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The Confident Judgment Method in the Selection of Multiple Criteria Solutions

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Abstract—The problem of multiple criteria decision making in which the alternatives are characterized by partial criteria and can depend on uncertain factors is considered. A method that allows a decision maker to choose an alternative solution easily and soundly based on natural reasoning is proposed. The method does not use artificial tricks aimed at the formalization of the problem by finding a supposedly unique adequate way to account for uncertainties; rather, it uses all possible ways to resolve uncertainties.

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INTRODUCTION

Presently, the decisions to be made by decision makers have become more complicated, and they need various factors to be taken into account. The gain achieved by making a good decision can be considerably increased, while the cost of a bad decision has simultaneously grown. Fortunately, advances in science and technology have created conditions for the successful solution of this problem by using information technologies and sophisticated computationally intensive mathematical methods.

Any decision is ultimately made by a person or a small group of persons called decision makers (DMs). This is because any, even a bicriteria decision making problem is mathematically not closed. For this reason, the DM should complete the problem statement to make it closed, ultimately arrange the alternatives by their effectiveness, and obtain the most rational decision. The DM has an informal understanding of the problem and virtually any method used to support the decision making procedure is aimed at formalization of this understanding (almost always in a mathematical form).

Therefore, the method used for this purpose must be understandable for the DM, not restrict his or her decision making options due to the specific features of the method, not assume that the DM possesses knowledge beyond the DM's typical scope, and be not very laborious. It was shown in [1] that no methods that simultaneously satisfy these requirements are presently available. For example, the widespread linear scalarization method is clear for DMs; however, it can miss the Pareto optimal solutions and assumes that the DM can give accurate quantitative values of the weighting coefficients involved in the scalarization function, which can hardly be achieved even if competent experts are engaged (taking into account the unreliability of their choice and the inevitable differences in their assessments).

A promising direction for improving decision making methods that makes it possible to combine the above requirements is to drop the attempts at getting out of the DM his or her methods of taking uncertainties into account but rather enable him to rely on the *whole set of possible ways of resolving uncertainties*; the computational complexity in this case is imposed on a computer (desktop or a cloud computer). Such an approach was implemented at the beginning of the 1970s in the PRINN method [2, 3, 4], which was further developed and used in [6–8]. However, this method used certain simplifications (a fixed size of the ε-network in the space of ways used to resolve uncertainties). These simplifications were aimed at reducing the computational complexity of the method. Their use was not directly dictated by the nature of the decision making problem and implied mathematical techniques that were hardly grasped by the DMs. Modern information technologies allow us to remove these simplifications and propose a new method that, in our opinion, puts the DM in the center of making complex decisions.

1. FORMALIZATION OF WAYS FOR RESOLVING UNCERTAINTIES

Consider the classical multiple criteria optimization problem. Let Y be a set of alternatives and $f(y) = \{f^1(y), f^2(y), \ldots, f^m(y)\}$, where $y \in Y$ is a vector function of the m partial optimality criteria defined on a set of alternatives. The DM wants to select the most rational alternative.

In this problem, the most rational alternative $\bar{y} \in Y$ must be Pareto optimal; i.e., it must satisfy the well-known condition

$$(\exists \hat{y} \in Y : (f^j(\hat{y}) \le f^j(\bar{y})\ j = \overline{1,m}) \wedge (\exists j \in \{\overline{1,m}\} : f^j(\hat{y}) < f^j(\bar{y})))$$

(if one wants to minimize each partial criterion). Since all Pareto optimal solutions can be considered equally rational, the DM should use additional information or reasoning to select one of them.

It is reasonable to introduce a scalar combined optimality criterion $F(f(y))$ that takes into account the relative significance of different partial criteria and allows one to select the most rational alternative in a rigorous mathematical way:

$$F(f(\bar{y})) = \min_{y \in Y} F(f(y)).$$

Therefore, the decision making is no longer a multiple criteria problem and, if the function $F(f)$ is given, the most rational alternative is found by scalar optimization. However, since the DM does not know the specific form of $F(f)$, we have a set of different ways of accounting for uncertainty—the set of possible scalarization functions $s \equiv F(f)$, which represents possible ways of reducing the partial criteria S to a scalar form. For brevity, we will call the uncertainty in scalarizing the partial criteria (the vector f) into the scalar F simply the set of uncertainty resolution methods.

Without loss of generality, we assume that the values of all the partial criteria and the combined criterion are normalized and lie in the interval between 0 and 1. Then, each uncertainty resolution method is a strictly monotonic function defined on a unit hypercube that assigns to each vector its numerical value also in the interval from 0 through 1. In order to distinguish this meaning of designation $F(f)$ from the combined criterion for the specific argument value f, we will use the notation $F_s(f)$ in the latter sense.

The majority of existing formalized decision making methods are aimed at finding an adequate way of accounting for uncertainty $\bar{s} \equiv \bar{F}(f)$; then, the most rational alternative $\bar{y} \in Y$ is determined purely mathematically and typically uniquely. The simplest and most widespread example of this approach is the use of the linear scalarization function

$$\bar{F}(f) = \sum_{j=1}^{m} \alpha^j f^j, \quad \alpha^j \ge 0, \quad j = \overline{1,m}, \quad \sum_{j=1}^{m} \alpha^j = 1, \tag{1.1}$$

where the weighting coefficients α^j ($j = \overline{1,m}$) are specified by experts.

Let us discuss the validity of this method. By choosing this method, the DM relies on two assumptions:

(1) linear scalarization is adequate in the decision making problem in question;

(2) the experts, the expert evaluation procedure, and the method used to process the experts' assessments yield absolutely reliable values of the weighting coefficients.

Both assumptions can be disputed. Indeed, linear scalarization has a number of well-known drawbacks. In particular, it can "miss" some Pareto optimal solutions regardless of the set of weighting coefficients (see [1]). Therefore, a natural requirement for the set of uncertainty resolution methods S, which states that each Pareto optimal solution in the set of feasible solutions Y must be associated with at least one function $F(f) \in S$ such that this solution turns out to be the most rational one when this function is used, is violated. The failure to satisfy this requirement reduces the DM's choice due to purely mathematical reasons, which is unacceptable. It was shown in [8] that in the class of continuous functions only Germeier's scalarization function

$$F(f) = \max_{j=\overline{1,m}} \alpha^j f^j,$$
$$\alpha^j \ge 0, \quad j = \overline{1,m}, \tag{1.2}$$
$$\max_{j=\overline{1,m}} \alpha^j = 1$$

has the property of identifying arbitrary Pareto optimal solutions.

The second assumption also provokes objections—it is doubtful that expert evaluations can yield reliable values of the weighting coefficients in the linear scalarization or any other scalarization function $F(f)$.

In our opinion, a better way to solve the multiple criteria choice problem is to abandon the attempts to eliminate the uncertainty by selecting one appropriate scalarization function but rather use the whole set of uncertainty resolution methods, which, once the structure of the scalarization function is established, is described by the whole set of feasible values of the weighting coefficient vector. Due to the role of Germeier's scalarization function mentioned above, we believe that it should be used. Then, it follows from (1.2) that

$$S = \{\alpha^j \geq 0,\ j = \overline{1,m},\ \max_{j=\overline{1,m}} \alpha^j = 1\}. \tag{1.3}$$

2. DM's CONFIDENT JUDGMENTS RATING, AND SOFT RATING

Under this approach, the DM does not have to choose the structure of the scalarization function and the unique vector $\alpha = \{\alpha^j\}_{j=\overline{1,m}}$. The DM's subjective opinion, which is his indefeasible right, is taken into account by means of his two confident judgments.

Confident judgment of the first type. *The DM can classify the partial criteria into different significance groups.* For instance, criteria 1 and 4 may be considered as most important, criteria 2 and 6 are simply important, and criterion 5 is of the least importance.

We note that the DM does not give a quantitative evaluation of the degree of partial criteria's relative importance; only a qualitative comparison is needed. This judgment is easily taken into account by introducing the additional inequalities

$$\alpha^2 \geq \alpha^5,\ \alpha^6 \geq \alpha^5,\ \alpha^1 \geq \alpha^2,\ \alpha^4 \geq \alpha^2,\ \alpha^1 \geq \alpha^6,\ \alpha^4 \geq \alpha^6$$

into system (1.2).

Confident judgment of the second type. *Optionally, the DM may construct pairs of Pareto incomparable vectors of the partial criteria for which he is confident that one vector is "better" than the other one.* It is not required that these vectors reflect the efficiency of certain real-life objects. For instance, if f_1 and f_2 is a pair of such vectors in which f_1 is surely better than f_2, then this narrows the set S to the set

$$S_{12} = \{s : F_s(f_1) \leq F_s(f_2)\ \forall s \in S\}.$$

Note that the proposed method of taking into account fuzzy judgments by modifying the set of uncertainties S makes it possible to add to the decision making problem interval and qualitative estimates of the initial data in the form of inequalities. We will demonstrate this by way of an example below.

Thus, we consider the set of values of the criterion function $F_s(f_i)$ on the set of uncertainties $S = \{s\}$ for n distinct alternatives. It is important that all the elements of the set of uncertainties $s \in S$ are of equal significance similarly to events in probability theory. This allows us to consider the relative measure (with respect to the measure of the entire S) of the subset S on which an alternative is better than the other alternatives in terms of the criterion function as a characteristic of this alternative's efficiency. This measure will be called the **rating** R_i of the alternative i:

$$R_i = \int_{s\in Q} ds \bigg/ \int_{s\in S} ds, \tag{2.1}$$
$$Q = \{s \in S, F_s(f_i) \leq F_s(f_k), k = \overline{1,n},\ k \neq i\}, \quad i = \overline{1,n}.$$

Continuing the analogy with probability theory, we may say that the alternative's rating is the chance (probability) that this alternative is the best one with regard to all the possible ways of resolving uncertainty that can be used in the specific decision making problem. Figuratively, by considering each way of resolving the uncertainty as an independent tantamount expert and the whole set of uncertainty resolution methods as a group of such experts reflecting all the reasonable views of uncertainty resolution, we may consider the rating of an alternative as a part of the expert community that believes this alternative to be the best one.

It can also be interesting for the DM to know the extent to which the best alternative is superior to the other alternatives. This information can be provided by the alternative's **soft rating** AR_i, which is defined

Table 1. Some performance indicators of carrier rockets (provisional data)

Carrier rocket	Reliability forecast for the maiden launch	Forecast of the control system efficiency	Minimal time for the development of an emergency situation in the passage of oxygen of a liquid-propellant engine, s	Launch pad safety forecast	Crew safety forecast	Payload mass reserve	Potentials of increasing the rocket engine thrust with its cost assessment	Ratio of the payload to the total mass	Ratio of the payload to the mass of the empty rocket	Ratio of the payload to the engine power	Development cost, bln rubles	Specific cost of payload orbital injection, k rubles/kg
						%						
	max										min	
A	0.97	0.9	0.2	0.9995	0.995	0.8	1.3	2.7	30	1.75	15	75
B	0.98	0.5	0.1	0.999	0.99	0.9	2.3	2.5	40	1.85	20	100
C	0.96	0.9	0.2	0.9995	0.995	1.2	2	2.4	20	1.65	18	60
D	0.96	0.9	0.25	0.9995	0.995	1	3	2	35	1.6	22	80

as follows. The average of the criterion function over all the uncertainty resolution methods i is computed and then subtracted from unity to enable the DM to assess the alternative in the conventional way—the higher the soft rating the better the alternative:

$$AR_i = 1 - \int_{s\in S} F_s(f_i))ds \Big/ \int_{s\in S} ds, \; i = \overline{1,n}. \tag{2.2}$$

The integrals in (2.2) can easily be computed on modern computers using the Monte Carlo method.

The proposed method, which we call the confident judgment, allows the DM to make justified decisions in multiple criteria selection problems with the quantitative and qualitative criteria of different significance for the quantitative, ordinal, and interval initial data without using artificial quantitative assessments of the DM's preferences.

We illustrate the application of this method using two examples—comparative assessment of carrier rockets and optimization of the operation of resource-constrained systems.

3. COMPARISON OF CARRIER ROCKETS

Suppose that four types of carrier rockets are under development (versions A–D). Each type has some advantages and disadvantages. The efficiency of each type is characterized by 12 indicators the provisional values of which are presented in Table 1. We want to find out which version is preferable.

To answer this question, we compare the versions using the confident judgment method.

First, we explain the idea underlying the proposed method by selecting the preferable version using only two indicators—the specific cost of orbital injection and the ratio of the payload mass to the mass of the empty rocket ($M_{\text{payload}}/M_{\text{empty}}$), which will be called mass defect for brevity (see Table 2). In this simplified example, the Monte Carlo method is not needed to compute the alternatives' ratings—they can be found graphically.

The versions with their performance indicators are illustrated in Fig. 1, where the normalized values of these indicators are used so that the optimization objective is to minimize the criterion function.

Consider the family of level curves of Germeier's scalarization function for certain fixed values of the coefficients α^1, α^2. This is a family of "angles" that rest on a straight line (axis of the criterion function) passing through the origin. The criterion function decreases in the direction to the origin. We see that the criterion function illustrated in this figure identifies version D as the Pareto optimal solution because it

Table 2. Simplified carrier rocket selection based on two indicators

Carrier rocket	Indicators	
	Normalized deviation from the best value of $M_{payload}/M_{empty}$, %	normalized cost of payload orbital injection
A	0.5	0.38
B	0	1.00
C	1	0.00
D	0.25	0.50

takes a lower value on this alternative than on the others. For different coefficients α^1, α^2, the axis will have a different position, and other versions can be Pareto optimal.

Figure 2 shows the sectors such that when the criterion function passes within such a sector, a specific alternative is the Pareto optimal solution. The greater the measure of the set of values of the coefficients α^1, α^2 at which the axis is within a sector the greater the rating of the alternative corresponding to this sector.

The set of coefficients α^1, α^2 is shown on the sides of the unit square ABCD depicted in Fig. 3 by a bold line. The segment BC shows the possible values of α^1 multiplying $M_{payload}/M_{empty}$ in Germeier's scalarization function when α^2 multiplying the specific cost is equal to unity; the segment DC shows the possible values of the second coefficient when the first coefficient is equal to unity.

To determine the ratings of the alternative, we enumerate the alternatives from 1 through n arranging them in increasing order of the abscissa. Denote by c_i and d_i $(i = \overline{1,n})$ the values of the horizontal and vertical coordinates of the points reflecting different alternatives. Next, we calculate the ratios c_{i+1}/V for $i = 1, \ldots$ until they exceed unity. Otherwise, the coefficient in the scalarization function whose maximum

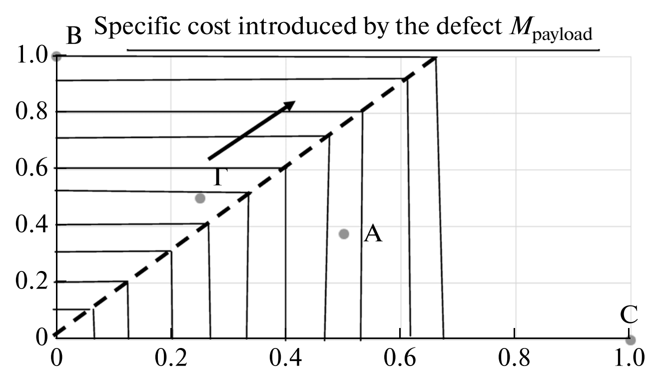

Fig. 1. Simplified carrier rocket selection problem based on two performance indicators.

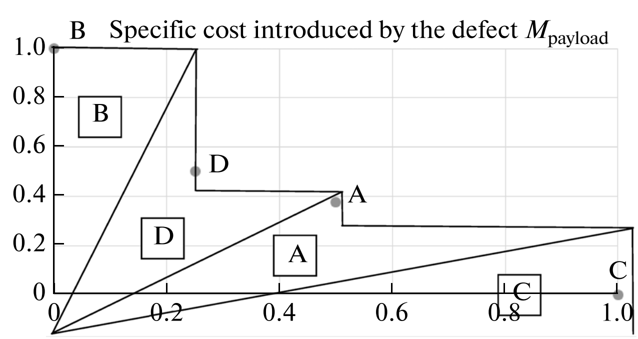

Fig. 2. Sectors that identify different Pareto optimal solutions.

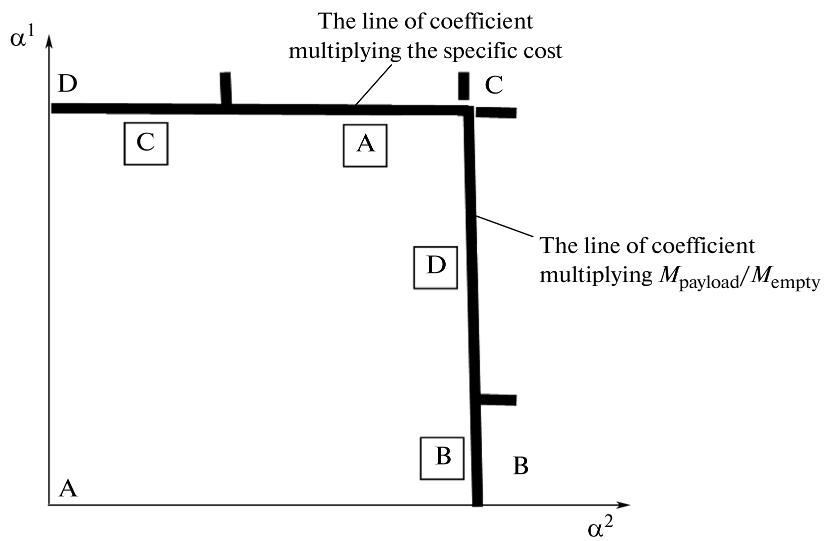

Fig. 3. Intervals of the set of uncertainties in which different versions of carrier rockets are optimal.

value is calculated is no longer less than the second coefficient in Germeier's scalarization function. On the right-hand vertical side of the unit square ABCD, we successively plot, beginning from the lower endpoint B, the marks at the calculated distances from this vertex, and enumerate the intervals by the numbers 1, 2, etc.

Similarly, we calculate the ratios d_{i-1}/c_i $(i = n, n-1, \ldots)$ until they exceed unity. On the upper horizontal side of ABCD, beginning from the vertex D, we successively plot the marks at the calculated distances from this vertex, and enumerate the intervals between them by numbers beginning from n.

If the DM believes that all the partial criteria are equally important, then the lengths of the enumerated intervals are proportional to the chances of the corresponding alternatives to be optimal. By multiplying (in this example) these lengths by 50, we obtain more conventional values on a percentage basis.

If the DM believes, for instance, the *cost* criterion to be more important than *efficiency*, then the line corresponding to the less important criterion is excluded from the examination. The alternatives whose intervals are on the remaining line have chances to be optimal. To obtain values on a percentage basis, the interval length must by multiplied by 100 in this case.

The results for this example are presented in Table 3. It is seen that, if the DM believes that both indicators are of equal importance, then alternative D is the optimal choice (its rating is 37.5%). Alternative A has a close rating of 31%. If the cost criterion is more important, then alternative D is much better than all the others. However, if the efficiency is more important than the cost, then rocket A is preferable.

To compare the four carrier rockets using all the 12 indicators shown in Table 1, software implementing the Monte Carlo method is needed (10000 cases). The results of such an analysis are shown in Table 4.

For the case when the DM believes that all the partial criteria are equally important, the solution is presented in columns 2 and 3 of Table 4. For the case when the DM believes that safety is the most important factor (the first five indicators in Table 1), the result is shown in columns 4 and 5 of Table 4. If we add economic indicators to the list of the most important factors, then we obtain the result shown in columns 6 and 7 of Table 4. Summarizing the results, we conclude that alternative A is the best one for the initial data under examination because is ratings are the highest ones in all the cases.

4. OPTIMIZATION OF THE OPERATING STRATEGIES FOR RESOURCE-CONSTRAINED SYSTEMS

The example discussed in this section demonstrates the capabilities of the proposed method as applied to weakly formalized problems. This class includes multistep problems, in particular, in the social and economic field, in which considerable uncertainty is induced not only by the variety of objectives and criteria but also by the impossibility to quantitatively estimate some initial data. One such problem is the optimization of resource-constrained system management. The resource-constrained systems, which were, for

Table 3. Results of the carrier rocket selection based on two indicators

Indices in increasing order i	Carrier rocket	Normalized deviation from the best value of $M_{payload}/M_{empty}$, %, c_i	Normalized cost of payload orbital injection, d_i	$\frac{c_{i+1}}{d_i}$, $i = 1, \ldots$	Interval length	$\frac{d_{i-1}}{c_i}$, $i = n, \ldots$	Interval length	Rating when the criteria are equally important	Rating if the cost is more important than the efficiency, %	Rating if the efficiency is more important than the cost, %
1	B	0	1.00	0.25	0 .25			12.5	25	
2	D	0.25	0.50	1.0	0.75			37.5	75	
3	A	0.5	0.38			1.0	0.62	31		62
4	C	1	0.00			0.38	0.38	19		38

Table 4. Results of the carrier rocket selection based on 12 indicators

Carrier rocket	Basic selection policy		High importance of safety indicators		High importance of safety and cost indicators	
	rating	soft rating	rating	soft rating	rating	soft rating
A	47.28	24.55	99.86	53.16	98.45	53.21
B	10.9	7.98	0.14	1.89	0.04	2.20
C	32.26	19.57		18.49	1.51	19.80
D	9.56	12.77		18.49		11.12

example, considered in [9], require a certain resource for their operation that is distributed between subsystems that also can produce this resource in the course of their operation according to certain rules.

A typical example of a resource-constrained system is the system of a person's competence formation in the course of its activity, taking motivation into account, which plays the role of a resource in this case. As applied to the work with talented students, this problem was originally formulated in [10–13] and was fairly widely developed. This problem is based on the model that considers the formation of students' research competence as a controlled dynamic process described by an unclosed system of ordinary differential equations [14].

This model is based on the hypothesis that the research capabilities include four components—intellect, creativity, skills, and motivation. The first two components do not change after the age of 15 or 16 years. However, the skills and motivation are dynamic and can vary; furthermore, the research skills are formed exclusively in the process of the student's research activity.

According to this hypothesis, the quantitative indicators describing the research skills of a student are his or her capability to accomplish the following main elements of research activities:

(1) search for a topic,

(2) formulation (comprehension) of the research topic,

(3) formation of the key idea (plan) of the solution,

(4) selection, mastering, and implementation of the required techniques,

(5) implementation of some solution elements (elements of the solution plan),

(6) synthesis of the solution (research as such),

(7) description of the solution,

(8) introduction into scientific discourse, defense, and maintenance of the solution,

(9) internal critical analysis of the solution.

The intensity of this activity, i.e., the student's motivation, is characterized by the time allocated for research activity (hours per month). This time is divided between the work corresponding to different elements of research activity. This work stimulates the student in different degrees—some of it is interesting, and the student's motivation increases, other parts seem to be dull, and they reduce the student's motivation. The problem of optimal control of such a resource-constrained system is to form a sequence of the student's actions in the learning phase that yields the maximum research competence and motivation at the end of the learning period.

Thus, we have ten partial optimality criteria (the level of each competence and motivation at the end of the learning period). The values of these elements for a fixed strategy (sequence of a student's actions) are determined by integrating a system of ordinary differential equations that are derived for the initial level of research activity from the mathematical model proposed in [14].

Let us outline this model. Introduce the following notation: $i = \overline{1,9}$ are the indices of the main elements of the research activities; M is the person's creative activity (motivation) measured in the amount of time allocated for the research activity (hours per month); m_i is the time allocated for element i of the research activity (hours per month) so that $\sum_{i=1}^{9} m_i = M$; and x_i are the phase coordinates that characterize the current estimate of the person's skills with respect to individual elements of research activities i measured in fractions of the degree of mastering these elements, where

$$0 \le x_i \le 1, \quad i = \overline{1,9}.$$

The phase coordinates vary in time depending on the student's resource activity so that they satisfy the differential equations

$$\frac{dx_i}{dt} = u\beta_i IKm_i x_i (1 - x_i).$$

Here, t is the current time counted from an initial point when the student's research activity begins to develop in months; I and K are estimates of the intellect and creativity in the psychological sense (e.g., determined by psychological testing) in points; and u is the proportionality factor that in particular reflects the influence of training techniques on the effectiveness of the research activity.

The coefficients β_i of dimensionality 1/h determine the rate of increase of the skills as a result of a person's activity possessing certain creative potential. These coefficients depend not only on the specific features of the research activity element i but also on the person's skills in the allied elements of this activity element:

$$\beta_i = \beta_i^0 + \beta_i^1 \sum_{r=1}^{9} \gamma_r^i x_r.$$

Here, γ_i^r are the coefficients accounting for the influence of skills in element r on the skills rate of increase in element i; they are normalized by the condition

$$\sum_{r=1}^{9} \gamma_r^i, \quad i = \overline{1,9}.$$

The relations between the coefficients β_i^0, β_i^1 show the relative contribution of the element itself and the other affecting elements to the complexity of mastering this element by the person.

In turn, the person's motivation in the course of research activity satisfies the differential equation

$$\frac{dM}{dt} = \left(a_0 + \sum_{i=1}^{9} a_i m_i + a_x X_{\text{recogn}} \right) (M_{\max} - M).$$

Here, a_0, a_i, a_x are the coefficients accounting for the relative significance of the three key factors—mission, preferences of specific kinds of activity for the person, and incentives; $M_{\max}$ is the physiologically maximum motivation level; $X_{\text{recogn}} = x_8$ is the person's skills level recognized by the society; and $(M_{\max} - M)$ is the damping factor reflecting fatigue, i.e., the slowdown of motivation increase rate when approaching the physiological maximum.

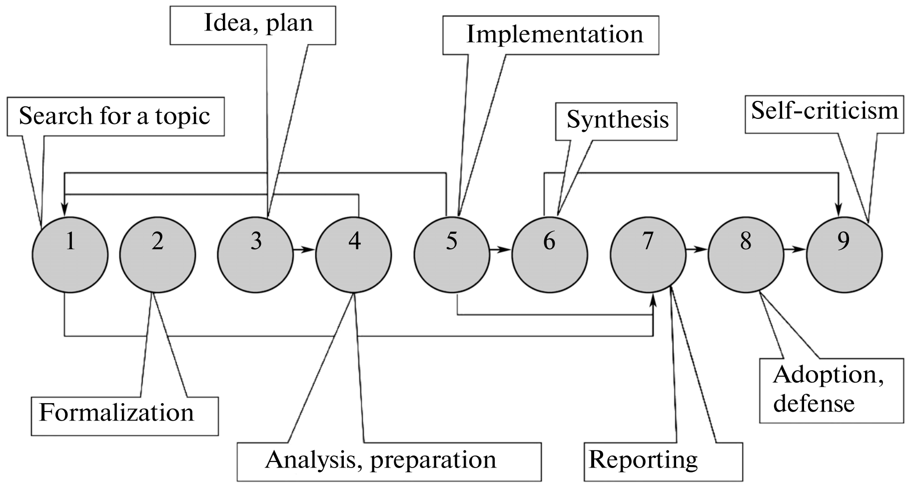

Fig. 4. DM's confident judgments on the sequence of the active formation of research competence.

The system contains ten first-order differential equations, ten phase variables, and nine controls, where the controls are the student's activities at each instant of time.

The problem is to determine the elements of research activity on which a student should concentrate in each semester to ensure the maximum (in the vector sense) research competence and the maximum motivation degree for research activities by the end of his learning period. It is assumed that in each semester the student's work should be concentrated on not more than two elements of research activity.

This problem is difficult to formalize not only because it has multiple criteria but also because some coefficients in the model are uncertain and fuzzy. These coefficients, of which the majority is presented in Table 4, are introduced for the first time, and there are no reliable techniques for their quantitative estimation. They can be specified only using ordinal scales in which a greater index corresponds to a greater value of the indicator. However, it is impossible to directly use the available interpretation of the solution to a system of differential equations with qualitative rather than quantitative coefficients. Here we use the feature of the proposed method which operates the set of uncertain factors including not only undetermined weighting coefficients in Germeier's scalarization function but also undetermined initial data. Thus, the proposed approach makes it possible to obtain specific recommendations with respect to the formation of research competence even in the case of a high level of uncertainty. The results of the solution to this problem are described below.

Figure 4 depicts in graphical form the confident judgments of a DM concerning the rational sequence of activities that help form research competence. The arrow leading from one element of activity to another indicates that, according to the DM's confident judgment, the action at the beginning of the arrow should be activated before the action at the end of the arrow. The callouts contain brief names of the actions, which facilitates the examination of the figure (the full names were presented above). These judgments narrow the set of strategies, but still leave more than four thousand of them.

All the data presented in Table 5 and Fig. 4 are collected based on long-term studies performed at the faculty of information systems and technologies of the Samara State Building and Architecture University and at the faculty of system analysis and control of the Moscow Aviation Institute (National Research University). These data are an integral part of the problem—the underlying methodological concept of forming students' research competence during seven semesters (for training Bachelors'of science).

The most effective strategies of organizing research activity are shown in Fig. 5. The diagrams for training specialists of three types—executive, developer, and analyst—are presented. The rows in the diagrams correspond to semesters (the semesters from the first to the seventh one go from bottom to top, while the eighth semester is left for the completion of learning and preparing the bachelor thesis). The shaded cells show the type of activity that is the main one in the corresponding semester. In other words, the diagrams show which research competence should be preferably developed in each semester.

It is seen from Fig. 5 that, for the training of executives and developers, the following strategy is most rational (the upper diagram in Fig. 5). In the first semester, mathematics and computer science are taught, in the second semester the ability to make working plans, in the fourth one the development of tools, in particular, software for research activities, etc. For developers, another equally effective strategy for devel-

Table 5. Comparative estimate of the initial state of research competence (importance groups: 0 stands for ignored, 1 stands for the ordinary importance, 2 stands for the high importance, 3 stands for the critical importance)

Short names of research activity types and the corresponding competence	Initial level of students' competence, $x_i(0)$	Goal of student training, c_i			Level of the research activity types on motivation, a_i	Level of the research activity types on the formation of competence, β_i
		executive	developer	analyst		
Search for a topic	1	0	1	2	1	3
Formalization	1	0	1	2	2	2
Ideas and plans	1	0	1	3	2	3
Mastering	2	1	2	1	3	1
Implementation	2	2	2	1	3	1
Synthesis	1	0	1	2	2	3
Reporting	2	2	2	1	2	1
Defense	2	0	1	2	2	2
Self-criticism	1	1	2	3	3	3

oping competence can be proposed, which is shown in the middle of Fig. 5. A significantly different strategy is more suitable for training analysts.

The rating of the strategy (the highest one among other alternative strategies) is show in parenthesis (for most alternatives, this rating is zero). We see that this rating is not high. This is explained by the high level

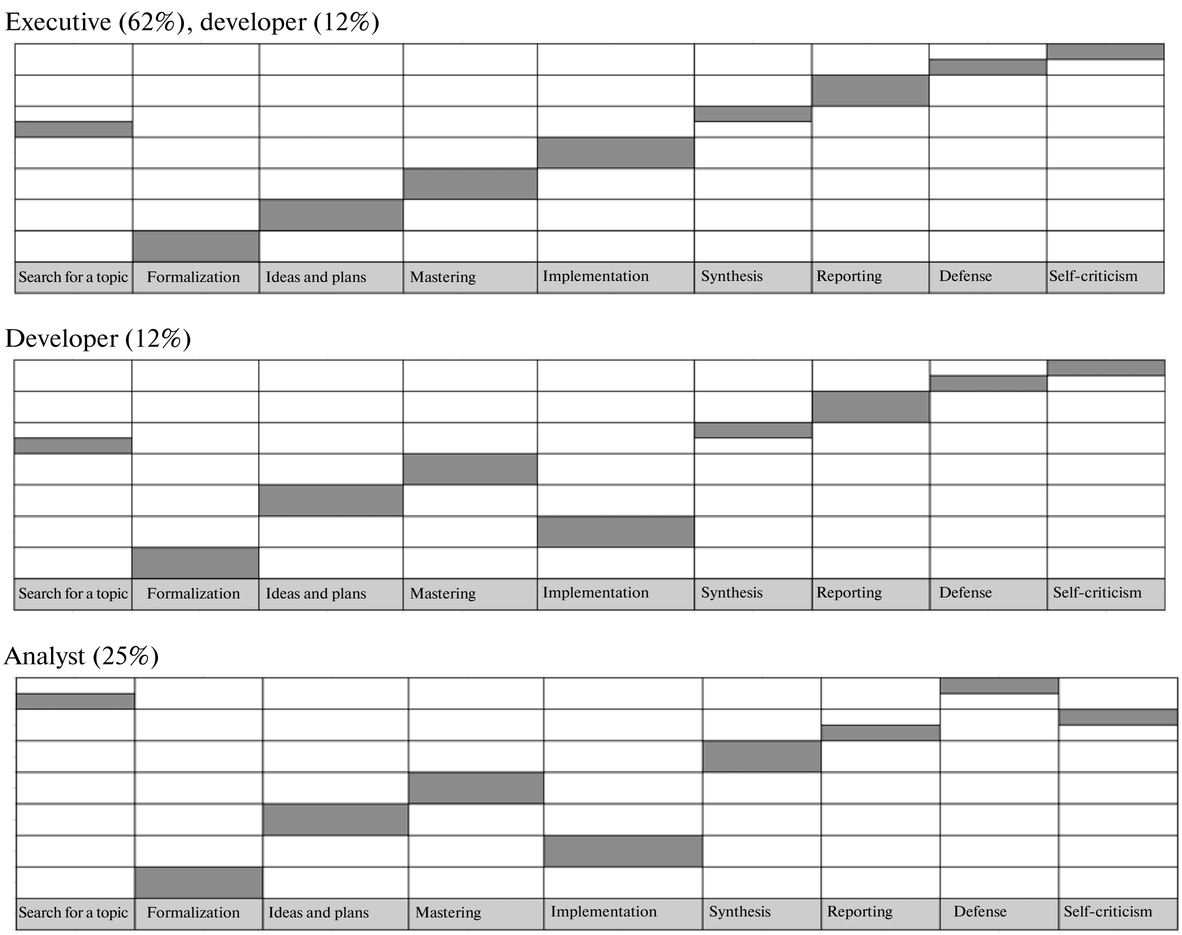

Fig. 5. The most rational strategies of forming research competence (the Key: strategy's ratings are shown in parenthesis).

of uncertainty in the problem. A higher rating for the best solution can be achieved only by reducing the level of uncertainty or by using more sophisticated techniques for determining the initial data, which may ultimately make it possible to use quantitative rather than qualitative indicators; another option is to use the stronger confident judgments of the DM, for instance, about the training goals.

CONCLUSIONS

The confident judgment method proposed in this paper makes it possible to give well-founded comparative estimates of objects characterized by a set of quantitative and qualitative indicators in the case when the techniques for the scalarization of the partial criteria and the initial data are uncertain. No superfluous assumptions imposed by the state of the problem under examination are needed, while only concepts that are natural and clear for the DM are used.

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