Lecture Notes in Networks and Systems 69

Kohei Arai Rahul Bhatia *Editors*

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Advances in Information and Communication

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Muhammad Babar, Waseem Iqbal, and Sarah Kaleem



Two Approaches to Country Risk Evaluation

Ramin Rzayev¹, Sevinj Babayeva¹(⊠), Inara Rzayeva², and Adila Ali³

¹ Department of Information Systems, Institute of Control Systems, ANAS ICS, Baku, Azerbaijan {raminrza, babayevasevinj}@yahoo.com ² Department of International Economics, Azerbaijan State University of Economics, UNEC, Baku, Azerbaijan ina3r@mail.ru ³ Department of MSc Business Analytics, University College London, UCL, London, UK aliadelae@gmail.com

Abstract. Weighted attribute estimates and fuzzy inference methods are based on two approaches to evaluate the levels of country risk which are considered on the base of expert judgments. To obtain the final estimates of the country risk levels for an arbitrary set of alternatives these approaches are used on the base of expert conclusions regarding factors of country risk. The study is completed by comparative analysis of finale estimates of country risks.

Keywords: Country risk · Concordance coefficient · Estimate · Expert conclusion · Fuzzy set · Fuzzy conclusion

1 Introduction

Country risk (CR) is a multifactor category that is characterized by a combined system of financial, economic, socio-political, and legal factors, which distinguishes the market of any country. According to the degree of risk, all countries are ranked by quantitative assessments of CR levels. A consolidated risk indicator *R* is used, which aggregates the relative influence of the considered number of factors (variables) of CR x_i (i = 1-n) by the function $R = R(x_1, x_2, ..., x_n)$.

Ranking of countries by degree of CP includes the following stages:

- selection the financial, economic, socio-political and legal variables of the CR;
- identification of the weights of the selected CR variables, based on their relative impact on the CR-level;
- expert evaluation of CR-factors using the expert scale;
- determination of a weighted index reflecting the CR-level.

Currently, many world rating agencies and international institutions, such as the Economist Intelligence Unit, Euromoney, Institutional Investor, Mood's Investor

© Springer Nature Switzerland AG 2020 K. Arai and R. Bhatia (Eds.): FICC 2019, LNNS 69, pp. 793–812, 2020. https://doi.org/10.1007/978-3-030-12388-8_54 Service, Standart & Poor's Rating Group, The European Bank for Reconstruction and Development (EBRD), the World Bank (WB), etc., range countries on the CR levels and their approaches are determined by qualitative and/or quantitative, economic, combined and structurally-qualitative methods of CR estimation.

To date, there are quite a lot of numerical methods for solving this type of problem. In particular, in Boolean case such estimates can be realized by Boolfilter and BoolNet package vignettes, which were respectively considered in [1, 2]. However, the main purpose of this study is to evaluate the levels of country risk by applying the fuzzy inference for identification the function $R = R(x_1, x_2, ..., x_n)$.

2 Selection of the List of CR-Factors

The CR evaluation is a multi-criteria procedure, implying the use of the composite rule of aggregating the assessment for each of the selected risk factors. To date, there is no unified approach to calculating the CR index, since there are different points of view regarding the composition of CR factors. For example, in the process of ranging analysts of EBRD use indicators such as macroeconomic stability, taxation conditions, the quality of the judicial system, the level of corruption in the country, the finances of the leading base enterprises, the infrastructure. Another authoritative opinion on the investment attractiveness of states is the WB rating, which is established on the base of CR evaluations. At the same time, the WB assessment methodology takes into account the CR factors, such as the risks of nationalization and expropriation, risks related to private and foreign capital, the level of state policy, including the government's stable policy and its popularity among citizens, the industrial cycle stage, market capacity and the resulting financial and currency risks, labor force qualification.

For visual demonstration of the proposed methods for CR evaluation, we chosen a rather limited list of risk factors used by the audit company Pricewaterhous Coopers in the process of its ranging of the investment attractiveness of states [3]. Namely: x_1 —the level of corruption; x_2 —compliance with legislation; x_3 —level of economic development; x_4 —state policy on accounting and control; x_5 —state regulation.

3 Ranking of CR-Variables in the Orders of Experts' Preferences

Suppose that expert estimates of the importance degrees for CR-factors x_i (i = 1-5) are determined by separate survey of 15 core specialists. Each expert was invited to arrange the variable x_i according to the principle: the most important variable should be designated by the number "1", the next less important one—by the number "2" and further in descending order of importance. Obtained all rank estimates are summarized in the form of Table 1.

Expert number	Expert number CR-variables and													
	their rank estimates													
	(<i>r</i> _{<i>ij</i>})													
	x_1	<i>x</i> ₂	<i>x</i> ₃	<i>x</i> ₄	<i>x</i> 5									
01	1	2	4	3	5									
02	1	3	2	4	5									
03	2	1	5	4	3									
04	1	2	4	5	3									
05	2	1	3	4	5									
06	1	2	4	3	5									
07	2	1	4	3	5									
08	1	2	4	5	3									
09	1	3	2	4	5									
10	1	3	2	5	4									
11	1	3	4	2	5									
12	1	2	3	5	4									
13	2	1	4	3	5									
14	3	1	2	4	5									
15	1	2	5	4	3									
$\sum r_{ij}$	21	29	52	55	65									

 Table 1. Ranking of CR-variables

To establish the degree of consistency of expert opinions, we use the Kendall concordance coefficient, which demonstrates the multiple rank correlation of expert opinions. According to [4, 5], this coefficient is calculated by the formula:

$$W = \frac{12 \cdot S}{m^2(n^3 - n)},\tag{1}$$

where m is the number of experts, n is the number of CR-variables, and S is the deviation of expert conclusions from the average value of the CR-variables ranking, which is calculated, for example, by the formula [3]:

$$S = \sum_{i=1}^{n} \left(\sum_{j=1}^{m} r_{ij} - \frac{m(n+1)}{2} \right)^2,$$
(2)

where $r_{ij} \in \{1; 2; 3; 4; 5\}$ is the rank of *i*-th CR-variable established by *j*-th expert. Then at the value of S = 1450 calculated on the base formula (2) and data from Table 1, the value of the Kendall concordance coefficient is W = 0.6444 > 0.6. This indicates a sufficiently *strong* agreement of expert conclusions regarding the importance degree of CR-variables.

4 Identification of Weights of the CR-Variables

Now, suppose that at the preliminary stage of separate questionnaire each expert was also instructed to establish the values of the normalized estimates of CR-variables, which determine the specific density (weight) of the influence of each factor on the scale of the unit interval. The results of this questionnaire are summarized in Table 2.

Expert number	r CR-variables and their normalized							
	estima	tes (α_{ij})						
*****	<i>x</i> ₁	<i>x</i> ₂	<i>x</i> 3	<i>x</i> ₄	x_5			
01	0.300	0.250	0.150	0.225	0.075			
02	0.350	0.175	0.200	0.150	0.125			
03	0.225	0.250	0.150	0.175	0.200			
04	0.275	0.250	0.175	0.100	0.200			
05	0.250	0.275	0.200	0.175	0.100			
06	0.300	0.250	0.150	0.200	0.100			
07	0.200	0.375	0.150	0.175	0.100			
08	0.325	0.300	0.150	0.025	0.200			
09	0.275	0.175	0.200	0.100	0.250			
10	0.300	0.200	0.250	0.100	0.150			
11	0.300	0.175	0.150	0.250	0.125			
12	0.300	0.250	0.200	0.100	0.150			
13	0.225	0.250	0.175	0.200	0.150			
14	0.200	0.300	0.250	0.150	0.100			
15	0.300	0.250	0.125	0.150	0.175			
$\sum \alpha_{ij}$	4.125	3.725	2.675	2.275	2.200			

 Table 2.
 Normalized estimates of CR-variables

Starting from the data presented in Table 2, let us make preliminary calculations for the subsequent identification of the weights of CR-variables: it is necessary to define their group estimates and the numerical characteristics (degrees) of competence of each expert.

To calculate the average value of α_i for *i*-th group of normalized estimates of CR-variables it is possible use the weighted degrees of expert competence by following difference equation:

$$\alpha_i(t+1) = \sum_{j=1}^m w_j(t)\alpha_{ij},\tag{3}$$

where $w_j(t)$ is the weight characterizing the competence degree of the *j*th expert (j = 1-m) at time *t*. It is clear that the process of finding of group estimates of the normalized values has an iterative character, which is completed under condition:

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$$\max\{|\alpha_i(t+1) - \alpha_i(t)|\} \le \varepsilon,\tag{4}$$

where ε is the allowable accuracy of calculations, which is set in advance. In our case, let it be $\varepsilon = 0.0001$.

At the initial stage t = 0 we assume that experts have the same degrees of competence. Then, assuming for the general case the value $w_j(0) = 1/m$ as initial value of the competence degree of each expert, the average value for the *i*-th group of normalized estimates of CR-variables in the first approximation is obtained from the particular equality:

$$\alpha_i(1) = \sum_{j=1}^m w_j(0) \alpha_{ij} = \frac{1}{m} \sum_{j=1}^m \alpha_{ij}.$$
(5)

In accordance with (5), the averaged estimates of CR-variables into divisions in the first approximation are the following corresponding numbers: { $\alpha_1(1)$; $\alpha_2(1)$; $\alpha_3(1)$; $\alpha_4(1)$; $\alpha_5(1)$ } = {0.27500; 0.24833; 0.17833; 0.15167; 0.14667}. It is not difficult to see that requirement (4) is not satisfied for the first approximation. Therefore, before move up to the next iteration step, it is necessary calculate the normalizing coefficient as:

$$\eta(1) = \sum_{i=1}^{5} \sum_{j=1}^{15} \alpha_i(1) \alpha_{ij} = 3.2042.$$

Then the competence indicators of experts can be calculated according to the following expressions:

$$\begin{cases} w_j(1) = \frac{1}{\eta(1)} \sum_{i=1}^{5} \alpha_i(1) \cdot \alpha_{ij} \ (j = \overline{1, 14}), \\ w_{15}(1) = 1 - \sum_{j=1}^{14} w_j(1), \\ \sum_{j=1}^{15} w_j(1) = 1, \end{cases}$$
(6)

where $w_{15}(1)$ is the competency indicator of the 15-th expert. Thus, on the base of expressions (6), in the 1-st approximation there are following competence indicators of experts:

$$\begin{cases} w_1(1); w_2(1); w_3(1); w_4(1); w_5(1); w_6(1); w_7(1); w_8(1); \\ w_9(1); w_{10}(1); w_{11}(1); w_{12}(1); w_{13}(1); w_{14}(1); w_{15}(1) \end{cases}$$

= {0.0676; 0.0676; 0.0645; 0.0666; 0.0668; 0.0675;
0.0674; 0.0698; 0.0645; 0.0668; 0.0652; 0.0679; 0.0648; 0.0660; 0.0672}.

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Now we can proceed to the calculation of the mean group estimate of CR-variables in the 2-nd approximation by the formula (3), or more precisely by its particular expression:

$$\alpha_i(2) = \sum_{j=1}^{15} w_j(1) \alpha_{ij}.$$

In this case, the average estimates of the CR-variables for groups $i = 1 \div 5$ are the following numbers: { $\alpha_1(2)$; $\alpha_2(2)$; $\alpha_3(2)$; $\alpha_4(2)$; $\alpha_5(2)$ } = {0.27547; 0.24876; 0.17821; 0.15116; 0.14640}.

Checking these values for the fulfillment of condition (4) and making sure that it is not fulfilled again:

$$\max\{|\alpha_i(2) - \alpha_i(1)|\} = 0.0005 > \varepsilon,$$

let us calculate the normalizing coefficient as:

$$\eta(2) = \sum_{i=1}^{5} \sum_{j=1}^{15} \alpha_i(2) \alpha_{ij} = 3.2056.$$

Then the expert competence indicators at the 2-nd approximation $w_j(2)$ (j = 1-15) will be: $w_j(2)$ (j = 1-15) will be: $\{w_1(2); w_2(2); w_3(2); w_4(2); w_5(2); w_6(2); w_7(2); w_8(2); w_9(2); w_{10}(2); w_{11}(2); w_{12}(2); w_{13}(2); w_{14}(2); w_{15}(2)\} = \{0.0676; 0.0676; 0.0645; 0.0666; 0.0666; 0.06675; 0.0674; 0.0699; 0.0645; 0.0668; 0.0652; 0.0679; 0.0647; 0.0660; 0.0672\}.$

The average group estimates for the CR-variables in the 3-rd approximation can be obtained from the following particular case of formula (3), namely: $\alpha_i(3) = \sum_{j=1}^{15} w_j(2)\alpha_{ij}$. In this case, the average estimates of the CR-variables for groups $i = 1 \div 5$ are the following numbers: $\{\alpha_1(3); \alpha_2(3); \alpha_3(3); \alpha_4(3); \alpha_5(3)\} = \{0.27547; 0.24876; 0.17821; 0.15115; 0.14640\}.$

As can be seen, the accuracy of group estimates of the CR-variables in the 3-rd approximation already satisfies condition (4), i.e.: $\max\{|\alpha_i(3) - \alpha_i(2)|\} = 0.00001 < \varepsilon$, which is the reason for stopping the calculations. In this case, the values of the group estimates of the CR-variables, i.e. $\{\alpha_1(3); \alpha_2(3); \alpha_3(3); \alpha_4(3); \alpha_5(3)\}$ are the final (consolidated) weights of the variables x_i (i = 1-5).

5 Determination of Weighted CR-Level on the Base of Expert Estimations

The method of expert assessments involves discussing the factors that affect the CR-level of a particular country by a group of experts specially involved for this purpose. Each of the experts is provided with a list of possible risks on the basis of the

CR-variables x_i (i = 1-5) and they are invited to give an separate assessment of the probability of their occurrence in percentage terms on the base of the following five-point rating system:

- 5—insignificant risk;
- 4—the risk situation will not come for most probability;
- 3—about the possibility of risk it is impossible to say anything definite;
- 2-the risk situation will most probably come;
- 1—the risk situation will surely come.

Further, expert assessments of risk situations are analyzed for consistency (or inconsistency) according to the rule: the maximum allowable difference between two expert opinions for any type of risk relative to x_i (i = 1-5) should not exceed a value of 3. This rule allows to filter out inadmissible deviations in expert assessments of the probability of risk occurrence for the separate CR-variable.

The calculation of the total index, theoretically ranging from 0 to 100, can be carried out by the following evaluation criterion:

$$R = \frac{\sum_{i=1}^{5} \alpha_{i} e_{i}}{\max_{i} \sum_{i=1}^{5} \alpha_{i} e_{i}} \times 100$$
(7)

Interval	CR-level	Explanation
(90; 100]	Too low or absent	The financial-economic, socio-political, and state-legal statuses are estimated as stable in the long-term outlook
(80; 90]	Very low or insignificant	The financial-economic, socio-political, and state-legal statuses are estimated as stable in the medium-term outlook
(70; 80]	More than low	The financial-economic, socio-political, and state-legal statuses are estimated as stable in the near-term outlook
(60; 70]	Low	The main indicators of the financial-economic, socio-political, and state-legal conditions are estimated as satisfactory and stable in the near-term outlook
(50; 60]	High	The main indicators of the financial-economic, socio-political and state-legal conditions are estimated as satisfactory, but their stability is doubtful
(40; 50]	More than high	The main indicators of financial-economic, socio-political, and state-legal conditions are estimated as close to satisfactory, but their stability is more than doubtful
(30; 40]	Very high or significant	The financial-economic, socio-political, and state-legal statuses are estimated as unsatisfactory or close to satisfactory, but unstable
[0; 30]	Too high or impermissible	Financial-economic, socio-political and state-legal statuses are estimated as stably unsatisfactory

	Table 3.	Gradation	of	the	total	weighted	estimates	of	CF
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where α_i is the weight of the significance of *i*-th CR-variable, e_i is the expert estimate of the probability of risk occurrence for *i*-th CR-variable based on the five-point rating system. In this case, the minimum index means the maximum risk, and vice versa, and the index of CR-level is established on the assumption of the graduation of the resulting weighted estimates, which summarized in Table 3.

Now let us assume that the expert community is offered to test 10 alternative countries a_k (k = 1-10) on the five-point system to assess the degree of influence of financial, economic, socio-political and state-legal factors in these countries on their. Thus, for these countries the consolidated (average) expert opinions based estimates of the CR-level are obtained by application of the total evaluation criterion (7). These estimates are summarized in Table 4.

State	Identifie	es $\alpha_i(3)$	Ratio			
	0.2755	0.2488	0.1782	0.1512	0.1464	
	Normal	ized estin	mates of	CR-vari	ables	
	<i>e</i> ₁	e ₂	<i>e</i> 3	<i>e</i> ₄	e5	
a_1	4.5	4.75	4.5	4.75	4.25	91.27
a_2	4.85	4.50	4.55	2.75	3.75	84.62
<i>a</i> ₃	3.75	4.00	3.25	3.85	3.25	73.30
<i>a</i> ₄	4.25	3.45	2.85	2.75	1.85	64.47
<i>a</i> ₅	4.00	2.55	3.00	2.25	1.85	57.64
<i>a</i> ₆	3.55	2.85	2.00	1.25	0.85	47.13
a7	2.25	1.75	1.25	1.85	1.50	35.54
a_8	2.25	1.85	1.25	0.75	0.25	29.06
<i>a</i> 9	5.00	4.75	4.85	4.85	4.75	97.04
<i>a</i> ₁₀	3.25	2.85	3.75	4.25	3.50	68.55

 Table 4. Total estimates of CR-levels

6 Determination of the CR-Level Using the Fuzzy Inference

All existing models of CR-evaluation have certain advantages and disadvantages. For example, the approach described above, which based on the application of the expert evaluation system, is criticized for absence there a cause-effect relations. In particular, the gradation of the CR-levels, presented in Table 3, was chosen conditionally—without any objective justifications. As a rule, such gradation is established by the expert community or heuristic knowledge. Therefore, before we begin to form a model for estimating the CR-level, it is necessary to construct a justified gradation scale.

A. CR-levels classification

CR-level evaluation being a multi-criteria procedure implies application of the composite rule of aggregation of the evaluation in each specific case. To estimate the CR-level we choose eight estimated concepts (or terms): u_1 —"too low"; u_2 —"very

low"; u_3 —"more than low"; u_4 —"low"; u_5 —"high", u_6 —"more than high", u_7 —"very high", u_8 —"too high". More simply, by the set $C = (u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8)$ we will mean the set of criterions of classification of the CR-levels. Then, assuming the factors of CR as linguistic variables, the CR-level estimation can be realized by application of the sufficient set of consistent rules of the form "lf < ... >, then < ... >" and based on them it is possible to establish the corresponding scale for gradation the final estimates of the CR-levels. The basic judgments can be formulate as follows:

 d_1 : "If there is no corruption and economic development is observed, then the CR-level is acceptable";

 d_2 : "If in addition to the above requirements the state policies on accounting and control are implemented, then the CR-level is more than acceptable";

 d_3 : "If in addition to the conditions stipulated in d_2 there is appropriate legislation and state regulation is implemented, then the CR-level is low";

 d_4 : "If there is no corruption, there is appropriate legislation, economic development is observed, the state policies on accounting and control are implemented, then the CR-level is very acceptable";

 d_5 : "If there is adequate legislation, economic development is observed, and state policies on accounting and control are implemented, but there is display of corruption, the CR-level is still acceptable";

 d_6 : "If there is display of corruption, there is no development of the economy, and there is no state regulation, then the CR-level is unacceptable".

In the above statements, reflecting the internal cause-effect relations, the factors influencing the CR-level will be considered as inputs in the form of linguistic variables x_i (i = 1-5), and the output is a linguistic variable y whose terms reflect the CR-levels. Then, having specified the corresponding terms of these variables, on the basis of the above statements it is possible to construct implicative rules as following [6]:

 d_1 : "If x_1 = absent and x_3 = observed, then y = acceptable";

 d_2 : "If x_1 = absent and x_3 = observed and x_4 = implemented, then y = more than acceptable";

 d_3 : "If x_1 = absent and x_2 = exist and x_3 = observed and x_4 = implemented and x_5 = implemented, then y = low";

 d_4 : "If x_1 = absent and x_2 = exist and x_3 = observed and x_4 = implemented, then y = very acceptable";

 d_5 : "If x_1 = display and x_2 = exist and x_3 = observed and x_4 = implemented, then y = very acceptable";

 d_6 : "If x_1 = display and x_3 = not visible and x_5 = not implemented, then y = unacceptable".

Linguistic variable y can be defined on the discrete set $J = \{0; 0.1; 0.2; ...;1\}$. Then, $\forall j \in J$ its terms can be described by fuzzy subsets of J by following membership functions [6]: S = acceptable, $\mu_S(j) = j$; MS = more than acceptable, $\mu_{MS}(j) = \sqrt{j}$; L = low, $\mu_L(j) = 1$, if j = 1 and $\mu_L(j) = 0$, if j < 1; VS = very acceptable, $\mu_{VS}(j) = j^2$; US = unacceptable, $\mu_{US}(j) = 1 - j$.

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The fuzzification of terms in the left-hand parts of the rules can be realized by Gaussian membership function: $\mu(u) = \exp\{-(u - u_0)^2/\sigma_i^2\}$ (i = 1-5), which restore fuzzy subsets of the discrete universe $C = (u_1, u_2, u_3, ..., u_8)$, where $u_k = (a_{k+1} + a_k)/2$ (k = 1-8) (see Fig. 1). In this case, the density of elements distribution σ_i^2 for the *i*-th factor is chosen individually on the assumption of condition of its criticality. It should be noted that the inaccuracy as a result of an arbitrary density choice is eliminated during the intersection of fuzzy sets in the left-parts of the rules. In Fig. 1, the gradation of CR-factors is presented in a general form. However, it is obvious the segment $[a_0, a_8]$ can be easily reduced to the unit segment [0; 1] by a simple transformation $t = (u - a_0)/(a_8 - a_0)$, where $u \in [a_0, a_8]$, $t \in [0; 1]$.



Fig. 1. Uniform gradation of CR-factors



Fig. 2. Uniform gradation of CR-factors at the scale of the unit segment

Estimating the CR-level from the point of view of the factors x_i (i = 1-5), which are graded at the scale of the unit segment (Fig. 2), where $a_k = 0.125 \ k \ (k = 0-8)$, all terms from the left-hand parts of the rules can be fuzzyfied in the following form:

- Absent (corruption): $A = \{0.9070/u_1; 0.6766/u_2; 0.4152/u_3; 0.2096/u_4; 0.0870/u_5; 0.0297/u_6; 0.0084/u_7; 0.0019/u_8\};$
- Exist (appropriate legislation): $B = \{0.9070/u_1; 0.6766/u_2; 0.4152/u_3; 0.2096/u_4; 0.0870/u_5; 0.0297/u_6; 0.0084/u_7; 0.0019/u_8\};$
- Observed (economic development): $C = \{0.9394/u_1; 0.7788/u_2; 0.5698/u_3; 0.3679/u_4; 0.2096/u_5; 0.1054/u_6; 0.0468/u_7; 0.0183/u_8\};$
- Implemented (state policies on accounting and control): $D = \{0.9497/u_1; 0.8133/u_2; 0.6282/u_3; 0.4376/u_4; 0.2749/u_5; 0.1557/u_6; 0.0796/u_7; 0.0367/u_8\};$
- Implemented (state regulation) $E = \{0.9575/u_1; 0.8406/u_2; 0.6766/u_3; 0.4994/u_4; 0.3379/u_5; 0.2096/u_6; 0.1192/u_7; 0.0622/u_8\}.$

Then taking into account these formalisms, the implicative rules in the symbolic expression will be as:

 $\begin{array}{l} d_1: \ (x_1 = A)\&(x_3 = C) \Rightarrow (y = S);\\ d_2: \ (x_1 = A)\&(x_3 = C)\&(x_4 = D) \Rightarrow (y = MS);\\ d_3: \ (x_1 = A)\&(x_2 = B)\&(x_3 = C)\&(x_4 = D)\&(x_5 = E) \Rightarrow (y = L);\\ d_4: \ (x_1 = A)\&(x_2 = B)\&(x_3 = C)\&(x_4 = D) \Rightarrow (y = VS);\\ d_5: \ (x_1 = \neg A)\&(x_2 = B)\&(x_3 = C)\&(x_4 = D) \Rightarrow (y = S);\\ d_6: \ (x_1 = A)\&(x_3 = \neg C)\&(x_5 = \neg E) \Rightarrow (y = US). \end{array}$

Further, for the left-parts of these rules, it necessary to find the membership functions of appropriate fuzzy sets obtained by intersection [6]:

 $\begin{aligned} d_1: \ \mu_{M1}(u) &= \min\{\mu_A(u), \ \mu_C(u)\}, \ M_1 &= \{0.9070/u_1; \ 0.6766/u_2; \ 0.4152/u_3; \ 0.2096/u_4; \ 0.0870/u_5; \ 0.0297/u_6; \ 0.0084/u_7; \ 0.0019/u_8\}; \\ d_2: \ \mu_{M2}(u) &= \min\{\mu_A(u), \ \mu_C(u), \ \mu_D(u)\}, \ M_2 &= \{0.9070/u_1; \ 0.6766/u_2; \ 0.4152/u_3; \ 0.2096/u_4; \ 0.0870/u_5; \ 0.0297/u_6; \ 0.0084/u_7; \ 0.0019/u_8\}; \\ d_3: \ \mu_{M3}(u) &= \min\{\mu_A(u), \ \mu_B(u), \ \mu_C(u), \ \mu_D(u), \ \mu_E(u)\}, \ M_3 &= \{0.9070/u_1; \ 0.6766/u_2; \ 0.4152/u_3; \ 0.2096/u_4; \ 0.0870/u_5; \ 0.0297/u_6; \ 0.0084/u_7; \ 0.0019/u_8\}; \\ d_4: \ \mu_{M4}(u) &= \min\{\mu_A(u), \ \mu_B(u), \ \mu_C(u), \ \mu_D(u)\}, \ M_4 &= \{0.9070/u_1; \ 0.6766/u_2; \ 0.4152/u_3; \ 0.2096/u_4; \ 0.0870/u_5; \ 0.0297/u_6; \ 0.0084/u_7; \ 0.0019/u_8\}; \\ d_5: \ \ \mu_{M5}(u) &= \min\{1-\mu_A(u), \ \mu_B(u), \ \ \mu_C(u), \ \ \mu_D(u)\}, \ M_5 &= \{0.0930/u_1; \ 0.3234/u_2; \ 0.4994/u_3; \ 0.2910/u_4; \ 0.1453/u_5; \ 0.0622/u_6; \ 0.0228/u_7; \ 0.0072/u_8\}; \\ d_6: \ \ \mu_{M6}(u) &= \min\{1-\mu_A(u), \ 1-\mu_C(u), \ 1-\mu_E(u)\}, \ M_6 &= \{0.0425/u_1; \ 0.1594/u_2; \ 0.3234/u_3; \ 0.5006/u_4; \ 0.6621/u_5; \ 0.7904/u_6; \ 0.8808/u_7; \ 0.9378/u_8\}. \end{aligned}$

As a result, the rules can be described as:

 $d_1: (x = M_1) \Rightarrow (y = S);$ $d_2: (x = M_2) \Rightarrow (y = MS);$ $d_3: (x = M_3) \Rightarrow (y = L);$ $d_4: (x = M_4) \Rightarrow (y = VS);$ $d_5: (x = M_5) \Rightarrow (y = S);$ $d_6: (x = M_6) \Rightarrow (y = US).$

These rules are transformed by Lukasiewicz's implication [7]:

$$\mu_{U \times J}(u,j) = \min\{1, 1 - \mu_U(u) + \mu_J(j)\},\tag{8}$$

as a result of which for each pair $(u, j) \in U \times J$ the fuzzy relations are obtained in the form of correspondent matrix:

	Г	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1]	
	0.9070	0.0930	0.1930	0.2930	0.3930	0.4930	0.5930	0.6930	0.7930	0.8930	0.9930	1.0000	
	0.6766	0.3234	0.4234	0.5234	0.6234	0.7234	0.8234	0.9234	1.0000	1.0000	1.0000	1.0000	
	0.4152	0.5848	0.6848	0.7848	0.8848	0.9848	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
$R_1 =$	0.2096	0.7904	0.8904	0.9904	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	;
	0.0870	0.9130	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
	0.0297	0.9703	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
	0.0084	0.9916	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
	0.0019	0.9981	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	

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$R_2 =$	0.9070 0.6766 0.4152 0.2096 0.0870 0.0297 0.0084 0.0019	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0.3162 0.4093 0.6396 0.9010 1.0000 1.0000 1.0000 1.0000	0.4472 0.5403 0.7706 1.0000 1.0000 1.0000 1.0000 1.0000	0.5477 0.6408 0.8711 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.6325 0.7255 0.9558 1.0000 1.0000 1.0000 1.0000 1.0000	0.7071 0.8001 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.7746 0.8676 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.8367 0.9297 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.8944 0.9875 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.9487 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	1 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
$R_3 =$	0.9070 0.6766 0.4152 0.2096 0.0870 0.0297 0.0084 0.0019	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	1 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
$R_4 =$	0.9070 0.6766 0.4152 0.2096 0.0870 0.0297 0.0084 0.0019	0 0.0930 0.3234 0.5848 0.7904 0.9130 0.9703 0.9916 0.9981	$\begin{array}{c} 0.01 \\ 0.1030 \\ 0.3334 \\ 0.5848 \\ 0.8004 \\ 0.9230 \\ 0.9803 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c} 0.04 \\ 0.1330 \\ 0.3634 \\ 0.6248 \\ 0.8304 \\ 0.9530 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	0.09 0.1830 0.4134 0.6748 0.8804 1.0000 1.0000 1.0000	0.16 0.2530 0.4834 0.7448 0.9504 1.0000 1.0000 1.0000	0.25 0.3430 0.5734 0.8348 1.0000 1.0000 1.0000 1.0000	0.36 0.4530 0.6834 0.9448 1.0000 1.0000 1.0000 1.0000	0.49 0.5830 0.8134 1.0000 1.0000 1.0000 1.0000 1.0000	$\begin{array}{c} 0.64 \\ 0.7330 \\ 0.9634 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c} 0.81 \\ 0.9030 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c}1\\1.0000\\1.0000\\1.0000\\1.0000\\1.0000\\1.0000\\1.0000\\1.0000\\1.0000\end{array}];$
$R_{5} =$	0.0930 0.3234 0.4994 0.2910 0.1453 0.0622 0.0228 0.0072	0 0.9070 0.6766 0.5006 0.7090 0.8547 0.9378 0.9772 0.9928	$\begin{array}{c} 0.1 \\ 1.0000 \\ 0.7766 \\ 0.6006 \\ 0.8090 \\ 0.9547 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c} 0.2 \\ 1.0000 \\ 0.8766 \\ 0.7006 \\ 0.9090 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c} 0.3 \\ 1.0000 \\ 0.9766 \\ 0.8006 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c} 0.4 \\ 1.0000 \\ 1.0000 \\ 0.9006 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	$\begin{array}{c} 0.5\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\end{array}$	0.6 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.7 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	$\begin{array}{c} 0.8\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\\ 1.0000\end{array}$	$\begin{array}{c} 0.9 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \\ 1.0000 \end{array}$	1 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
$R_6 =$	0.0425 0.1594 0.3234 0.5006 0.6621 0.7904 0.8808 0.9378	1 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000	0.9 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 0.9622	0.8 1.0000 1.0000 1.0000 1.0000 1.0000 0.9192 0.8622	0.7 1.0000 1.0000 1.0000 1.0000 0.9096 0.8192 0.7622	0.6 1.0000 1.0000 1.0000 0.9379 0.8096 0.7192 0.6622	0.5 1.0000 1.0000 0.9994 0.8379 0.7096 0.6192 0.5622	0.4 1.0000 1.0000 0.8994 0.7379 0.6096 0.5192 0.4622	0.3 1.0000 1.0000 0.9766 0.7994 0.6379 0.5096 0.4192 0.3622	0.2 1.0000 1.0000 0.8766 0.6994 0.5379 0.4096 0.3192 0.2622	0.1 1.0000 0.9406 0.7766 0.5994 0.4379 0.3096 0.2192 0.1622	$\begin{array}{c} 0\\ 0.9575\\ 0.8406\\ 0.6766\\ 0.4994\\ 0.3379\\ 0.2096\\ 0.1192\\ 0.0622\\ \end{array}$

As a result of intersection of fuzzy relations $R_1, R_2, ..., R_6$ we finally obtain a general functional solution R reflecting the cause-effect relations between the factors x_i (i = 1-5), on the one hand, and, in fact, the CR-level, on the other.

	Г	0	0.1	0.2	0.3	0.4	0.5	0.6	07	0.8	0.0	1 7	1
	u_1	0.0930	0.0930	0.0930	0.0930	0.0930	0.0930	0.0930	0.0930	0.0930	0.0930	0.9575	
	<i>u</i> ₂	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.8406	
	<i>u</i> ₃	0.5006	0.5848	0.5848	0.5848	0.5848	0.5848	0.5848	0.5848	0.5848	0.5848	0.6766	
R =	<i>u</i> ₄	0.7090	0.7904	0.7904	0.7904	0.7904	0.7904	0.7904	0.7904	0.6994	0.5994	0.4994	
	<i>u</i> 5	0.8547	0.9130	0.9130	0.9130	0.9130	0.8379	0.7379	0.6379	0.5379	0.4379	0.3379	
	и6	0.9378	0.9703	0.9703	0.9096	0.8096	0.7096	0.6096	0.5096	0.4096	0.3096	0.2096	
	<i>u</i> 7	0.9772	0.9916	0.9192	0.8192	0.7192	0.6192	0.5192	0.4192	0.3192	0.2192	0.1192	
	$\lfloor u_8$	0.9928	0.9622	0.8622	0.7622	0.6622	0.5622	0.4622	0.3622	0.2622	0.1622	0.0622	

To determine the CR-level it is necessary to apply the rule of composite conclusion in a fuzzy environment [6]:

$$E_k = G_k^{\circ} R, \tag{9}$$

where E_k is the acceptability degree of risk relative to the k-th CR-level (k = 1-8), G_k is the mapping of the k-th CR-level in the form of a fuzzy subset of the discrete universe J. Then, choosing a composite rule as [6]

$$\mu_{E_k}(j) = \max_{j \in J} \{ \min[\mu_{G_k}(j), \mu_R(j)] \},$$
(10)

and assuming that in this case $\mu_{G_k}(j) = \begin{cases} 0, j \neq j_k; \\ 1, j = j_k, \end{cases}$ finally we have: $\mu_{Ek}(u) = \mu_R(j_k, u),$

that is, in other words, E_k is the k-th row of the matrix R.

Now, to classify the CR-levels defuzzification procedure for the fuzzy outputs of the applied model is used. So, for the estimated concept u_1 of risk acceptability, the fuzzy interpretation of the corresponding CR-level will be the following fuzzy subset of the universe *J*: $E_1 = \{0.0930/0; 0.0930/0.1; 0.0930/0.2; 0.0930/0.3; 0.0930/0.4; 0.0930/0.5; 0.0930/0.6; 0.0930/0.7; 0.0930/0.8; 0.0930/0.9; 0.9575/1\}.$

Setting the level sets $E_{1\alpha}$ and calculating the corresponding powers $M(E_{1\alpha})$ by the formula $M(E_{1\alpha}) = \sum_{r=1}^{n} \frac{x_r}{n}$, we have:

- for $0 < \alpha < 0.0930$: $\Delta \alpha = 0.0930$, $E_{1\alpha} = \{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{1\alpha}) = 0.5$;
- for $0.0930 < \alpha < 0.9575$: $\Delta \alpha = 0.8645$, $E_{1\alpha} = \{1\}$, $M(E_{1\alpha}) = 1$.

For numerical estimations of fuzzy outputs E_k (k = 1-8) following formula can be applied [8, 9]:

$$F(E_k) = \frac{1}{\alpha_{\max}} \int_{0}^{\alpha_{\max}} M(E_{k\alpha}) d\alpha, (k = 1 - 5), \qquad (11)$$

where α_{\max} is the maximum value on E_k . Thus, in this case we have:

$$F(E_1) = \frac{1}{0.9575} \int_{0}^{0.9575} M(E_{1\alpha}) d\alpha = \frac{0.5 \cdot 0.0930 + 1.0 \cdot 0.8645}{0.9575} = 0.9514.$$

For estimated concept u_8 of risk acceptability, the reflection of the corresponding CR-level will be following fuzzy set: $E_8 = \{0.9928/0; 0.9622/0.1; 0.8622/0.2; 0.7622/0.3; 0.6622/0.4; 0.5622/0.5; 0.4622/0.6; 0.3622/0.7; 0.2622/0.8; 0.1622/0.9; 0.0622/1\}, for which we have, respectively:$

- for $0 < \alpha < 0.0622$: $\Delta \alpha = 0.0622$, $E_{8\alpha} = \{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{8\alpha}) = 0.5$;
- for 0.0622 < α < 0.1622: $\Delta \alpha$ = 0.1, $E_{8\alpha}$ = {0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9}, $M(E_{8\alpha}) = 0.45$;
- for 0.1622 < α < 0.2622: $\Delta \alpha$ = 0.1, $E_{8\alpha}$ = {0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8}, $M(E_{8\alpha})$ = 0.40;
- for 0.2622 < α < 0.3622: $\Delta \alpha$ = 0.1, $E_{8\alpha}$ = {0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7}, M($E_{8\alpha}$) = 0.35;
- for $0.3622 < \alpha < 0.4622$: $\Delta \alpha = 0.1$, $E_{8\alpha} = \{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6\}$, $M(E_{8\alpha}) = 0.30$;
- for 0.4622 < α < 0.5622: $\Delta \alpha = 0.1$, $E_{8\alpha} = \{0; 0.1; 0.2; 0.3; 0.4; 0.5\}$, $M(E_{8\alpha}) = 0.25;$
- for $0.5622 < \alpha < 0.6622$: $\Delta \alpha = 0.1$, $E_{8\alpha} = \{0; 0.1; 0.2; 0.3; 0.4\}$, $M(E_{8\alpha}) = 0.20$;
- for $0.6622 < \alpha < 0.7622$: $\Delta \alpha = 0.1$, $E_{8\alpha} = \{0; 0.1; 0.2; 0.3\}$, $M(E_{8\alpha}) = 0.15$;
- for $0.7622 < \alpha < 0.8622$: $\Delta \alpha = 0.1$, $E_{8\alpha} = \{0; 0.1; 0.2\}$, $M(E_{8\alpha}) = 0.10$;
- for $0.8622 < \alpha < 0.9622$: $\Delta \alpha = 0.1$, $E_{8\alpha} = \{0; 0.1\}$, $M(E_{8\alpha}) = 0.05$;
- for $0.9622 < \alpha < 0.9928$: $\Delta \alpha = 0.0307$, $E_{8\alpha} = \{0\}$, $M(E_{8\alpha}) = 0$.

Then the numerical estimate of the fuzzy output E_8 will be:

$$F(E_8) = \frac{1}{0.9928} \int_{0}^{0.9928} M(E_{8\alpha}) d\alpha = 0.2579.$$

Point estimates for remaining fuzzy outputs are calculated by similar actions: for the estimated concept u_2 of risk acceptability— $F(E_2) = 0.8077$; u_3 — $F(E_3) = 0.5741$; u_4 — $F(E_4) = 0.4689$; u_5 — $F(E_5) = 0.3964$; u_6 — $F(E_6) = 0.3324$; u_7 — $F(E_7) = 0.2863$.

 $F(E_8) = 0.2579$ is the least defuzzified output of the applied model of the multicriterion assessment of the CR-level, as the upper bound it corresponds to the consolidated estimation of the CR-level "too high or impermissible". From the point of view of the influence of the CR-factors, for others the defuzzified outputs we have, respectively:

- 0.2863 is upper bound of estimate "very high or significant";
- 0.3324 is upper bound of estimate "more than high";
- 0.3964 is upper bound of estimate "high";

- 0.4689 is upper bound of estimate "low";
- 0.5741 is upper bound of estimate "more than low";
- 0.8077 is upper bound of estimate "very low or insignificant";
- 0.9514 is upper bound of estimate "too low or absent".

As a criterion for the forming of the final estimation the following equality

$$E = \frac{F(E_k)}{F_{\text{max}}} \times 100 \tag{12}$$

is applied, where $F(E_k)$ is the estimate of the k-th CR-level (to wide extent also any other estimate); $F_{\text{max}} = F(E_1) = 0.9514$. Then, in the accepted assumptions, the justified scale for estimation the CR-level within the framework of the segment [0; 100] is summarized in Table 5.

Interval	CR-level
(84.90; 100]	Too low or absent
(60.34; 84.90]	Very low or insignificant
(49.29; 60.34]	More than low
(41.66; 49.29]	Low
(34.94; 41.66]	High
(30.09; 34.94]	More than high
(27.11; 30.09]	Very high or significant
[0; 27.11]	Too high or impermissible

Table 5. Gradation of CR-levels using the fuzzy inference

B. CR-levels classification

To construct the fuzzy inference system according to the CR-level estimation, the basis verbal model is chosen by above statements d_1-d_6 . As alternatives, ten hypothetical states a_k (k = 1-10) are used, which having passed expert examination on a five-mark grading system for the influences of CR-factors x_i (i = 1-5) on their CR-levels (see Table 4). In this case, for the terms from the left-hand parts of the rules d_1-d_6 , the procedure for fuzzification can be applied somewhat differently, namely: each term is reflected as a fuzzy subset of the final set of estimated alternatives (countries) $\{a_1, a_2, ..., a_{10}\}$ as $A_i = \{\mu_{Ai}(a_1)/a_1; \mu_{Ai}(a_2)/a_2; ...; \mu_{Ai}(a_{10})/a_{10}\}$, where $\mu_{Ai}(a_t)$ is the value of the membership function of the fuzzy set A_i , i.e. it characterizes the country a_t with respect to the assessment criterion A_i . As a membership function, Gaussian function is chosen in the form of:

$$\mu_{Ai}(a_t) = \exp\{-[e_i(a_t) - 5]^2 / \sigma_i^2\},\$$

where $e_i(a_t)$ is the consolidated expert evaluation of the country a_t (t = 1-10), which is given by five-mark grading system for compliance with the *i*-th CR-factor as non-

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existent; σ_i^2 is the density of the location of the nearest elements, which is chosen as 4 for all cases of the fuzzification. Then, assuming each of the CR-factors CP x_i (i = 1-5) as the linguistic variable, one of its terms, namely "non-existent risk » can be described in the form of the corresponding fuzzy subset A_i . of the discrete universe $U = \{a_1, a_2, ..., a_{10}\}$ as follows [7]:

- $A_1 = \{0.9394/a_1; 0.9944/a_2; 0.6766/a_3; 0.8688/a_4; 0.7788/a_5; 0.5912/a_6; 0.1510/a_7; 0.1510/a_8; 1.0000/a_9; 0.4650/a_{10}\};$
- $A_2 = \{0.9845/a_1; 0.9394/a_2; 0.7788/a_3; 0.5485/a_4; 0.2230/a_5; 0.3149/a_6; 0.0713/a_7; 0.0837/a_8; 0.9845/a_9; 0.3149/a_{10}\};$
- $A_3 = \{0.9394/a_1; 0.9506/a_2; 0.4650/a_3; 0.3149/a_4; 0.3679/a_5; 0.1054/a_6; 0.0297/a_7; 0.0297/a_8; 0.9944/a_9; 0.6766/a_{10}\};$
- $A_4 = \{0.9845/a_1; 0.2821/a_2; 0.7185/a_3; 0.2821/a_4; 0.1510/a_5; 0.0297/a_6; 0.0837/a_7; 0.0109/a_8; 0.9944/a_9; 0.8688/a_{10}\};$
- $A_5 = \{0.8688/a_1; 0.6766/a_2; 0.4650/a_3; 0.0837/a_4; 0.0837/a_5; 0.0135/a_6; 0.0468/a_7; 0.0036/a_8; 0.9845/a_9; 0.5698/a_{10}\}.$

Then, taking these formalisms into account and presented above formal descriptions of terms from the right-hand parts of the rules d_1-d_6 , the basic model is written as following:

 $\begin{aligned} &d_1: (x_1 = A_1)\&(x_3 = A_3) \Rightarrow (y = S); \\ &d_2: (x_1 = A_1)\&(x_3 = A_3)\&(x_4 = A_4) \Rightarrow (y = MS); \\ &d_3: (x_1 = A_1)\&(x_2 = A_2)\&(x_3 = A_3)\&(x_4 = A_4)\&(x_5 = A_5) \Rightarrow (y = L); \\ &d_4: (x_1 = A_1)\&(x_2 = A_2)\&(x_3 = A_3)\&(x_4 = A_4) \Rightarrow (y = VS); \\ &d_5: (x_1 = \neg A_1)\&(x_2 = A_2)\&(x_3 = A_3)\&(x_4 = A_4) \Rightarrow (y = S); \\ &d_6: (x_1 = A_1)\&(x_3 = \neg A_3)\&(x_5 = \neg A_5) \Rightarrow (y = US). \end{aligned}$

Similarly, intersections of fuzzy sets from the left-parts of the rules are established. In the discrete case, these are determined by finding the minimum of the corresponding values of membership functions, namely:

 $\begin{aligned} &d_1: \ \mu_{M1}(u) = \min\{\mu_{A1}(u), \ \mu_{A3}(u)\}, \ M_1 = \{0.9394/a_1; \ 0.9506/a_2; \ 0.4650/a_3; \ 0.3149/a_4; \ 0.3679/a_5; \ 0.1054/a_6; \ 0.0297/a_7; \ 0.0297/a_8; \ 0.9944/a_9; \ 0.4650/a_{10}\}; \\ &d_2: \ \mu_{M2}(u) = \min\{\mu_{A1}(u), \ \mu_{A3}(u), \ \mu_{A4}(u)\}, \ M_2 = \{0.9394/a_1; \ 0.2821/a_2; \ 0.4650/a_3; \ 0.4650/a$

 $u_{2} \mu_{M2}(u) = \min\{\mu_{A1}(u), \mu_{A3}(u), \mu_{A4}(u)\}, M_{2} = \{0.9394/a_{1}; 0.2821/a_{2}; 0.4650/a_{3}; 0.2821/a_{4}; 0.1510/a_{5}; 0.0297/a_{6}; 0.0297/a_{7}; 0.0109/a_{8}; 0.9944/a_{9}; 0.4650/a_{10}\};$

 $d_3: \mu_{M3}(u) = \min\{\mu_{A1}(u), \mu_{A2}(u), \mu_{A3}(u), \mu_{A4}(u), \mu_{A5}(u)\}, M_3 = \{0.8688/a_1; 0.2821/a_2; 0.4650/a_3; 0.0837/a_4; 0.0837/a_5; 0.0135/a_6; 0.0297/a_7; 0.0036/a_8; 0.9845/a_9; 0.3149/a_{10}\};$

 $\begin{array}{l} d_4: \ \mu_{M4}(u) = \min\{\mu_{A1}(u), \ \mu_{A2}(u), \ \mu_{A3}(u), \ \mu_{A4}(u)\}, \ M_4 = \{0.9394/a_1; \ 0.2821/a_2; \\ 0.4650/a_3; \ 0.2821/a_4; \ 0.1510/a_5; \ 0.0297/a_6; \ 0.0297/a_7; \ 0.0109/a_8; \ 0.9845/a_9; \\ 0.3149/a_{10}\}; \end{array}$

 $d_5: \mu_{M5}(u) = \min\{1 - \mu_{A1}(u), \mu_{A2}(u), \mu_{A3}(u), \mu_{A4}(u)\}, M_5 = \{0.0606/a_1; 0.0056/a_2; 0.3234/a_3; 0.1312/a_4; 0.1510/a_5; 0.0297/a_6; 0.0297/a_7; 0.0109/a_8; 0.0000/a_9; 0.3149/a_{10}\};$

 $d_6: \ \mu_{M6}(u) = \min\{1 - \mu_{A1}(u), \ 1 - \mu_{A3}(u), \ 1 - \mu_{A5}(u)\}, \ M_6 = \{0.0606/a_1; \ 0.0056/a_2; \ 0.3234/a_3; \ 0.1312/a_4; \ 0.2212/a_5; \ 0.4088/a_6; \ 0.8490/a_7; \ 0.8490/a_8; \ 0.0000/a_9; \ 0.3234/a_{10}\}.$

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As a result, the rules are described in a more compact form:

 $d_1: (x = M_1) \Rightarrow (y = S);$ $d_2: (x = M_2) \Rightarrow (y = MS);$ $d_3: (x = M_3) \Rightarrow (y = L);$ $d_4: (x = M_4) \Rightarrow (y = VS);$ $d_5: (x = M_5) \Rightarrow (y = S);$ $d_6: (x = M_6) \Rightarrow (y = US).$

As above these rules are transformed by Lukasiewicz's implication (8) into the fuzzy relations R_1 , R_2 , ..., R_6 , intersection of which creates the following general matrix solution R.

	Γ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1]
	a_1	0.0606	0.0706	0.1006	0.1312	0.1312	0.1312	0.1312	0.1312	0.1312	0.1312	0.9394
	a_2	0.0444	0.1494	0.2494	0.3494	0.4494	0.5494	0.6494	0.7179	0.7179	0.7179	0.9944
	a ₃	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.6766
	<i>a</i> ₄	0.6851	0.7279	0.7579	0.8079	0.8779	0.9163	0.9163	0.9163	0.9163	0.9163	0.8688
R =	<i>a</i> ₅	0.6321	0.7321	0.8321	0.9163	0.9163	0.9163	0.9163	0.9163	0.9163	0.8788	0.7788
	<i>a</i> ₆	0.8946	0.9803	0.9865	0.9865	0.9865	0.9865	0.9865	0.8912	0.7912	0.6912	0.5912
	a7	0.9703	0.9703	0.9510	0.8510	0.7510	0.6510	0.5510	0.4510	0.3510	0.2510	0.1510
	a8	0.9703	0.9964	0.9510	0.8510	0.7510	0.6510	0.5510	0.4510	0.3510	0.2510	0.1510
	<i>a</i> 9	0.0056	0.0155	0.0155	0.0155	0.0155	0.0155	0.0155	0.0155	0.0155	0.0155	1.0000
	<i>a</i> ₁₀	0.5350	0.6350	0.6851	0.6851	0.6851	0.6851	0.6851	0.6851	0.6851	0.6851	0.6766

On the discrete set J the matrix R reflects the cause-effect relations between the consolidated expert assessments of countries by CR-factors x_i (i = 1-5), on the one hand, and, corresponding their CR-levels, on the other

According to (9) and (10), the *k*-th row of the matrix *R* is a fuzzy conclusion relative to the aggregated CR-level for the *k*-th alternative (country). In order to numerically interpret each of these fuzzy conclusions it necessary to apply the defuzzification procedure based on the method of point estimation of fuzzy sets. In particular, for a fuzzy conclusion regarding the CR-level of the first alternative $E_1 = \{0.0606/0; 0.0706/0.1; 0.1006/0.2; 0.1312/0.3; 0.1312/0.4; 0.1312/0.5; 0.1312/0.6; 0.1312/0.7; 0.1312/0.8; 0.1312/0.9; 0.9394/1\}$ according to the above arguments, we have:

- for $0 < \alpha < 0.0606$: $\Delta \alpha = 0.0606$, $E_{1\alpha} = \{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{1\alpha}) = 0.5$;
- for 0.0606 < α < 0.0706: $\Delta \alpha$ = 0.01, $E_{1\alpha}$ = {0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1}, $M(E_{1\alpha})$ = 0.55;
- for 0.0706 < α < 0.1006: $\Delta \alpha$ = 0.03, $E_{1\alpha}$ = {0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1}, $M(E_{1\alpha}) = 0.60;$
- for 0.1006 < α < 0.1312: $\Delta \alpha$ = 0.0306, $E_{1\alpha}$ = {0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1}, M ($E_{1\alpha}$) = 0.65;
- for $0.1312 < \alpha < 0.9394$: $\Delta \alpha = 0.8082$, $E_{1\alpha} = \{1\}$, $M(E_{1\alpha}) = 1$.

Then, according to (11) the numerical estimate of E_1 is:

$$F(E_1) = \frac{1}{0.9388} \int_{0}^{0.9388} M(E_{8\alpha}) d\alpha = 0.9388.$$

The point estimates of fuzzy conclusions about CR-levels for other alternative countries are established by similar actions: $F(E_2) = 0.7687$; $F(E_3) = 0.6047$; $F(E_4) = 0.5370$; $F(E_5) = 0.5206$; $F(E_6) = 0.4552$; $F(E_7) = 0.3055$; $F(E_8) = 0.3001$; $F(E_9) = 0.9927$; $F(E_{10}) = 0.5140$. As a result, according classification presented in Table 5, the ratio of the total estimates of the CR-levels on the scale of the interval [0; 100] are obtained by simply multiplying these values by 100.

7 Conclusion

So, two approaches to the evaluation of CR-levels are considered on the base of the application of expert conclusions regarding the degrees of influence of the factors x_i (i = 1-5) on the CR-level.

As a result of applying the method of weighted estimates of attributes, it was possible to determine the coefficient of rank correlation of CR-factors x_i (i = 1-5), which indicated sufficiently high degree of agreement between expert opinions, but also a close relationships between the considered CR-factors.

In addition, within the framework of this approach the generalized values of the weights of the CR-factors x_i (i = 1-5) were calculated by analytical reasoning, which became the basis for justifying and developing recommendations for the formation of final estimates of the CR-levels by the established comparison criterion at the scale of the interval [0; 100].

The method of weighted estimates can be used in the decision-making process as effective mechanism for multicriterion evaluation of alternatives characterized by a certain set of attributes.

In fact, fuzzy inference, which is the essence of the second approach similarly solves the discussed problem, with the only difference that it relies not on an indirect, but on a direct cause-effect relations between the factors x_i (i = 1-5) and CR-levels. As a result of the application of fuzzy inference, it was possible to formulate a valid scale of CR-levels gradation and it is relatively easy to obtain finale estimates of the CR-levels.

Comparative analysis of the results of estimations the CR-levels for hypothetical alternatives (countries) a_k (k = 1-10) obtained by both methods is presented in the form of Table 6.

As can be seen from Table 6, the orders of final estimates of the CR-levels only for alternatives a_4 , a_5 and a_{10} are different. With comparing by denominations of estimates, the CR-levels do not always coincide too. It is explained by different approaches to the formation of a grading scale for the final estimates of the CR-levels. Nevertheless, the

a_i	Weighted	estimation		Fuzzy inference				
	Finale estimate	CR-level according to uniform gradation	Order	Finale estimate	CR-level according to fuzzy gradation	Order		
a_1	91.27	Too low or absent	2	93.88	Too low or absent	2		
<i>a</i> ₂	84.62	Very low or insignificant	3	76.87	Very low or insignificant	3		
<i>a</i> ₃	73.30	More than low	4	60.47	Very low or insignificant	4		
a_4	64.47	Low	6	53.70	More than low	5		
a_5	57.64	High	7	52.06	More than low	6		
<i>a</i> ₆	47.13	More than high	8	45.52	Low	8		
<i>a</i> 7	35.54	Very high or significant	9	30.55	More than high	9		
<i>a</i> ₈	29.06	Too high or impermissible	10	30.01	Very high or significant	10		
<i>a</i> 9	97.04	Too low or absent	1	99.27	Too low or absent	1		
<i>a</i> ₁₀	68.55	Low	5	51.40	More than low	7		

 Table 6. Comparative analysis of the obtained results

fuzzy approach based classification of the final estimates is more confidence, since in this case the cause-effect relations between the influence factors and the CR-levels are traced, even though these relations are formulated on the base of trivial, but consistent and sufficiently valid implicative rules.

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