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Designing the cumulative indicators and criteria for educational process subjects competence assessment

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***Abstract*—This article shows different kinds of cumulative indicators in various fields of knowledge are widely used for the object's status or processes assessment. Its main purpose is to give a comprehensive assessment the selected object characteristics. Such indicators are easy to use and serve as a kind of sensors as their deviations from certain given values indicate changes in state of the object and its suggested further analysis. The indicator sensitivity to an object state changing at different levels of its hierarchy is directly connected with the choice of the object decomposition level on which the integral component constructed.**

***Keywords*—integral criteria, methods of artificial intelligence, information technology.**

I. Introduction

All local estimates in some area (time, spatial, situational) can be summarized in one global cumulative indicator. Local estimates are any quantitative assessments that are made on the basis of single measurement at a single point at some point in time, the point in the geometric space or state space. Formally, this aspect can be written as follows. Let all of estimates are contained in the set of points $z_1, z_2, ..., z_n : Z = \{z_i\}$. Each local estimate *h*, which is measured on each element, is $h(z_i)$. If the set *Z* is continuous, cumulative indicator can be written as the integral $H = \int h(Z)dZ$.

In accordance with the particular task the variety of methods and approaches have been used. The qualimetry models [1], methods for producing cumulative estimates of the human body state [2,3], cumulative estimates of professional readiness [4] and professional suitability [5] were used as basic. For the cumulative estimates and criteria formation for competency assessment the methods were chosen on the basis of the coagulation types methods analysis which are used in the qualimetry models. Cumulative estimates which were proposed can be divided into 4 types according to the used type convolution (Table 1). The criteria from Table 1 can be used for tasks related to the assessment of students' competence (for example, the academic ranking); and be included as the part of the decision rules for competence diagnose. Cumulative estimates and criteria formation algorithm for assessing students' competence components which based on the factor models are presented below.

TABLE I. CUMULATIVE ESTIMATES AND COMPETENCY EVALUATION CRITERIA

Convolution types	Cumulative estimates and criteria types	The estimated components of competencies and tasks
Functional convolution $\bar{\mu} = f(\mu_1, ..., \mu_n)$	Formal criteria as factor models	Cumulative estimates for personal and business skills assessment (entrepreneurial skills, teaching abilities, etc.)
Separable convolution $\bar{\mu} = \sum l(\lambda_i)\varphi(\mu_i)$	The adherence functions in form of membership functions	
Additive convolution $\bar{\mu} = \sum \lambda_i \mu_i$	Formal criteria as factor models	Cumulative estimates for personal and business skills assessment (entrepreneurial skills, teaching abilities, etc.)
Alternative conjunctive coagulation: convolution bivalent alternative quality measures {0;1} as a conjunction of predicates suitability (the "suitable" - 1; "not suitable" - 0).	Cumulative criteria as the production models	Professional suitability Integral criteria for a variety of University technical specialties

II. Formal criteria as factor models

Authors [6] demonstrated factor models in the cumulative estimate formation for assessing personal qualities. We use this approach for the cumulative estimates formation for assessing different types of competence (competence model components).

Wide interest in the factor analysis methods application is related to the fact that these methods allow to solve a problem of a classification scheme construction, i.e. compact meaningful description of the phenomenon under investigation, based on the processing of large data arrays. The basic factor analysis model is recorded as the following system of equations

$$x_i = \sum l_{ij} f_i + \varepsilon_i; \quad i = \overline{1, p}; \quad m \le p. \qquad (1)$$

Each characteristic value x_i can be expressed as amount of simple factors f_i whose number is less than the number of initial characteristics and a residual member ε_i, dispersion σ^2 acting only on x_i, which is called specific factor. l_{ij} – loadings from *i*-th variable on factor *j*-th or *j*-th factors loading on the *i*-th variable. Maximum possible number of factors m in a given number of attributes *p* defined by the inequality $(p + m) \le (p - m)^2$ which must be satisfied that the task does not degenerate into the trivial. This inequality is obtained by counting the freedom degrees available in the problem. Factor's analysis task can not be resolved uniquely. Equalities 1 is not amenable to direct verification, as the p initial signs given by other $(p + m)$ variables – simple and specific factors. Therefore, the representation of the correlation matrix factors can produce an infinite number of ways. If it were able to produce a correlation matrix factorization using a matrix of factor loadings *F*, then any linear orthogonal transformation *F* (orthogonal rotation) lead to the same factorization.

Authors used orthogonal rotation factors which are realised by varimax method. This method was chosen because it allows to simplify the interpretation of factors (while quartimaks - variables and ekvamaks - and factors and variables simultaneously). These factors are linear functions of the form:

$$F_i = f_{11} \cdot x_1 + f_{12} \cdot x_2 + ... + f_{1p} \cdot x_p; \qquad (2)$$
$$i = \overline{1, m}; \quad j = 1,2,..p.$$

where x_i – variables; *m* – number of factors; *p* – number of variable; f_{ij} – *i*-th factors loading on the *j*-th variable. Function as (2) was used as a formal criterion for assessing the quality of the educational process objects. This approach is most effective when the object under study is characterized by a kind of output quality *Y*, which is determined apriori (not necessarily unique) by the set of identifiable and measurable ”inputs” $x_1, x_2, ..., x_p$. For example, the level of pedagogical skill *Y* is characterized by signs of $x_1, x_2, ..., x_p$ that can be ”measured” by the results of the students questionnaire survey.

This approach is demonstrated on the example of the generalized criteria's formation for evaluating and analyzing the special competence's structure for the technical college graduates who are involved in the teaching activities. Professional activity sphere for technical colleges graduates is quite diverse; inter alia it includes some teaching activities (mainly related to the teaching of special subjects).

In this study, the students acted as experts. They took part in questionnaire survey ”As students see the teacher”. These responses were used as expert estimates. This questionnaire is used in the Tomsk Polytechnic University and a number of other Russian universities when the certification of teachers. But the standard method of processing and analyzing the results for this questionnaire is incorrect from the viewpoint of mathematical statistics. For example, can not use the average value as a measure of central tendency for the rank scale's measurements. Also, outlying observations are not considered (estimates of experts – ”heretics”) in the final evaluation, etc. In this regard, for the analysis and processing of the survey results were used expert and statistical algorithms developed by authors [7].

Presentation of above algorithms is presented below on the example of the processing and analysis survey results for senior students one of the Tomsk Polytechnic University departments. Students evaluated teachers providing educational disciplines related to the future profession. There were evaluated: Group 1: 16 teachers (the set {P1,P3,P4.....P17}); Group 2: 13 teachers (the set {P1,P2,P3.....P13}). According to the questionnaire, it was necessary to evaluate on a 9-point scale, 18 properties (valued qualities are presented in Table 2).

TABLE II. THE RESULTS OF THE EXPERT ESTIMATING

Estimated indicator	**The number of ”heretics”**		**The number of ”heretics”**	**After exclusion of ”heretics”**	
	Me	***W_0***		***Me***	***W_1***
1. He/she presents the teaching material clearly, available for students	6	0.437	7	6.5	0.719
2. Explains difficult moments	5.5	0.596	3	6	0.620
3. Highlights the main points	5.5	0.611	4	6	0.798
4. He/she is able to induce and maintain audience interest	5	0.394	4	5	0.410
5. Monitoring the audience's reaction	5	0.568	6	5.5	0.662
6. Asks questions to encourage discussion	5.5	0.626	1	5.5	0.649
7. Follows the logic in the presentation	6.5	0.579	1	6.5	0.597
8. Demonstrates speech culture, clarity of diction, normal rate of presentation	6	0.713	1	6	0.719
9. He/she able to relieve tension and fatigue audience	5	0.632	3	5	0.743
10. He/she is able to orient students on the use of the material studied in future work	4.5	0.650	10	5	0.768
11. Creativity and interest in the work	6	0.500	5	6.5	0.542
12. Friendliness in dealing with students	4.5	0.654	5	6	0.792
13. Patience	6.5	0.354	6	7	0.425
14. Exactingness	6	0.587	5	7	0.663
15. Interest in student success	4.5	0.493	8	6	0.589
16. Objectivity in the assessment of knowledge	6	0.608	7	6.5	0.754
17. Respect for students	6	0.564	8	7	0.654
18. High erudition, demeanor, appearance	6	0.654	8	7	0.754

Y_Personality – criterion for assessing the teachers personal qualities:

Y_Personality = $0{,}93x_9 + 0{,}73x_{12} + 0{,}60x_{13} + 0{,}54x_{18}$;

Y_ProfCompetence – criterion assessing the teachers professional competence:

$$Y\_ProfCompetence = 0,86x_{10} + 0,51x_{11}$$

TABLE III. FACTOR LOADINGS

Variables (indicators)	Factors		
	Factor 1	***Factor 2***	***Factor 3***
1. He/she presents the teaching material clearly, available for students	0.87	0.12	0.11
2. Explains difficult moments	0.87	0.04	0.12
3. Highlights the main points	0.92	-0.25	0.04
4. He/she is able to induce and maintain audience interest	0.83	-0.24	-0.25
5. Monitoring the audience's reaction	0.88	0.02	-0.24
6. Asks questions to encourage discussion	0.78	0.06	0.02
7. Follows the logic in the presentation	0.89	-0.34	0.06
8. Demonstrates speech culture, clarity of diction, normal rate of presentation	0.68	0.93	-0.34
9. He/she able to relieve tension and fatigue audience	-0.06	-0.02	0.93
10. He/she is able to orient students on the use of the material studied in future work	0.21	0.24	-0.02
11. Creativity and interest in the work	0.19	0.73	0.24
12. Friendliness in dealing with students	-0.28	0.60	0.73
13. Patience	0.12	-0.39	0.60
14. Exactingness	0.79	0.11	-0.39
15. Interest in student success	0.01	0.07	0.11
16. Objectivity in the assessment of knowledge	0.39	-0.32	0.07
17. Respect for students	0.41	0.54	-0.32
18. High erudition, demeanor, appearance	-0.41	0.54	0.34

In [8–10], are presented the experimental effectiveness verification of the developed formal criteria.

III. DECISION MAKING ON THE FUZZY MODELS BASED

The issue of objects selection and their ordering in the context of education occurs quite often, and we can list a number of practical problems associated with this issue [8,11]:

1. Detection of students at the risk of psychophysiological and social exclusion (at-risk students)
2. The competitive selection for postgraduate studies and Master's degree
3. The selection of students, having completed Bachelor's programme, for the next level of study (engineer training)
4. The competitive selection of young scientists for the candidate pool
5. The formation of the database on graduates according to the available vacancies
6. The occupational guidance for prospective students (selection of the most suitable department) and the competitive selection (by additional criteria) among applicants with equal score on the results of entrance examinations
7. The competitive selection of students to study at the reserve-officer training department.

For these problems solving the authors have employed different methods and approaches, one of which is presented in this article. In the performance of the task of objects selection the original set X is divided into two classes: the class of admissible objects (feasible set) and a class of inadmissible objects. The utility value of objects is estimated on the basis of their characteristic symptoms.

In the case of the selection of non-dominated objects the precedence of one object over another is given only in case, when according to all criteria the first object (dominating) is not worse than the second object (dominated), and is better concerning at least one of criteria given. The set consisting of non-dominated objects is called the Pareto set. Algorithms for finding the Pareto set and limitations for the use of this method are detailed in [9].

In [9] for further ordering of objects included in the Pareto set it is proposed to use the apparatus of the fuzzy-set theory. In addition, the results of our studies, as well as analysis of other authors' works on the issue of selection and ordering of objects, whose signs turn up to be the elements and components of competence, have shown that the use of fuzzy models and algorithms of fuzzy logic is considered to be the most promising approach.

For further discussion it counts to provide a number of definitions and principles of the fuzzy-set theory and fuzzy logic, so let us briefly consider such concepts such as fuzzy rule and fuzzy inference.

In the fuzzy logic values of all variables are not represented by numbers but by words of a natural language and are called terms. Thus, to define the value of such linguistic variable as intellect the terms very high, high, medium, and so on can be used. Figure 1 shows the example illustrating the definition of the terms for such variable as intelligence quotient (IQ).

The determination of the precise physical values of the terms are regarded necessary to implement a linguistic variable. Suppose, for example, the variable ***intelligence (IQ)*** can take any value ranging from 60 to 140 points according to Amthauer's Intelligence Structure Test.

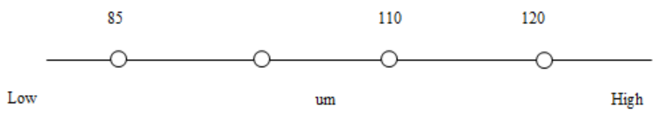

Fig. 1. Term range for the variable intelligence (IQ)

According to the fuzzy set theory, each value of IQ within the range of 140 points can be associated with a number from zero to one, which determines the degree of membership of the IQ value (for example, 100 points) to a particular term of the linguistic variable intellect. In our case, the IQ 120 point coefficient demonstrates the degree of membership to the term very high, equal to 0.85 and to the term medium equal to 0,15. The precise definition of the degree of membership is only possible when working with experts.

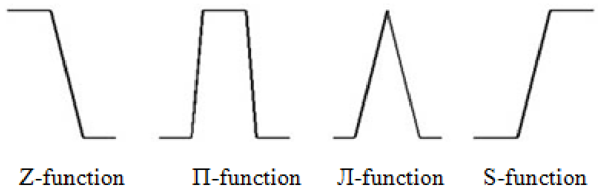

Fig. 2. Standard membership functions

The membership of each precise value to one of the terms of the linguistic variable is determined by ***the membership function***. It can be of any model, however the concept of the so-called standard membership functions has been recently formed (Fig.2). These standard membership functions can be easily applicable to most problem solving. We will use the method based on the interval estimates to construct the membership function.

The theory of possibilities is based on the assumption that there is an interval of criterion value of h [h^*, h^0], which corresponds to the concept of a ‘good’ object, and the boundary interval values have the following interpretation. Suppose h^a is the result of the measurement of the characteristic h of the object a, then h^a is the boundary of an ideal area, i.e. if $h^a \geq h^*$, the object must be considered to be the perfect correspondence to the concept of ‘good’. The possibility of such statement $\mu(u) = 1$ (where u is a subjective event coming from the expert’s viewpoint that the object is in a ‘good’ state). In case $h^a \leq h^0$, the situation is interpreted as follows: the possibility that the object is ‘good’ $\mu(u) = 0$. Obviously, when $h^0 < h^a < h^*$, the possibilities have values $0 < \mu(u) < 1$.

It is evident that with the approach of h^a to the boundary h^* the possibility of regarding a a ‘good’ object increases linearly (Fig. 3). At the same time for determination of the membership function the following formula:

$$\mu(u) = \begin{cases} 0, & if \quad h^a \leq h^0; \\ \dfrac{h^a - h^0}{h^* - h^0}, & if \quad h^0 < h^a \leq h^*; \\ 1, & if \quad h^a \geq h^*. \end{cases} \tag{3}$$

Table 1 shows threshold values of h^0 and h^* for some elements of subject-activity competence, which are obtained from the study of literature and our own research [12, 13]. In [11] the methods of alternatives selection in terms of fuzziness and our own developed algorithms on the basis of these methods are being considered. As the main decision-making criterion the minimax approach is used, it is necessary to dwell on this issue in more detail.

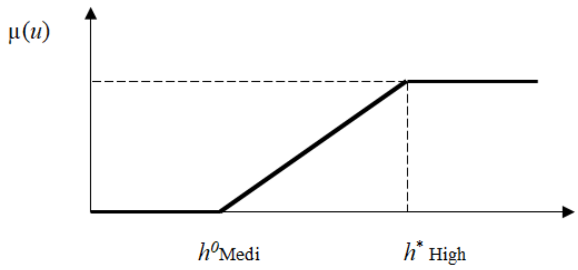

Fig. 3. Graphic representation of membership function

TABLE IV. THRESHOLD VALUES OF H^0 AND H* OF PSYCHOGNOSTIC INDICATORS

Indicators of psychological testing		Faculty of Cybernetics		Faculty of Mechanical Engineering		Faculty of Humanities	
		h0	***h****	***h0***	***h****	***h0***	***h****
Verbal intelligence	IQ1	90	120	80	115	100	125
Numeracy	IQ5	100	125	90	115	80	110
Mechanical intelligence	IQ6	100	125	105	125	80	100
Combinatorial thinking	IQ7	100	125	105	125	85	105
Spatial perception	IQ8	80	110	95	125	90	115
The ability to memorize and reproduce information	IQ9	85	115	90	115	95	125
Communicative skills	A	3	8	4	8	6	10
Logical thinking	B	6	10	5	8	4	8
Creativity	M	5	9	3	7	4	8
The ability to give nonstandard solutions	Q1	3	11	2	10	2	8

Note: IQ1, IQ5, IQ6, IQ7, IQ8, IQ9 – Amthauer's Intelligence Structure Test indicators; *A*, *B*, *M*, *Q1* – Cattell's 16 Personality Factors Test indicators.

IV. DECISION-MAKING ON THE BASIS OF THE MINIMAX CRITERION

The decision-making represents the selection of one option from the set of variants under consideration: $E_i \in E$. Each E_i determines a certain result e_i. The purpose is to select the variant with the maximal result $\max_i e_i$. In addition it is assumed that estimates e_i characterize such variables as benefit, reliability and usefulness. The opposite situation is examined similarly by minimizing the estimate or by analyzing the negative utility. Thus, the choice of the best variant is performed by using the criterion [12]:

$$E_0 = \{E_{i0} \mid E_{i0} \in E \wedge e_{i0} = \max_i e_i\} \tag{4}$$

This choice law usually means the following: the set of optimal variants E_0 consists of those variants E_{i0} that belong to the set of variants E and the estimate e_{i0} of which is maximal among all estimates e_i.

The maximum result $\max_i e_i$ can be achieved in the set of results repeatedly, so the choice of the optimal variant in accordance with the criterion (4) is not, generally speaking, unique as the necessity to choose one from several equally good solutions in practice does not usually cause any difficulties.

The case, when a decision in which each option corresponds to a unique external condition, is considered to be simple and quite common. In more complex structures, different external conditions (states) F_i and decision results e_{ij} may correspond to each valid variant E_i due to various external conditions. In this case e_{ij} is understood as having utility value, corresponding to variants E_i and conditions F_i.

There are a lot of decision criteria: the minimax criterion, the Bayes-Laplace criterion, extended minimax criterion; the Hurwitz criterion; the Savage criteria and some others [12]. For instance, the minimax criterion (MM) uses the evaluation function corresponding to the position of extreme caution. At

$$Z_{MM} = \max_i e_{ir} \text{ и } e_{ir} = \min_j e_{ij} \tag{5}$$

the relation is valid

$$E_0 = \{E_{i0} \mid E_{i0} \in E \wedge e_{i0} = \max_i \min_j e_{ij}\} \tag{6}$$

where Z_{MM} is a valuation function of MM-criterion.

In accordance with MM-criterion the decision rule can be interpreted as follows. Decision matrix $\|e_{ij}\|$ is complemented with another column containing minimum results e_{ir} of each line. The variants E_{io} having maximum value of e_{ir} in the column should be chosen.

Selected in such a way variants eliminate the risk completely. This means that the decision maker cannot face a worse outcome than the one he is focusing. No matter what conditions F_i occur, the result cannot be lower than Z_{MM}. This property makes the minimax criterion to be one of the fundamental ones [12], and that determined the choice of the criterion for the solution of the thesis work objective.

Decision-making is defined as choosing an alternative, which simultaneously satisfies the fuzzy goals and fuzzy constraints. In this regard, goals and constraints are symmetric with respect to the decision that blurs the distinction between them and allows to represent the solution as a fusion of fuzzy goals and constraints.

Having regard to the above, writing this work the modified algorithms for choosing alternatives under uncertainty were used to solve decision-making problems concerning the competence of students and graduates of the technical university [10]

V. Decision-making on the basis of the minimax criterion

Let assume that next sets are known: $X = \{x_1, x_2, ..., x_k)$ is a variety of options, which are subject to multi-criteria analysis; $G = \{G_1, G_2, ..., G_n)$ is set of quantitative and qualitative criteria, which evaluates alternatives. The goal of multi-criteria analysis is ordering of X elements according to the criteria of the set G. Let say that $\mu G_i(x_j)$ is a number in the range [0,1], which character rizes the level of assessment options $x_i \in X$ by $G_i \in G$ criteria. The greater the number $\mu G_i(x_j)$, the higher score x_j on the criterion G_i, $i = \overline{1,n}$, $j = \overline{1,k}$. Then the criterion G_i can be written as:

$$\overline{G}_i = \left\{ \frac{\mu G_i(x_1)}{x_1}, \frac{\mu G_i(x_2)}{x_2}, ..., \frac{\mu G_i(x_k)}{x_k} \right\} \tag{7}$$

where $\mu G_i(x_j)$ is degree of x_j membership of $\overline{G}_i$ fuzzy set. To determine the degree of fuzzy sets we use the method of construction of membership functions on the basis of paired comparisons. To do this, create a matrix of pairwise comparisons of options for each criterion. The total number of such matrices matches the number of criteria and equals n. The best option will be the one that at the same time the best in all criteria. Fuzzy decision $\overline{D}$ is calculated as intersection of partial criteria:

$$D = \overline{G}_1 \cap \overline{G}_2 \cap ... \cap \overline{G}_n = \tag{8}$$
$$\left\{ \frac{\min\limits_{i=1,n} \mu G_i(x_1)}{x_1}, \frac{\min\limits_{i=1,n} \mu G_i(x_2)}{x_2}, ..., \frac{\min\limits_{i=1,n} \mu G_i(x_k)}{x_k} \right\}$$

According to the obtained fuzzy set $\overline{D}$ the best option will be the one for which the degree of belonging is the greatest. Based on (8) we have next form if criteria have different ratio of importance:

$$\overline{D} = \left\{ \frac{\min\limits_{i=1,n} (\mu G_i(x_1))^{\alpha_i}}{x_1}, ..., \frac{\min\limits_{i=1,n} (\mu G_i(x_k))^{\alpha_i}}{x_k} \right\} \tag{9}$$

where a_i is relative ratio of importance criteria G_i, $\alpha_1+\alpha_2+...+\alpha_n=1$. Exponent α_i in (9) indicates the concentration of fuzzy set $\bar{G}_i$ in accordance with importance ratio of criteria. Factors of relative importance criteria can be determined by various methods, for example by means of paired comparisons of Saatyscale.

VI. Fuzzy multi-criteria analysis of the applicants competence for the vacant position

As an example of decision-making under fuzzy conditions according to the Bellman-Zadeh scheme, let us consider the comparison of professional levels of three technical university graduates (x_1, x_2, x_3) applying for the same vacant position.

In order to assess the candidates' competence we use the following criteria: G_1 – expertise; G_2 – social competence; G_3 – communicative competence; G_4 – intellectual competence; G_5 – creativity; G_6 – innovation potential. When the expert compared applicants (x_1, x_2, x_3) by criteria $(G_1, G_2,..., G_6)$, the linguistic statements presented in Table 2 were obtained.

TABLE V. Pairwise comparisons of graduates' competence according to the Saaty Rating Scale

Criterion	**Pairwise comparison**
G_1	Equal importance of x_1 and x_2 Strong advantage of x_3 over x_1
G_2	Moderate Plus advantage of x_1 over x_3 Moderate advantage of x_2 over x_3
G_3	Strong advantage of x_1 over x_2 Extreme advantage of x_1 over x_3
G_4	Moderate advantage of x_2 over x_1 Slight advantage of x_3 over x_1
G_5	Strong advantage of x_1 over x_2 Demonstrated advantage of x_1 over x_3
G_6	Moderate Plus advantage of x_1 over x_2 Slight advantage of x_3 over x_1

The given below matrix of pairwise comparisons $A(G_i)=\{x_{ij}\}$ corresponds to the expert statement:

$$A(G_1)=\begin{bmatrix}1 & 1 & 0.2\\ 1 & 1 & 0.2\\ 5 & 5 & 1\end{bmatrix},\qquad A(G_2)=\begin{bmatrix}1 & 1.35 & 4\\ 0.75 & 1 & 3\\ 0.25 & 0.33 & 1\end{bmatrix},$$

$$A(G_3)=\begin{bmatrix}1 & 5 & 7\\ 0.2 & 1 & 1.4\\ 0.14 & 0.71 & 1\end{bmatrix},\qquad A(G_4)=\begin{bmatrix}1 & 0.33 & 0.5\\ 3 & 1 & 1.5\\ 2 & 0.67 & 1\end{bmatrix},$$

$$A(G_5)=\begin{bmatrix}1 & 5 & 6\\ 0.2 & 1 & 1.2\\ 0.17 & 0.83 & 1\end{bmatrix},\qquad A(G_6)=\begin{bmatrix}1 & 4 & 0.5\\ 0.25 & 1 & 0.13\\ 2 & 8 & 1\end{bmatrix}.$$

Items matching pairwise comparisons from Table. 5 are shown in these matrices in semi-bold. Other elements have been found in the assumption of the compatibility of pairwise comparisons, i.e. taking into account that the matrix of pairwise comparisons is diagonal and has properties of transitivity and inverse symmetry.

$$\bar{G}_1=\left\{\frac{0.14}{x_1},\frac{0.14}{x_2},\frac{0.72}{x_3}\right\},\ \bar{G}_2=\left\{\frac{0.5}{x_1},\frac{0.38}{x_2},\frac{0.12}{x_3}\right\},$$

$$\bar{G}_3=\left\{\frac{0.74}{x_1},\frac{0.15}{x_2},\frac{0.11}{x_3}\right\},\ \bar{G}_4=\left\{\frac{0.17}{x_1},\frac{0.5}{x_2},\frac{0.33}{x_3}\right\},$$

$$\bar{G}_5=\left\{\frac{0.73}{x_1},\frac{0.15}{x_2},\frac{0.12}{x_3}\right\},\ \bar{G}_6=\left\{\frac{0.31}{x_1},\frac{0.08}{x_2},\frac{0.61}{x_3}\right\}.$$

According to the formula (8) we obtain $\bar{D}=\left\{\frac{0.14}{x_1},\frac{0.08}{x_2},\frac{0.11}{x_3}\right\}$ which indicates a strong advantage of applicant x_1 over applicant x_2 and a moderate advantage of applicant x_1 over applicant x_3. Assume that the criteria for $G_1, G_2,..., G_6$ are not in equilibrium. To determine the criterion ranking we use the method of pairwise comparisons and set the following linguistic statements concerning the importance of criteria:

- Moderate Plus advantage of G_2 over G_6
- Extreme advantage of G_3 over G_1
- Moderate advantage of G_3 over G_5
- Slight advantage of G_4 over G_6
- Equal importance of G_5 and G_6

The following matrix of pairwise comparisons $A=\{G_{ij}\}$ corresponds to the expert statements:

$$A=\begin{bmatrix}1 & 0.25 & 0.14 & 0.21 & 0.43 & 0.43\\ 4 & 1 & 0.57 & 0.86 & 1.71 & 1.71\\ 7 & 1.75 & 1 & 1.5 & 3 & 3\\ 4.67 & 1.17 & 0.67 & 1 & 2 & 2\\ 2.33 & 0.58 & 0.33 & 0.5 & 1 & 1\\ 2.33 & 0.58 & 0.33 & 0.5 & 1 & 1\end{bmatrix}$$

Let the criteria ranks $G_1, G_2,..., G_6$ be defined as follows: $\alpha_1=0.04$; $\alpha_2=0.19$; $\alpha_3=0.33$; $\alpha_4=0.22$; $\alpha_5=0.11$; $\alpha_6=0.11$, which marks the communicative competence (G_3) and intellectual competence (G_4) to be of most importance. Using the (9) we obtain the fuzzy sets:

$$\bar{G}_1=\left\{\frac{0.14^{0.04}}{x_1},\frac{0.14^{0.04}}{x_2},\frac{0.72^{0.04}}{x_3}\right\}=\left\{\frac{0.91}{x_1},\frac{0.91}{x_2},\frac{0.98}{x_3}\right\};$$

$$\bar{G}_2=\left\{\frac{0.5^{0.19}}{x_1},\frac{0.38^{0.19}}{x_2},\frac{0.12^{0.19}}{x_3}\right\}=\left\{\frac{0.88}{x_1},\frac{0.83}{x_2},\frac{0.68}{x_3}\right\};$$

$$\overline{G}_3 = \left\{ \frac{0.74^{0.33}}{x_1}, \frac{0.15^{0.33}}{x_2}, \frac{0.11^{0.33}}{x_3} \right\} = \left\{ \frac{0.91}{x_1}, \frac{0.53}{x_2}, \frac{0.48}{x_3} \right\};$$

$$\overline{G}_4 = \left\{ \frac{0.17^{0.22}}{x_1}, \frac{0.5^{0.22}}{x_2}, \frac{0.33^{0.22}}{x_3} \right\} = \left\{ \frac{0.68}{x_1}, \frac{0.86}{x_2}, \frac{0.79}{x_3} \right\};$$

$$\overline{G}_5 = \left\{ \frac{0.73^{0.11}}{x_1}, \frac{0.15^{0.11}}{x_2}, \frac{0.12^{0.11}}{x_3} \right\} = \left\{ \frac{0.97}{x_1}, \frac{0.81}{x_2}, \frac{0.79}{x_3} \right\};$$

$$\overline{G}_6 = \left\{ \frac{0.31^{0.11}}{x_1}, \frac{0.08^{0.11}}{x_2}, \frac{0.61^{0.11}}{x_3} \right\} = \left\{ \frac{0.88}{x_1}, \frac{0.76}{x_2}, \frac{0.95}{x_3} \right\}.$$

As a result of the intersection of fuzzy sets $G_1, G_2, ..., G_6$ we get the following: $\overline{D} = \left\{ \frac{0.68}{x_1}, \frac{0.53}{x_2}, \frac{0.48}{x_3} \right\}$, that demonstrates a strong advantage of graduate x_1 over the graduates x_2 and x_3, and a moderate advantage of graduate x_2 over the graduate x_3.

On the basis of the presented algorithm the authors developed a universal program COMPETENCE for evaluating the competence of professionals of any profile.

VII. Conclusion

In conclusion are noted the following. Firstly, the cumulative indicators construction technology and criteria for competence estimates have been designed and demonstrated. On this criteria base the rating forming algorithms were developed. They allowing to minimize the role of the subjective factor in above tasks solution. Next, cumulative criteria which are derived from fuzzy set theory have been designed. The proposed approaches is demonstrated on practical examples.

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