culture of the organization, the global goals of its management, the state of the organization, etc., the problem of determining the minimum values of the minimax criterion on the set of all possible rankings may be set:

$$R^{HV} = \max_{i=1,...,k} d(R^i, R) \to \min_{R \in \Omega^n}. \tag{10}$$

The solution to problem (10) was called the compromise median or HV-median.

Thus, based on the results of the strategic session, the resulting ranking of the directions of the organization's development which meets the minimum criterion (9) or criterion (10) should be determined.

5.1.2. Distances to the resulting ranking

In the problem described in this work, determining the distances from the given expert rankings of alternatives to the calculated resulting ranking (harmonized, compromise, smoothed, aggregated, integral, inegrative) can be an additional problem that allows determining the coefficients of relative competence of experts [33-36]. In addition, the determined distances can be used for reference - as a quantitative expression of the degree of satisfaction of the wishes of each of the participants of the strategic session. At the same time, distances can serve as an indirect way of revealing the relative coherence of a team of top managers, etc. [36-38].

The algorithm for determining the competence coefficients of experts in ranking problems for decision-making in fuzzy conditions in the form of a membership function to fuzzy set , developed by the authors, was considered in [36]. Additional heuristics should be introduced to determine the fixed values of the coefficients of relative competence of experts.

Heuristics E4. We will assume that the relative competence of experts is greater, the closer the individual ranking of alternatives given by the expert is to the calculated resulting ranking.

So, it is assumed that there is an inversely proportional relationship between the distance to the calculated ranking and competence. It should be noted that such a heuristic is a direct consequence of the axiom of unbiasedness, which, in turn, is also a heuristic.

To determine the relative coefficients of experts' competence, the next algorithm should be performed.

Step 1. Calculation of distances from each given expert ranking to the Cook-Sayford median

$$d\left(R^i, R^{KS}\right), i \in I. \tag{11}$$

Step 2. Determination of the maximum distance among the distances (7)

$$d^M = \max_{i \in I} d\left(R^i, R^{KS}\right). \tag{12}$$

Step 3. Calculation of ratios according to the formula

$$d_i = d^M / d\left(R^i, R^{KS}\right). \tag{13}$$

Step 4. Normalization of the ratios of type (13)

$$\rho_i = d_i / \sum_{j \in I} d_j. \tag{14}$$

Step 5. The normalized coefficients of the relative competence of experts of type (9) can be presented in an idealized form [39, 40]:

$$\rho_i' = \rho_i / \max_{j \in I} \rho_j. \tag{15}$$

Step 6. Normalized coefficients of the type (6) and idealized coefficients of the type (7) of the relative competence of experts can be brought to a 100-percent scale by multiplying the values of (6) and (7) by 100. Such a scale is psychologically better perceived by research participants and thus is subjectively more informative [39-41].

5.2. Heuristics of a stable set of alternatives

When applying the H2 heuristic (stable set of alternatives), the number of possible development directions identified by experts can be large for the application of direct selection, since the so-called "curse of dimensionality" occurs. For situations where the total number of alternatives selected by experts is more than 10-12, branch-and-bound methods or sequential analysis of options can be used to solve such problems. At the same time, evolutionary computations methods and algorithms can also be successfully applied in such cases [42, 43]. The most important problem in this case is to take into account the features of the ranking problems: each number of the alternative participating in the ranking must be unique. At the same time, all alternative numbers must be present in each ranking [25].

After solving this problem of providing restrictions on the type of solutions of the problem, which should be rankings, that is, permutations of numbers from 1 to , the ideas of evolutionary calculations can be applied [25, 42]. Note that a whole family of evolutionary computations methods and algorithms has been well researched and continues to be successfully developed:

- genetic algorithm;
- differential evolution [44];
- symbiotic organization;
- ant algorithm for the traveling salesman problem;
- bee algorithm;
- method of deformed stars;
- simulation of annealing;
- memetic algorithm;
- cooperative algorithm;
- method of gray wolves;
- method of altruism;
- method of fireflies;
- method of cuckoos;
- method of falling drops, etc.

5.3. Genetic algorithm for rankings

The application of methods and algorithms of evolutionary calculations to ranking problems will be illustrated using the example of the application of the genetic algorithm. In general, the genetic algorithm is well researched and widely used. But in order to use the ideas embedded in this algorithm for ranking tasks, new approaches need to be invented, which was demonstrated by the authors in previous works [25, 45].

5.3.1. Methods of obtaining reference solutions for the application of the genetic algorithm for determining medians

One of the ways to determine the median of expert rankings is to use the genetic algorithm developed by the authors, described in [25]. An important element of this algorithm is the selection of a reference solution. We can offer several options for choosing such a solution:

- generate a reference ranking, in which the first elements repeat the ranking of the first expert, the following alternatives appear in the ranking as the set of alternatives obtained by entering incomplete rankings from the following experts is supplemented;
- modified [25, 45, 46] Cook-Sayford medians, GV-median, Kemeny-Snell median, VG-median, Litvak median and LK-median, the computational complexity of which is small, can be used as a reference solution [46, 47];
- choose reference rankings obtained by voting rules [48, 49]: by Condorcet, Borda, Simpson, Nanson, Copeland, Kemen-Young, Tiedemann, Schulze, Baldwin, alternative votes, relative majority, etc. [50-52].

At the next stage, among the generated reference solutions, we choose the one that has the best value according to the criterion, taking into account which the current problem of type (9) or type (10) is solved, to continue the operation of the algorithm.

5.3.2. A genetic algorithm for determining the medians of expert rankings of alternatives

Genetic algorithms use mutations and crossovers to generate new generations [53]. But for rankings, classic crossover techniques don't work because a strict ranking $R \in \Omega^R$ must consist of non-repeated n elements.

In the case of a single mutation, we will rearrange two random elements $r_i, r_j \in R,\ i \neq j,\ i, j \in \{1,...,n\}$, in the resulting ranking R^* relative to their initial position. The mutation function $f(R)$ will look like this [25]:

$$f(R) = \begin{cases} \exists r_i, r_j \in R,\ i \neq j : \\ (r_{i-1} > r_i > r_{i+1}) \ \vee \ (r_{j-1} > r_j > r_{j+1}), \\ \exists r_i^*, r_j^* \in R^* : \\ (r_{i-1} > r_j^* > r_{i+1}) \ \vee \ (r_{j-1} > r_i^* > r_{j+1}), \\ r_i = r_i^*,\ \ r_j = r_j^*, \end{cases}$$

where R^* is the ranking obtained as a result of mutation. This transformation is repeated m times, so, we have $f^m(R),\ m \in \{0,1,2,3,4\}$.

The crossover of the pair R^1, R^2 will be the ranking R^*. Let's define the crossover function $g(R^1, R^2, i, j)$: $R^* \cap R^1\ \forall r_k \in R^1,\ i \geq k \geq j,\ R^* \cap R^2\ \forall r_k \notin R^* \cap R^1$.

Thus, part of the elements of the resulting ranking R^* will be ordered as in R^1, and all other elements R^* will be ordered as in R^2.

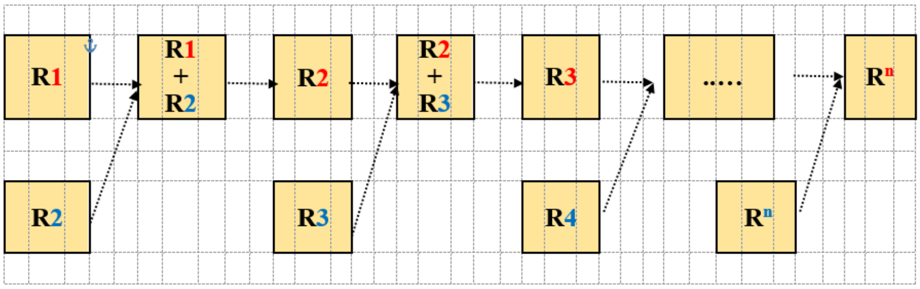

Figure 1: Scheme of generation of alternative ranking populations

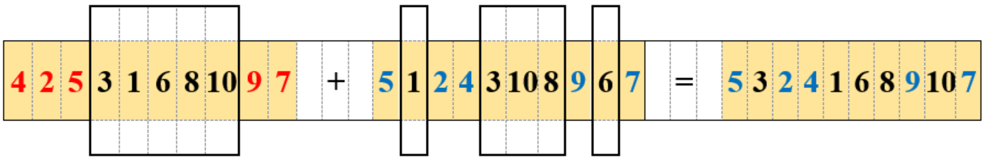

Figure 2: Scheme of transformation of elements in the new ranking of alternatives - a crossover for the application of the genetic algorithm in ranking problems

Let's consider different variations of mutation schemes for different cases of applying the genetic algorithm to the problem of collective ranking of alternatives.

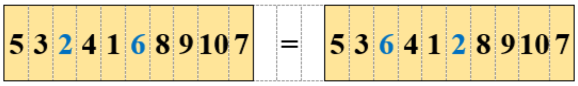

Figure 3: Scheme of 20 percent mutation when applying the genetic algorithm to the problem of collective ranking with 10 alternatives - or 1% probability of mutation with 200 alternatives

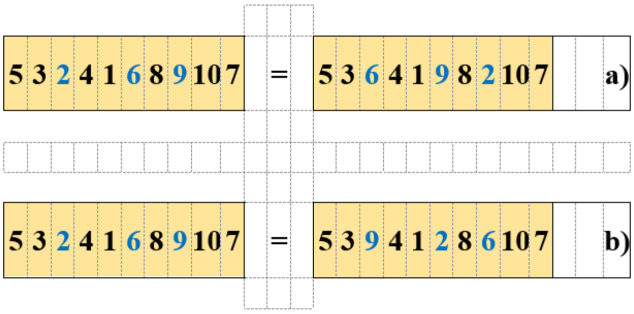

Figure 4: Schemes of 30 percent mutation when applying the genetic algorithm to the problem of collective ranking with 10 alternatives - or 5% probability of mutation with 60 alternatives

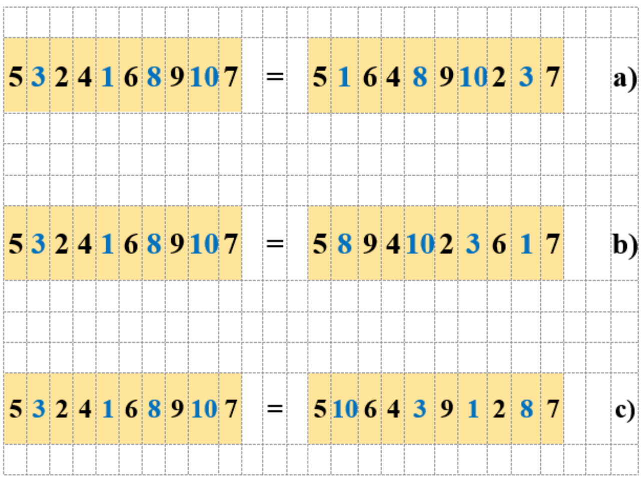

Figure 5: Schemes of 40 percent mutation when applying the genetic algorithm to the problem of collective ranking with 10 alternatives - or 4% probability of mutation with 100 alternatives

Thus, the peculiarities of the application of the genetic algorithm to ranking problems are taken into account - when using the crossover operator (scheme 1, scheme 2) and when applying mutation with different probabilities (scheme 3, scheme 4 - cases a), b) and scheme 5 - cases a), b), c)).

We will describe a step-by-step genetic algorithm taking into account that the ranking can be considered a phenotype, that is a sequence of genes, where each gene will correspond to the order of a specific alternative in the ranking [25]. The population is a set of expert rankings supplemented to complete rankings by applying heuristics. We will take the starting population (R^0) as the rankings given by experts. The algorithm for finding a compromise ranking will look like this.

Step 1. Creation child rankings $(R^{(i)}*)$ based on existing ones and add them to the new population $(R^{(i)} + R^{(i)}*)$.

Step 2. Calculation of the fitness function for each ranking.

Step 3. Sorting the rankings of the alternatives by the values of their fitness functions.

Step 4. Screening of optimal rankings in the new generation $(R^{(i+1)})$.

Step 5. Repeating the cycle.

At the next stage of using the selected approach for the generation of new individuals, the following approach is used.

Step 1. Two random rankings are selected from the initial population.

Step 2. The second ranking of alternatives is copied into the result.

Step 3. The subsequence from the first ranking is selected.

Step 4. We rearrange the elements of the new ranking, which are included in the subsequence, in the order that corresponds to the current sequence of alternatives.

Step 5. Mutation: swap pairs of elements in the new ranking of alternatives.

Next, we need to define a fitness function for all new rankings. By applying a target metric, we can estimate how far a given ranking is from all others. The sum of the divisions from the expert rankings will be the fitness function. Since, in this case, we solve the problem of minimizing this parameter, we sort the new population by growth. After that, we screen out the "worst" individuals.

Thus, the ranking with the minimum fitness function in the last generation (RN) will be the optimal solution to problem (5) or (6).

5.3.3. Results of a computational experiment using a genetic algorithm

In order to study the described algorithm, the authors conducted computational experiments with different numbers of experts and alternatives.

Numerous computational experiments conducted using the genetic algorithm show the promising application of this approach. For randomly generated rankings Ω^R of 40-50 alternatives, the program calculates the medians in the space of all possible rankings, which according to criteria (5)-(6) are approximately 20% closer to the medians given by experts than the reference rankings. Using a genetic algorithm, we improve them in each of the selected directions [25].

5.4. Nearest search algorithms

The idea of the nearest search algorithm is to use the features of the structure of the domain of admissible solutions for ranking problems. The analysis shows that around each ranking of n alternative there are always other $(n-1)$ rankings that are closest to it (at a distance of 2 according to Cook's metric (4) [53].

5.4.1. Nearest search algorithm of Cook-Sayford median

Let us consider the Cook-Sayford median search algorithm developed by the author in the problem of determining the resulting ranking of objects. At the same time, at the beginning of the algorithm, it is logical to choose the modified Cook-Sayford median as the reference solution, that is, the one that delivers the best value of criterion (9) on the set of individual rankings of the type (4) given by experts

$$R^{MKS} = \sum_{i=1}^{k} d(R^i, R) \to \min_{R \in \{R^1,...,R^k\}}, \quad (16)$$

Step 1. Calculation of the minimum values of the additive criterion of type (16) among the individual rankings of n objects given by experts. The ranking $R^0 = R^{MKS}$ at which this minimum is reached is called the reference ranking R^0.

Step 2. Generating of $(n-1)$ rankings based on the Cook-Sayford median, followed by pairwise replacement of object ranks.

Let $r^0 = (r^0_{i_1}, ..., r^0_{i_n})$ is the vector of object ranks in the reference median.

We take the ranking $R^0 = (a^0_{i_1}, ..., a^0_{i_n})$ as a basis and look for all possible rankings that are at a distance of 2 from it. The number of such rankings is equal $(n-1)$, that is, in this ranking, we interchange neighboring elements one by one: $(a^0_1 \leftrightarrow a^0_2)$, then $(a^0_2 \leftrightarrow a^0_3)$ and so on, until $(a^0_{n-1} \leftrightarrow a^0_n)$.

That is, the cycle by $t = 1,...,n$ is organized: $R^t = (r^t_1, ..., r^t_n)$, where $r^t_i = r^0_i$ for $i \neq t$, $i \neq t+1$, and for $r^t_i = r^0_{t+1}$, $r^{t+1}_i = r^0_t$.

After each such replacement, we check whether a ranking that is at a distance of 2 from $(a^0_1 \leftrightarrow a^0_2)$ is closer to all the rankings given by experts than the one we took as a basis, i.e. $(a^0_1, ..., a^0_n)$.

Determination of distances from the next ranking formed in the cycle $t = 1,...,n$ to the initial rankings set by experts.

Step 3. If we improved the result, that is, found a ranking that is better than the reference, then it becomes the reference. Go to step 2.

Step 4. After finding new rankings, their distance to the given rankings by experts is calculated one by one according to the metric of the mismatch of ranks of form (1). Based on the found distances, the value of the adative criterion of the form (2) is calculated. If the value of the found additive criterion has improved, the ranking from which it was obtained becomes the new median. The algorithm continues until none of the new generated rankings is better than the previous value of the additive criterion.

5.4.2. Nearest search algorithm of compromise median

Nearest search algorithm of compromise median, which is also called the HV-median, is very similar to the previous algorithm with a change in criteria: it is based on the same idea as the nearest search algorithm of Cook-Sayford median. But the organization of sorting through the nearest to the reference location of some solutions is very similar to the previous algorithm. The difference between these two algorithms is that when applying the nearest search algorithm of compromise median in the problem of determining the resulting ranking of objects, it is logical to choose for a reference solution a modified compromise median, which is also called a modified HV-median:

$$R^{MHV} = \max_{i=1,...,k} d(R^i, R) \to \min_{R \in \Omega^n}. \quad (17)$$

Step 1. Calculation of the minimum values of the minimax criterion of the type (17) among the k individual rankings of n alternatives given by experts. The ranking $R^0 = R^{MHV}$ at which this minimum is reached is called the reference ranking R^0.

Step 2. Generating of $(n-1)$ rankings based on the modified compromise median, followed by pairwise replacement of object ranks.

Let $r^0 = (r^0_{i_1},...,r^0_{i_n})$ is the vector of object ranks in the modified compromise median.

We take the ranking $R^0 = (a^0_{i_1},...,a^0_{i_n})$ as a basis and look for all possible rankings that are at a distance of 2 from it. The number of such rankings is equal $(n-1)$, that is, in this ranking, we interchange neighboring elements one by one: $(a^0_1 \leftrightarrow a^0_2)$, then $(a^0_2 \leftrightarrow a^0_3)$ and so on, until $(a^0_{n-1} \leftrightarrow a^0_n)$.

That is, the cycle by $t = 1,...,n$ is organized: $R^t = (r^t_1,...,r^t_n)$, where $r^t_i = r^0_i$ for $i \neq t$, $i \neq t+1$, and for $r^t_i = r^0_{t+1}$, $r^{t+1}_i = r^0_t$.

After each such replacement, we check whether a ranking that is at a distance of 2 from $(a^0_1 \leftrightarrow a^0_2)$ is closer to all the rankings given by experts than the one we took as a basis, i.e. $(a^0_1,...,a^0_n)$.

Determination of distances from the next ranking formed in the cycle $t = 1,...,n$ to the initial rankings set by experts. Step 3. If we improved the result, that is, found a ranking that is better than the reference, then it becomes the reference. Go to step 2. Step 4. After finding new rankings, their distance to the given rankings by experts is calculated one by one according to the metric of the mismatch of ranks of form (4). Based on the found distances, the value of the minimax criterion of the form (2) is calculated. If the value of the found minimax criterion has improved, the ranking from which it was obtained becomes the new median. The algorithm continues until none of the new generated rankings is better than the previous value of the minimax criterion.

5.5. Availability heuristics

When applying the availability heuristic, the most difficult problem is the presence of incomplete information. The incompleteness of expert information is a natural phenomenon, it is an attribute of many decision-making situations, often arises in practice and is one of the types of uncertainty - along with indistinctness, inaccuracy, unreliability, uncertainty, incorrectness, inadequacy, etc. The incompleteness of data and the impossibility of supplementing it naturally accompanies experts and decision-makers in their activities.

The concept of incomplete ranking introduced in such a way [25, 32]: it is a binary relation given on a subset of alternatives A', $A' \subset A$, which satisfies the properties of completeness, antisymmetry, and transitivity: but only on a subset A', $A' \subset A$, and not on the entire set A.

Let a group of experts set k incomplete rankings of alternatives $R^{iH}, i = 1,...,k.$ It is necessary to find some group (resulting, aggregated, collective, consensus, integrative) ranking of n alternatives $R^* = (a_{i_1},...,a_{i_n})$, $i_j \in I = \{1,...,n\}$, $j \in I,$ which is built according to the logic that characterizes the functioning processes of some organizational system. That is, the ranking R^* must be built on the basis of individual arrangements of problems performed by k elements of the system (experts) $R^{iH} = (a_{1_i},...,a_{n_i}), i \in J = \{1,...,k\},$, where n_i – the number of problems in the individual expert ranking $i \in J$.

Due to the peculiarities of calculating the generalized ranking with incomplete initial information, a number of heuristics are proposed to be used [25, 32]. In particular, the components of the distances in case of incomplete rankings of objects are described as follows.

Heuristics E5. The distance from incomplete rankings $R^{iH}, i = 1,...,k,$ given by experts to any ranking $R^{*(0)}$ consists of two components: the determined part of the distance and the probability part.

Heuristics E6. An alternative not specified by the expert generates unknown relations between all other alternatives and does not take part in the ranking, that is, this alternative is not represented in the incomplete ranking. Thus, given incomplete rankings for each expert, we have a number of alternatives:

- $n_i -$ alternatives given by expert in the ranking $R^{iH}, i = 1,...,k,$ which will make up a determined part of the distances;
- $(n - n_i) = \nu_i -$ alternatives not specified by the expert in the ranking $R^{iH}, i = 1,...,k,$ which make up the probabilistic part of the distances.

Heuristics E7. The probabilistic part of the distance from the expert-given ranking $R^{iH}, i = 1,...,k,$ to any reference ranking is always equal $\nu_i, i = 1,...,k,$ for the Cook metric.

The determined part of the distances is calculated according to formula (1).

6. Directions for further research

It is promising to develop parallel algorithms [54] using artificial intelligence methods, the use of which with the described approaches can contribute to obtaining a synergistic effect when:

• formalization and further optimization of business processes;

• solving problems of restoring information in relation to the preference of experts based on the determination of group ranking;

• applying the formalisms of the problem of determining the collective ranking to a wide class of classical combinatorial problems in the descriptions of the relevant formulations for the adaptation and interpretation of the formulation.

• for the successful application of the approaches described in this paper, this mathematical support must be software implemented in an accessible and widespread environment, for example, in the Android system for smartphones.

In many problems, the events to be ordered by using incomplete expert rankings must run in parallel or even occur at one time. Therefore, it is logical to formalize the given problem in the class of collective quasi-orders calculation [55-58].

7. Conclusions

The paper considers and formalizes some aspects of realization a strategic session in the organization. A mathematical model of the process of collective selection of priority directions of the organization development is proposed. In the case if the top managers have identified significantly more than ten important directions of the organization development, the authors suggested and well-founded finding the resulting ranking by applying the algorithms of evolutionary calculations or the algorithm of the nearest search. For cases of incomplete rankings, the algorithms developed by the authors, focused on incomplete data, can be applied. The additional task of determining the coefficients of the relative competence of experts, which in the context of the research can be interpreted as the degree of satisfaction of the desires of the managers of the functional directions of the organization, is also solved.

8. References

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