Method Of Assessing Investment Risks Based On Fuzzy Modeling Of The Net Present Value Of Innovative Projects

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Abstract

The article proposes an approach to assessing investment risks based on fuzzy modelling of the efficiency of innovative projects. The net present value indicator is considered as an efficiency model. In this indicator, the cash inflow parameter, considering its uncertainty, is specified by fuzzy linguistic estimates. A procedure for approximating linguistic estimates by fuzzy triangular and trapezoid numbers based on Gaussian membership functions is proposed. To simulate the efficiency indicator, the Neumann elimination method is used, in which Gaussian functions are considered as functions of the distribution density of cash inflow expectations. An example is provided to illustrate this approach.

Keywords

innovative project, risk, net present value, fuzzy sets, linguistic estimate, membership function, Neumann method.

1. Introduction

The last decades have vividly demonstrated the scientific and practical significance of innovative development as a key factor in the economic growth of national economies and all business entities [1-3]. A characteristic feature of innovative design is forward-looking characters of its results. Moreover, the more distant the time horizon of the forecast, the less accurate it is.

The uncertainty of the forecasted results leads to the risk that the goals set in the project may not be fully or partially achieved. Especially serious consequences can result from erroneous decisions regarding long-term investments. Therefore, when making decisions related to the implementation of innovative projects, risk assessment is one of the main components of investment analysis.

Many studies have been dedicated to the assessment of risks of innovative projects [4-8]. The analysis of innovative activity shows that the assessment of risks of innovative (venture) projects is characterized by the fact that such projects are aimed at the development and implementation of a new product (item) or technology. Consequently, there is no statistical information about the object of research, and it is often not possible to draw an analogy with similar projects. Therefore, those involved in the innovative process are forced to be guided not by data and calculations confirmed by previous practice, but largely by their own subjective feelings and assessments, including in relation to risks [5]. This, in turn, reduces the reliability of the initial data and parameters of the forecast model, which may lead to an incorrect risk assessment and, consequently, to a wrong investment decision.

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In order to increase the reliability of the results of forecast models under conditions of uncertainty, the values of their parameters can be specified by a standard min-max interval. However, such a representation is often unsatisfactory, since it is necessary to specify its boundaries. And these boundaries can be either overestimated or underestimated, which will raise doubts about the accuracy of the results.

Therefore, it is more appropriate to set these parameters fuzzy intervals. Firstly, such assessments are psychologically easier to give under conditions of uncertainty, and secondly, the fuzzy interval will necessarily contain the value of the given parameter, which will reduce a person's uncertainty about the correctness of his assessment [9].

The use of fuzzy estimates leads to the need for fuzzy risk modeling and their assessment. Recently, fuzzy modeling has become a promising area of research in the field of analysis and risk assessment of innovation and investment projects [10-15]. In particular, the works [14,15] consider the issues of fuzzy estimation of model parameters and the use of Gaussian membership functions in the modeling process.

This article further develops the ideas and approaches discussed in [15], in particular, the mechanism for estimating parameters in the models of the effectiveness of innovative projects and the procedure for modeling risks based on the Neumann method.

2. Efficiency indicator for innovative projects

Assessing the efficiency of innovative projects is one of the main elements of investment analysis. The more large-scale the innovative project and the more significant changes it brings to the business, the more accurate the calculations of cash flows and the methods of evaluating the efficiency of such projects must be [16].

In investment analysis, the net present value (NPV) of a project is most used as a predictive model of project efficiency. It characterizes the overall economic effect of an innovative project and allows one to assess the feasibility of investing funds. The net present value it is calculated by discounting (reducing to the present value, i.e., at the time of investment) the expected cash flows (both income and expenses) [17]:

$$NPV = \sum_{i=1}^{n} \frac{CF_i}{(1+p)^i} - IC, \tag{1}$$

where n is the total number of periods (horizon of calculation), p – interest rate or discount factor, IC– investment in the project, CF_i – cash inflow in the i-th year.

The interest rate p (Discount Rate) determines the investor's income from the implementation of an innovative project. Analyzing its possible options allows the investor to adopt an acceptable level of profitability for them as the discount rate.

Initial investments IC (Invest Capital) are associated with preparing production for the release of new or improved products. The goal of preparing new production is to transition the manufacturing process to a higher technical and socio-economic level, ensuring the effective operation of the enterprise. Therefore, to make an investment decision, a justified assessment of initial investments is necessary, which to some extent compensates for such risks.

The paper [15] examines in detail the approach to the assessment and justification of initial investments. In this approach, the volume of investments and the duration of the innovation process are determined using fuzzy linguistic estimates of the cost and time of work using β-distribution. This makes it possible to estimate the payback period of investments relative to the beginning of the innovation process, which is more informative for the investor than an assessment of only the investment period. Given the above, we will omit this important stage of innovation design.

The main parameter on the basis of which the calculation is made is the annual cash flow CF_i. The value of this parameter can be obtained by one of the known methods [18] or by combining these methods with the logical inference method [19].

At the same time, it should be noted that the uncertainty of this parameter is due to both economic factors (fluctuations in market conditions, prices, exchange rates, inflation, etc.) that are independent of investors' efforts, and non-economic factors (climatic and natural conditions, political relations, etc.). And since these factors cannot always be precisely determined, it is more rational to set this parameter using fuzzy expert assessments.

3. Fuzzy Linguistic Assessments

As noted, in conditions of uncertainty, in order to increase the reliability of the results of forecast models, it is advisable to define their parameters by fuzzy numbers and intervals. Moreover, it is desirable to represent such numbers and intervals by fuzzy statements that are natural for a person. Therefore, we will specify the expected cash inflow by fuzzy linguistic estimates. A linguistic evaluation is a numerical evaluation that is specified by a statement with the quantifier "approximately":

"the inflow is approximately equal to a" (2)

or

"the inflow is approximately in the range from a to b." (3)

Moreover, statements (2), as a rule, are used in the presence of minor uncertainty, and statements (3) are used in the presence of significant uncertainty.

Linguistic fuzzy assessments under conditions of uncertainty, of course, increase a person's confidence in their judgments, but at the same time they are subjective. Therefore, in such cases, a group examination is necessary, the reliability of the results of which depends on the consistency of the experts' assessments.

The issues of coordinating group expert assessments were considered in [18-21]. In particular, [21] provides a mechanism for checking the consistency of interval assessments, in which the coefficient of variation is used as a measure of consistency. If the expert assessments are given by statements (2), then this coefficient is calculated using the formula

$$V = \frac{s}{\overline{a}}, \tag{4}$$

where s is the standard deviation of the estimates a_j, $\overline{a}$ is their mean value.

Here

$$s = \sqrt{\sum_{j=1}^{k}(a_j - \overline{a})^2 r_j} \text{ and } \overline{a} = \sum_{j=1}^{k} a_j r_j,$$

where r_j is the weighting coefficient of the j-th expert, moreover $\sum_{j=1}^{k} r_j=1$.

When estimates are expressed by statements (3), then the coefficient of variation (4) is calculated separately for the left and right boundaries of the intervals.

Let $[a_1, b_1]$,...,$[a_k, b_k]$ be the intervals of fuzzy linguistic estimates given by k experts. Then, for the left boundaries of these intervals, the coefficients (4) are calculated using the formula

$$V_L = \frac{s_L}{\overline{a}_L}, \tag{5}$$

where

$$s_L = \sqrt{\sum_{j=1}^{k}(a_j - \overline{a}_L)^2 r_j}, \ \overline{a}_L = \sum_{j=1}^{k} a_j r_j; \tag{6}$$

and for the right boundaries by the formula

$$V_R = \frac{s_R}{\overline{b}_R}, \tag{7}$$

where

$$s_R = \sqrt{\sum_{j=1}^{k}(b_j - \overline{b}_R)^2 r_j}, \ \overline{b}_R = \sum_{j=1}^{k} b_j r_j \, . \tag{8}$$

In these formulas V_L and V_R are the variation coefficients, $s_L$and s_R are the standard deviations, $\overline{a}_L$ and $\overline{b}_R$ are the mean values of the interval boundaries $[a_k, b_k]$.

The practice of conducting expertise shows that their results are satisfactory when 0.2≤V≤0.3 and good when V<0.2. These criteria are the basis for refining the assessments.

After the linguistic evaluations have been agreed upon, they are represented by fuzzy numbers of the (L-R) type. Statements (2) are represented by triangular numbers (a, α, β), and statements (3) are represented by trapezoid numbers (a, b, α, β). Since a and b are given by linguistic estimates, it is therefore only necessary to calculate the fuzziness coefficients α and β, which determine the boundaries of the interval of possible values of cash inflow.

4. Calculation of fuzzy coefficients

These coefficients determine the boundaries of the carriers of fuzzy sets (2) or (3). In practice, the standard and combined (double) Gaussian membership functions are most widely used to represent fuzzy sets.

The standard Gaussian function is used to define fuzzy sets $\tilde{A} \triangleq$ "the number is approximately equal to a". According to [24], this function has the form:

$$\mu_{\tilde{A}}(x) = exp(-c(x-a)^2), \tag{9}$$

where $c = -\frac{4\,ln\,0.5}{b^2(a)}$, and b(a) determines the distance between the transition points.

The carrier of the fuzzy set described by function (9) is unlimited, therefore in practice it is limited to values at which the function is equal to 0.01. To find the fuzziness coefficients, one can either solve the equation $\mu_{\tilde{A}}(x) = 0.01$, the roots of which will be α and β, or calculate them using a simpler approximate method [15]:

$$\alpha = a - k \cdot \frac{b(a)}{2}, \quad \beta = a + k \cdot \frac{b(a)}{2}, \tag{10}$$

where k is the scaling coefficient that determines the boundaries of the fuzzy set carrier for the corresponding value of its membership function. For a value of 0.01, this coefficient is ≈2.55. In this case, the error of the approximate calculation is Δ<0.5, which is quite acceptable in practice.

The combined function describes the fuzzy sets $\tilde{C} \triangleq$ "the number is approximately in the interval from a to b". It has the form:

$$\mu_{\tilde{C}}(x) = \begin{cases} x < a, & \mu_{\tilde{A}}(x) \\ a \le x \le b, & 1 \\ x > b, & \mu_{\tilde{B}}(x) \end{cases}. \tag{11}$$

Here $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(x)$ are the membership functions of the fuzzy set A˜≜ "the number is near the number a" and the fuzzy set B˜≜ "the number is near the number b", respectively. In this case, the fuzziness coefficient α is found from the equation $\mu_{\tilde{A}}(x) = 0.01$ and the coefficient β from the equation $\mu_{\tilde{B}}(x) = 0.01$ or are calculated using the formulas

$$\alpha = a - k \cdot \frac{b(a)}{2}, \quad \beta = b + k \cdot \frac{b(b)}{2}. \tag{12}$$

Thus, the determination of fuzziness coefficients is reduced to calculating the distance between the transition points of function (9).

To calculate the distance between transition points, we will use the mechanism proposed in [24]. This mechanism is based on expert data, which for numbers approximately equal to N reflect transition points. For N∈[1,99], formulas for calculating distances between transition points were obtained on the basis of this data (Table 1).

If N>99, then the following algorithm is used.

Let the of least significant digit of a number N have order q. Also let r_q be the least significant digit of this number, and r_{q+1} be it digit whose order is one greater than the order of the digit r_q. Let us define classes of numbers $M_d, d \in \{0,1,2\}$, where d = q mod 3. Then:

1. if $N \in M_0$, then $b(N) = b(x) \cdot 10^{q-2}$, where $x = r_q \cdot 10$, and $b(x)$ is taken from Table 1.

2. if $N \in M_1$, then two cases are possible:

a) if $r_{q+1} = 0$, then $b(N) = b(x) \cdot 10^{q-1}$, where $x = r_q$;

b) if $r_{q+1} \neq 0$, then $b(N) = b(x) \cdot 10^{q-1}$, where $x = r_{q+1} \cdot 10 + r_q$.

3. if $N \in M_2$, then two cases are also possible:

a) if $r_{q+1} = 0$, then $x = r_q \cdot 10$; $b(N) = b(x) \cdot 10^{q-2}$;

b) if $r_{q+1} \neq 0$, then $x = r_{q+1} \cdot 10 + r_q$; $b(N) = b(x) \cdot 10^{q-1}$.

The result will be the value b(N). After this, the coefficients α and β are calculated using formulas (10) or (12).

Table 1
Calculating distances between transition points

Number x	Formula for calculating the distance b(x) between transition points for a number x
1, 2, 3, 4, 6, 7, 8, 9	$0{,}46\,x$
10, 20, 30, 40, 60, 70, 80, 90	$(0{,}357 - 0{,}00163x)x$
35, 45, 55, 65, 75, 85, 95	$(0{,}213 - 0{,}00067x)x$
5	2,8
15	6,48
25	6,75
50	24
For other numbers	$\frac{1}{2}\left(b\left(\left[\frac{x}{10}\right] \cdot 10 + 5\right) + b\left(x - \left[\frac{x}{10}\right] \cdot 10\right)\right)$

5. Modelling random scenarios and risk assessment

A random scenario is understood as a random value of the NPV indicator, which depends on the random variable X "cash inflow". To model the cash inflow on a fuzzy interval, one can use the β-distribution considered in [25]. However, given that the basis for constructing intervals of possible values of cash inflow CF_i is the standard Gaussian membership function, it can therefore be considered as a density function of the normal distribution of cash inflow expectations. And since the normal distribution function is tabulated, therefore, in this case, for modeling random scenarios, it is more rational to use the Neumann elimination method [26].

Let X be a random variable whose density function f(x) on the interval [a,b] is bounded from above. Also, let

$$x = a + (b - a)r_1,\ y = Mr_2, \tag{13}$$

where r_1, r_2 are independent values of a uniformly distributed random variable ξ, and

$M = \sup_{a \le x \le b} f(x)$.

If the condition $y < f(x)$ is satisfied, then x is the value of the random variable X. Taking into account the above, the NPV indicator is modeled as follows.

Let n be the number of periods (forecasting horizon). Also, let the range of possible values of the random variable X ≜ "cash inflow" in each year be represented by the following intervals $[a_1, b_1]$,…,$[a_n, b_n]$. On each interval $[a_i, b_i]$, the random variable X is modeled. Either the standard Gaussian function (9) or the combined function (11) is used as the density function $f_i(x)$ on these intervals.

The values $x = a_i + (b_i - a_i)r_1$ and $y = Mr_2$ are calculated, where M= 1. Then the condition $y < f_i(x)$ is checked and if it is true, then the value x is a realization of the random variable X and the value $K_i = \frac{CF_i}{(1+p)^i}$, where CF_i $=x$. After all the values of K_i are obtained, the indicator $NPV = \sum_{i=1}^{n} K_i - IC$ is calculated. As a result of multiple run of the model, we obtain a set of random scenarios $\{NPV\}$.

After this, the investment risk is assessed – the probability of the implementation of a scenario with a negative NPV value as an unprofitable result of the project implementation for the investor. This probability is defined as the ratio of the number of such scenarios to their total number:

$$P(NPV < 0) = \frac{k}{m},$$

where k is the number of negative values, m is the number of experiments conducted.

If the risk P(NPV<0)>0 is accepted by the investor, then, as a rule, the question of expected profit arises. The profit is the average value of the positive scenarios of the set $\{NPV\}$. Moreover, the discounted payback period (DPP) of the project occurs in the last year of its implementation. This is the period required to return the investments in the project due to the net cash flow, taking into account the discount rate.

If P(NPV<0)=0, then in this case the discounted payback period may occur before the end of the project implementation. This period is calculated using the formula [11]:

$$DPP = min\, n,$$

where n is the project implementation period at which $\sum_{i=1}^{n} K_i > IC$.

6. Practical implementation

Let us illustrate the proposed approach with the following example. Let us estimate the risk of investing in some three-year innovation project. Let us assume that the initial investment volume and interest rate are IC=265 and p=5%, respectively. Also, one expert was involved to estimate the expected cash inflow in the first and second years, and three experts were involved to estimate the cash inflow in the third year, since the uncertainty of the cash inflow increases every year. Table 2 also presents estimates of the expected profit from the project.

Table 2
Estimates of expected cash inflows

Expert	in the 1st year	in the 2nd year	in the 3rd year
1	approximately 95	approximately 115	Approximately from 87 to 123
2	-	-	from 90 to 134
3	-	-	from 93 to 145

First, we will check the consistency of the experts' estimates for the 3rd year, assuming their equal competence. For the boundaries of interval estimates, using formulas (5)–(8), we will obtain the following correlation coefficients V_L=0.03 and V_R = 0.08, i.e. the experts' estimates are fairly well-coordinated. Therefore, the average values of the boundaries of these estimates, i.e. 90 and 134, are taken as the boundaries of the cash inflow interval in the 3rd year.

Now we calculate the boundaries of the extended intervals of cash inflows for each year. These boundaries are equal to the oddity coefficients of the numbers (95, α, β), (115, α, β), (90,134, α, β). To calculate these coefficients, we find the values of b(95), b(115), b(90), and b(134).

The values of b(90) and b(95) are found directly from Table 1: b(90)= (0.357-0.00163·90)·90≈19, b(95) =(0.213-0.00067·95)·95=14.2. And the values of b(115) and b(134) are calculated according to the algorithm.

For the number 115 we have $q = 1, r_q = 5$ and $r_{q+1} = 1$. This number belongs to class M_1 since the remainder of q divided by 3 is 1. And since $r_{q+1} \neq 0$, then according to point 2b we have $x = r_{q+1} \cdot 10 + r_q = 15$ and $b(115) = b(15)$, which, according to Table 1, is equal to 6.48.

The value of b(134) is calculated similarly. For the number 134 we have $q = 1, r_q = 4, r_{q+1} = 3$. This number also belongs to the equivalence class M_1. And since $r_{q+1} \neq 0$, then $x = r_{q+1} \cdot 10 + r_q = 34$ and $b(134) = b(34)$. This distance is calculated by the formula

$$b(34) = \frac{1}{2}\left(b\left(\left[\frac{34}{10}\right] \cdot 10 + 5\right) + b\left(34 - \left[\frac{34}{10}\right] \cdot 10\right)\right) = \frac{1}{2}(b(35) + b(4)),$$

where $b(35)$ and b(4), according to Table 1, are equal to 6.63 and 1.84, respectively. As a result, b(134)=1/2(6.63+1.84)≈4.

Then, using formulas (10) and (12) the fuzziness coefficients of these numbers are calculated:

for the number (95, α, β) - α=95-2.55$\cdot\frac{14.2}{2}$≈77, β =95+2.55$\cdot\frac{14.2}{2}$≈113.

for the number (115, α, β) - α=115-2.55$\cdot\frac{6.48}{2}$≈107, β =125+2.55$\cdot\frac{6.48}{2}$≈123.

for the number (90,134, α, β) - α$= 90 - 2.55 \cdot \frac{19}{2} = 66$, β$= 134 + 2.55 \cdot \frac{4}{2} = 139$.

Therefore, the range of values of the random variable X ≜ "cash inflow" in each year is represented by the following intervals [77, 113], [107, 123], [66, 139].

After this, a random variable X is simulated on these intervals. The standard Gaussian function (9) is used as the density function f(x) on the intervals of the 1st and 2nd years, and the combined function (11) is used on the interval of the 3rd year:

on the 1st interval: $\mu_{\tilde{A}}(x) = exp(-a(x-95)^2)$, where $a = -\frac{4\,ln\,0.5}{14.2^2}$ =0.014;

on the 2nd interval: $\mu_{\tilde{A}}(x) = exp(-a(x-115)^2)$, where $a = -\frac{4\,ln\,0.5}{6.48^2} =$ =0.067;

on the 3rd interval: $\mu_{\tilde{C}}(x) = \begin{cases} x < 90, & \mu_{\tilde{A}}(x) \\ 90 \leq x \leq 134, & 1 \\ x > 134, & \mu_{\tilde{B}}(x) \end{cases}$, where

$\mu_{\tilde{A}}(x) = exp(-c(x-90)^2)$, $c = -\frac{4\,ln\,0.5}{19^2}$ =0.008; $\mu_{\tilde{B}}(x) = exp(-c(x-134)^2)$, $c = -\frac{4\,ln\,0.5}{4^2}$ =0.17.

Also for these intervals, according to (13), we obtain the following modeling parameters:

for the 1st: $M = 1,\ x = 77 + 36r_1,\ y = r_2$,

for the 2nd: $M = 1,\ x = 107 + 16r_1,\ y = r_2$,

for the 3rd: $M = 1,\ x = 66 + 73r_1,\ y = r_2$.

Then, at each interval, a random variable X is being played out drawn, the values $K_i = \frac{CF_i}{(1+p)^i}$, where $CF_i = x$, are calculated and then the $NPV = \sum_{i=1}^{3} K_i - IC$ indicator is calculated. 1000 runs of the model were made. The result of the statistical analysis of the obtained data is given in Table 3.

Table 3
Summary statistics of innovative risk assessment

Indicator	Value
Investment size	265
Interest rate	5%
Minimum value of NPV	1.15
Maximum value of NPV	66.59
Expected value of NPV	23.74
Cash inflow in first year K_1	90.72
Cash inflow in second year K_2	104.27
Cash inflow in third year K_3	93.27
Num. cases when NPV < 0	65
Investment risk	0.065

The following scale can be used for verbal expression the risk assessment of a project [15] (Table 4).

Table 4
Verbal risk assessments

Quantitative assessment	Verbal assessment
Less than 0.01	Low
0.01 – 0.1	Average
Over than 0.1	High

Thus, according to this table, the investment risk of the project is average. Let the received risk be accepted by the investor. Since the risk is greater than 0, the discounted payback period will occur in the third year of the project implementation, and the expected profit will be approximately 24 conventional units.

7. Conclusion

The approach to assessing investment risks based on fuzzy modeling of the effectiveness of innovative projects is considered. The net present value indicator serves as an efficiency model. In this indicator, the cash inflow parameter, taking into account its uncertainty, is specified by fuzzy linguistic estimates.

A procedure for approximating linguistic estimates by fuzzy triangular and trapezoid numbers based on Gaussian membership functions is proposed. An algorithm for calculating the distance between the transition points of these functions is considered, the use of which allows the approximation of linguistic estimates to be carried out automatically. Based on this algorithm, formulas for the approximate calculation of fuzziness coefficients of triangular and trapezoidal numbers with an error acceptable in practice are proposed.

To simulate the efficiency indicator, the Neumann elimination method is proposed, in which the Gaussian functions act as functions of the distribution density of cash inflow expectations. An example is given to illustrate this approach. This example demonstrated the practical feasibility of the approach, its simplicity and universality.

In general, the proposed approach, without claiming to be complete, can be used both as a basis for developing an appropriate methodological apparatus for assessing the risk of various innovative projects, and in a broader sense - for modeling random variables in various fields.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] G. Makhovikova, N. Efimova Innovation Management: Eksmo, 2010. 211 p.

[2] O. Kalivoshko, V. Kraevsky, K. Burdeha, I. Lyutyy and N. Kiktev, "The Role of Innovation in Economic Growth: Information and Analytical Aspect," 2021 IEEE 8th International Conference on Problems of Infocommunications, Science and Technology (PIC S&T), Kharkiv, Ukraine, 2021, pp. 120-124, doi: 10.1109/PICST54195.2021.9772201.

[3] K. Rəsulov. Economic Efficiency of Innovative Development in Industry. Traektoriâ Nauki (Section “Economics”). 2022. Vol. 8, No 4, pp. 2001-2007

[4] N. Kaverina. Theoretical and methodical approaches to the analysis and evaluation of the risks of innovation. Scientific Journal «ScienceRise». No5/3(5), 2014, pp.74-79. DOI: 10.15587/2313-8416.2014.34799
[5] T. Tkalich. Forecasting the risks of investment IT projects. Investments: practice and evidence. 2017. No. 6, pp. 9-14.
[6] A.M. Deptuła, Assessment Criteria of Innovations Risks: Analysis of Research Results. J Knowl Econ (2024). https://doi.org/10.1007/s13132-023-01659-1
[7] Yu.Ya. Samokhvalov, (2004) Distinctive features of using the method of analysis of hierarchies in estimating problems on the basis of metric criteria. Kibernetika i Sistemnyj Analiz, 40 (5), pp. 15-19.
[8] V. Gorokhovatskyi. Risk assessment of innovative projects: Development of forecasting models. CEUR-WS. https://ceur-ws.org / Vol-2927/ pp.18-37
[9] D. Dubois and H. Prade. Possibility theory: applications for knowledge representation in data processing. Masson, Paris, 1985. 248 p.
[10] R. Doskočil, (2015). An evaluation of total project risk based on fuzzy logic. Business: Theory and Practice, 17(1), 23-31. https://doi.org/10.3846/btp.2016.534
[11] A. Abreu, J.Martins, J. Calado. Fuzzy Logic Model to Support Risk Assessment in Innovation Ecosystems. 13th APCA International Conference on Automatic Control and Soft Computing (Controlo), 2018, Ponta Delgada, Azores, Portugal doi: 10.1109/CONTROLO.2018.8514281
[12] Mahant, Narendra. "Risk Assessment is Fuzzy Business – Fuzzy Logic Provides the Way to Assess Off-site Risk from Industrial Installations". Risk 2004. 2004. No. 206.
[13] E. Aliyev. (2020). Application of fuzzy logic for risk analysis of investment projects. (on the example of procurement production of the mechanical engineering industry). World Science, 1(2(54), 50-53. https://doi.org/10.31435/rsglobal_ws/28022020/6930
[14] O. Kalivoshko, A. Myrvoda, V. Kraevsky, N. Paranytsia, O. Skoryk and N. Kiktev, "Accounting and Analytical Aspect of Reflection of Foreign Economic Security of Ukraine," 2022 IEEE 9th International Conference on Problems of Infocommunications, Science and Technology (PIC S&T), Kharkiv, Ukraine, 2022, pp. 405-410, doi: 10.1109/PICST57299.2022.10238523.
[15] Y. Samokhvalov (2021) Risk Assessment of Innovative Projects Based on Fuzzy Modeling. In: S. Babichev, V. Lytvynenko, W. Wójcik, S. Vyshemyrskaya (eds) Lecture Notes in Computational Intelligence and Decision Making. ISDMCI 2020. Advances in Intelligent Systems and Computing, vol 1246. Springer, Cham. https://doi.org/10.1007/978-3-030-54215-3_17
[16] Innovation policy. Fact Sheets on the European Union. 2024 https://www.europarl.europa.eu/erpl-app-public/factsheets/pdf/en/FTU_2.4.6.pdf
[17] Lindon Robison; Steven Hanson; and J. Roy Black. Financial Management for Small Businesses: Financial Statements & Present Value Models. Michigan State University Libraries. 2021. 541 p.
[18] N. Asokan. All types of cash flow formulas explained. 2022 https://agicap.com/en/article/cash-flow-formulas/
[19] Y. Samokhvalov. Problem-oriented theorem-proving method in fuzzy logic (po-method). Cybern Syst Anal 31, 682–690 (1995). https://doi.org/10.1007/BF02366316
[20] Z. Gong, L. Wang, On Consistency Test Method of Expert Opinion in Ecological Security Assessment. Int. J. Environ. Res. Public Health 2017, 14, 1012; doi:10.3390/ijerph14091012
[21] Y.C. Dong, G.Q. Zhang, W.C. Hong, Y.F. Xu, Consensus models for AHP group decision making under row geometric mean prioritization method. Decis. Support Syst. 2010;49:281–289. doi: 10.1016/j.dss.2010.03.003
[22] S. Alonso, E. Herrera-Viedma, F. Chiclana, F. Herrera, A web based consensus support system for group decision making problems and incomplete preferences. Inf. Sci. 2010;180:4477–4495. doi: 10.1016/j.ins.2010.08.005.
[23] Yu.Ya. Samokhvalov, Matching of expert estimates in preference relation matrices. Upravlyayushchie Sistemy i Mashiny, 2002, №6, pp. 49-54

[24] A. Borisov, O. Krumberg, I. Fedorov, Decision making based on fuzzy models: examples of use. Knowledge, 184 p., Riga (1994).
[25] Y. Samokhvalov, (2020). Construction of the Job Duration Distribution in Network Models for a Set of Fuzzy Expert Estimates. In: Lytvynenko, V., Babichev, S., Wójcik, W., Vynokurova, O., Vyshemyrskaya, S., Radetskaya, S. (eds) Lecture Notes in Computational Intelligence and Decision Making. ISDMCI 2019. Advances in Intelligent Systems and Computing, vol 1020. Springer, Cham. https://doi.org/10.1007/978-3-030-26474-1_8
[26] J. Von Neumann, Various Techniques Used in Connection with Random Digits, Applied Mathematics Series 12, National Bureau of Standards, Washington, DC, 1951, pp. 36-38.