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FUZZY LOGIC DECISION-MAKING MODEL FOR TECHNOLOGY FORESIGHT[6]

A new decision-making model in technology foresight based on fuzzy logic is proposed. The choice of technology as disruptive or critical doesn't depend on the subjective expert's opinion, but bases on the mathematically justified limits of technologies criticality. The basis of the model is the fuzzy inference system by Mamdani algorithm. Five of the most important criteria of criticality have been used as input linguistic variables. A new approach to defining membership functions based on equidistant derivative points is proposed and described in detail. The functioning of the model is considered by example. The influence of the application of different membership functions on the criticality assessment is shown. A comparison between the fuzzy model and classic expert model is also conducted.
Keywords: critical technologies; disruptive technologies; fuzzy logic; membership function determination; technology foresight
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1. Introduction

Forecast research in the technological sphere (technology foresight) is one of the most important tools for national economic development. By identifying key scientific and technological areas and ensuring their research, development and implementation, advanced

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countries have built successful economic models. The most promising areas in the technological field are called critical technologies (CT) by many countries (Sotnyk & Kupchyn, 2020).

In business theory, the last two decades have been increasingly talked about disruptive technologies that are revolutionary and destructive to the traditional system of the technological sphere. In 2020, even NATO's Science and Technology Organization published a report "Science & Technology Trends 2020-2040", which identified emerging and disruptive technologies (EDT) in the defense sphere (NATO Science & Technology Organization, 2020). The EDT list is quite closely correlated with the CT list, but it is much narrower.

The article aims to improve the prognostic study, which can be applied to both critical and disruptive technologies. Therefore, we will operate only with the concept of CT.

Foresight projects are usually based on expert assessments using the different methods (Wonglimpiyarat, 2006; Gavigan & Scapolo, 1999; Kovářiková et al., 2017; Calof et al., 2020). The result of technology foresight is the formation of a technologies list with certain criticality estimates. Research customers usually do not set the requirements for the concrete number of technologies to be included in the list of critical ones. It is obvious the technologies with the highest rating will be included in the list of CT and with the lowest – no. Only one question is open – "How can we determine the selection limit?" or "How many technologies should be in the critical technologies list?".

Usually, the final list of CT is determined by an expert council voting. However, these decisions based on subjective expert opinions are not always correct.

If there are no clear limits of technology selection, this issue can be solved quite successfully by using fuzzy logic. The authors propose a new model for determination the clarity limits, namely the mathematically justified limit of technology selection to the list of critical ones. This is what the article is about.

Today, the fuzzy logic is the basis for modelling various processes of almost all areas of human life, from household devices to navigation systems, artificial intelligence, robotic complexes and even illness diagnosis (Omrane et al., 2016; Govindaet et al., 2017; Jaafari et al., 2019).

The practical application of fuzzy logic always has a topical question about the definition of the membership function. In this article, the authors propose to determine the membership function not by experts, but by using of certain mathematical calculations.

There are a lot of scientific works, both domestic and foreign, that are majoring to the issues of technology foresight.

Thus, the publications (Paladchenko, et al., 2018; Gorbulin, et al., 2018; Romanowski, Nadolny, 2018; Gibson, et al., 2018). describe the main and most popular methods of foresight, such as Delphi, expert panels, bibliometric and patent analysis, SWOT-analysis, etc. The basis of forecasting is the use of a set of expert methods and Delphi is one of them (Gavigan, Scapolo, 1999; Wonglimpiyarat, 2006; Bühring, Liedtka, 2018; Dovhopolyi, et al., 2019; Calof, et al., 2020).

Issues in the field of CT development and implementation are considered by many scientists. In particular, the current situation for formation the CT list is shown in (Kupchyn, Sotnyk, 2019). The approaches to the definition of the concept of "critical technologies" and the process of CT list forming in different countries are described in the papers (Gibson, et al., 2018; Paladchenko, Molchanova, 2018).

At the same time, the fuzzy logic, used for a number of forecasting applied issues has become quite popular. The analysis of the application of fuzzy inference systems, artificial neural networks and adaptive neuro-fuzzy inference system for inventory control has been done in (Aengchuan, Phruksaphanrat, 2018). The results of research on the software fault prediction are described in (Erturk, Sezer, 2016) and the forecast of economic development and finance is given in (Hussain, et al., 2020). Fuzzy logic is used even to identify effective innovations in higher education (Jakeline, et al., 2017). And this is not a complete list of predictive researches using fuzzy logic.

However, it is not known for the article authors about the fuzzy logic application for technology foresight. Foresight projects to determine the disruptive or critical technologies, which are described in (Paladchenko, Molchanova, 2018; Gorbulin, et al., 2018; Romanowski, Nadolny, 2018; Bühring, Liedtka, 2018), are not fundamentally different from each other and just outdated. Modern business conditions create new types of risks and the need to find new mechanisms for management decisions (Britchenko, Kniazevych, 2015; Tkachenko, 2016; Baranovsky, et al., 2020; Danylkiv, et al., 2020; Pryshchepa, et al., 2020; Levchenko, et al., 2021; Ostapenko, et al., 2021; Polinkevych, et al., 2021; Dankiewicz, et al., 2021; Lu, et al., 2021; Volosovych, et al., 2021).

Intensive discussion in the scientific community about the expediency and necessity of CT development is sufficient clear evidence that the article issue is urgent.

The purpose of this paper is to determine the mathematically justified limits of technology criticality by the fuzzy logic using and design a decision-making model in the technology foresight.

2. Materials and Methods

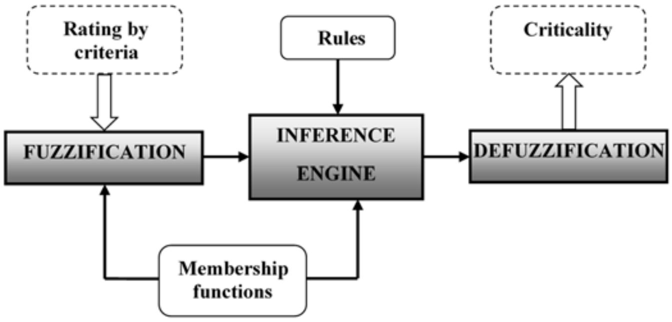
In early 2020, the authors of the article conducted an expert's survey to determine the most important criteria for the critical technologies selection. The study identified five the most important criteria, namely: the scope of application, prospects, scientific and technical potential of enterprises, economic expediency and efficiency. A detailed description of the survey and its results is not given in this article; it will be published separately later.

According to the existing methodology, which is reflected in (Sotnyk, et al., 2020), the preliminary list of technologies is evaluated by an expert group. As a result, the list with the corresponding estimates by each criterion is formed. Next, the expert council decides which technologies will be considered as critical and which will not.

The authors of the article propose to eliminate subjectivity in decision-making by finding a mathematically justified minimal satisfactory level of criticality. To do this, it is proposed to use a decision-making model applying fuzzy logic (Figure 1) (Shtovba, 2007; Feilong Liu, 2008; Yunlong, Zhirui, 2008; Kiran, Rajput, 2011; Xi, Byung-Jae, 2013).

Figure 1

Decision-making model based on fuzzy logic



Practically, the proposed model is a fuzzy inference system (FIS). The technology evaluations by criteria are given to the input. And the criticality of technologies is determined at the output.

The formation of a typical FIS includes the following steps (Yunlong, Zhirui, 2008; Feilong, 2008; Shtovba, 2007; Kiran, Rajput, 2011):

I. Determination of membership functions for input and output linguistic variables;

II. Rule base (knowledge base) formation;

III. Determination of fuzzy inference algorithm (fuzzification, fuzzy inference, defuzzification).

Let's consider the proposed decision-making model by steps.

2.1. Determination of membership functions for input and output linguistic variables.

Usually, the definition of membership functions (MF) is entrusted to experts or based on the subjective researcher opinion (Leonenkov, 2005; Shtovba, 2007; Gonzalez, et al., 2014; Keshtkar, Arzanpour, 2017; Kalantaievska, et al., 2018). This paper proposes a new principle of MF determination. The principle makes it possible to determine the limits of criticality based on mathematical calculations. The proposed solution to this problem consists of three steps.

<u>2.1.1. Approximation of technologies distribution according to criticality estimates by criteria</u>

We have generalised expert assessments for each criterion after receiving the expert survey results on determining the technology criticality.

For each technology, there are specific valuations of criticality by each criterion. After receiving these data, it is possible to conduct an approximation and find an approximate function that reflects the criticality assessment for each technology. If we place on the abscissa axis the technologies in ascending order of their criticality, we can get an approximate function that will be monotonically increasing.

During repeated calculations, the authors came to the conclusion that the most reliable approximate function is a polynomial function of the third and higher degree. The least-squares method, which will be used in this work, is the most common and effective for solving approximation issues (Mosayebidorcheh, et al., 2017; Dehghan, Mohammadi, 2017; Bota, Căruntu, 2017).

The authors propose to determine the minimal level of criticality by the approximate function of the criterion with the lowest weight coefficient, and the maximum – by the criterion with the highest weight coefficient. In this way, the maximum range of fuzziness will be ensured. It should be noted that the defined limits should be the same for all criteria.

2.1.2. Differentiation of the approximate function and finding the equidistant points

It's known, the geometric meaning of a derivative of a function is (Alekseeva et al., 2019, p.286):

$$f'(x) = \frac{\Delta y}{\Delta x} = tg\alpha \, , \tag{1}$$

At the point, where the derivative of a function is equal to one, the function increment and the argument increment are equal. The name of this point is not a common concept, so the authors propose to introduce the term "equidistant point of derivative" (Huybrechs, 2009; Žlepalo, Jurkin, 2018).

If the approximate function is represented as a polynomial function of the third degree, then we will have two equidistant points (the derivative function will have a second degree, so the solution will have two values). This function can be represented by two versions, which are shown in Figure 2 and Figure 3.

For both cases $f_1(x)$ and $f_2(x)$ (figure 2, 3) we have two intervals of function changes. For $f_1(x)$ on the interval $x<x_1$ and $x>x_2$ the function increment increases much more than the argument increment, in contrast to other interval $x_1<x<x_2$, where the function increment increases insignificantly in comparison with the argument. For $f_2(x)$ the situation is reversed, on the interval $x<x_1$ and $x>x_2$ the function increment increases much less than the argument increment, and on the interval $x_1<x<x_2$ the function increment expands much more than the increase of the argument.

This means, it is no matter type of approximate function, the nature of its change will always have two intervals. This is the principle of determining the clarity limits (not fuzzy).

Remember, the abscissa is an ascending order technologies list of their criticality. It is logical to conclude that the technologies before point x1 will have the lowest criticality, while the technologies after point x_2 – the highest. It is proposed to consider the interval between these points as a fuzzy interval. Besides, it does not matter which approximate function is used, the first or the second type, because in the one function, the nature of its change will be different on these intervals.

It is offered the denotations:

- Clarity interval: $x \in (0; x_1) \cup (x_2; x_n)$;
- Fuzzy interval: $x \in (x_1; x_2)$.

Figure 2

Approximate function $f_1(x)$

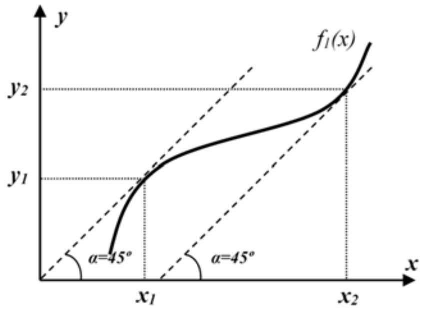
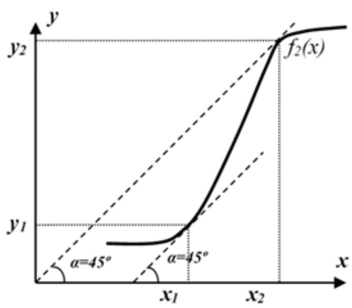


Figure 3

Approximate function $f_2(x)$



In terms of use, the fuzzy logic, these intervals form two fuzzy sets, which characterise the degree of technology criticality and are interesting for us:

1 – non-critical technologies set:

$$\mu(y)=1,\ \forall y \in (0; y_1) \text{ and } \mu(y)=0,\ \forall y \in (y_2; y_n),$$

2 – critical technologies set:

$$\mu(y)=0 \text{ for } \forall y \in (0; y_1) \text{ and } \mu(y)=1 \text{ for } \forall y \in (y_2; y_n),$$

$\mu(y)$ – membership function to a fuzzy set;

y_1; y_2 – values of the criticality at equidistant points;

y_n – maximum value of the criticality for studied technologies.

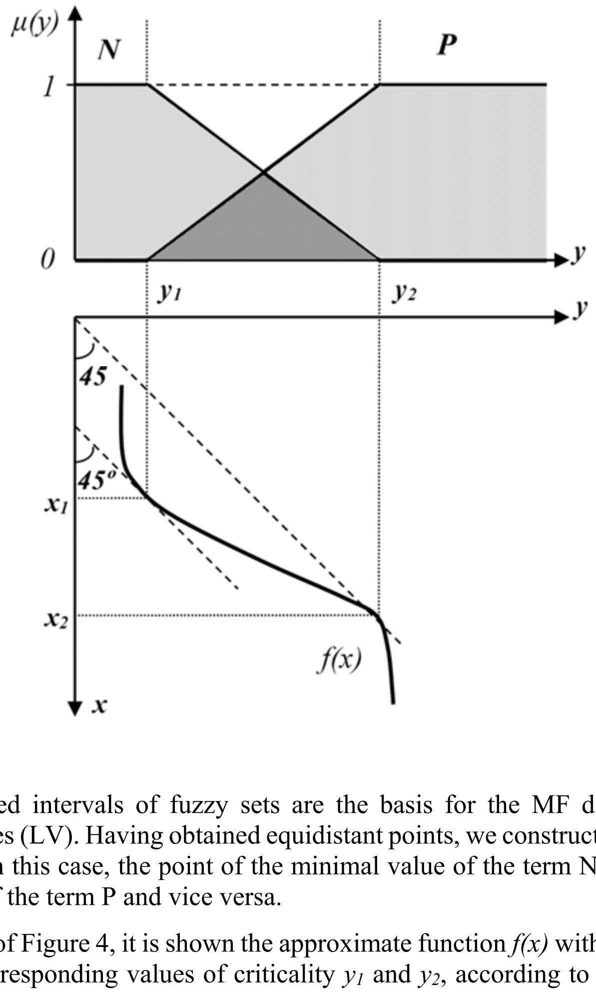
We find the values of y_1 and y_2 from the approximate function equation.

2.1.3. Determination of membership functions

Fuzzy sets theory does not oblige to choose the type of MF absolutely clearly or precisely (Leonenkov, 2005, p. 64). It can be clarified in the research process based on the results of solving the task. The most common MF are triangular and trapezoidal, which will be used in the proposed model (Leonenkov, 2005, p. 188; Shtovba, 2007, p. 19).

Figure 4

Membership function designing for a linguistic variable with the terms N and P



The predetermined intervals of fuzzy sets are the basis for the MF design of the input linguistic variables (LV). Having obtained equidistant points, we construct the corresponding MF (Figure 4). In this case, the point of the minimal value of the term N is the point of the maximal value of the term P and vice versa.

In the lower part of Figure 4, it is shown the approximate function *f(x)* with equidistant points x_1, x_2 and the corresponding values of criticality y_1 and y_2, according to a certain criterion.

The ordinate axis of the approximate function *f(x)* is the abscissa axis for MF *μ(y).* The upper part of the figure 4 shows the MF for the two terms N and P (negative, positive).

The design of the MF for the output LV is different. It is also proposed to use the triangular and trapezoidal function, but with others points.

First, we need to determine the universal set of the output LV (β). Let's say that the maximum value of the output LV is equal to one, the minimum is equal to zero. In this case, the maximum mark on the criterion is equal to its weight coefficient.

It follows, that a certain technology will have $\beta=1$ if all criterion marks will have the maximum scores, and $\beta=0$ if criterion marks will be minimum. The maximum criticality of any technology is calculated as the sum of all criterion weights, and it is equal to 1. Next, it is necessary to determine the required satisfactory level of criticality.

Based on the first basic rule, which will be presented in the next chapter, the lowest satisfactory value of criticality is identically equal to the sum of two the most important weight coefficients of criteria:

$$\beta_{CR} = \omega_1 + \omega_2 \ , \tag{2}$$

β_{CR} – the lowest satisfactory value of criticality;

ω_1, ω_2 – weight coefficients of two the most important criteria.

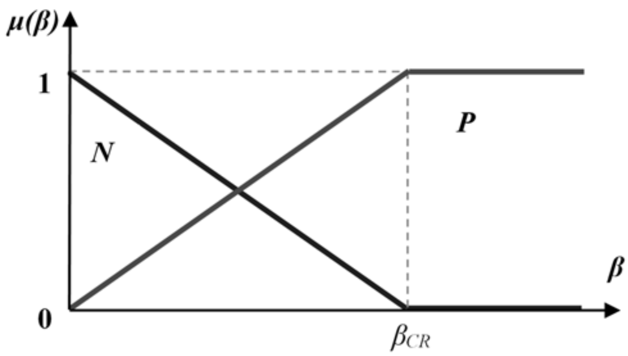
Therefore, the MF of output LV (for the term "positive") will take the following values:

$$\mu(\beta) = \begin{cases} 1, \beta \geq \beta_{CR} \\ 0, \beta = 0 \end{cases} . \tag{3}$$

Accordingly, for the term "negative", the MF will take inverse values (1 for $\beta=0$ and 0 for $\beta \geq \beta_{CR}$). Graphically, the MF of output LV is presented in Figure 5.

Figure 5

Membership function of output linguistic variables



2.2. Rules base (knowledge base) forming

At first, we should determine the input, output LV and their term-sets, before the rules are formed. In our case, the input LV will be presented as all technology criticality criteria, and the output variable will be the criticality level. We use the common abbreviations for the convenience of term-sets writing. For example, for the term-set {"low", "medium", "high"} or {"small", "medium", "large"} it is better to use the common analogue {«N», «Z», «P»} (negative, zero, positive) (Leonenkov, 2005, p. 188).

There are shown the names of LV and their term-sets in Table 1.

Table 1

Linguistic variables of the fuzzy inference system

<table>
<tr><th>Input LV</th><th colspan="2">Term-set for input LV</th><th>Output LV</th><th colspan="2">Term-set for output LV</th></tr>
<tr><td>α_1 – scope of application</td><td>«big»,
«small»</td><td>«P»,
«N»</td><td rowspan="5">β – criticality</td><td rowspan="5">«satisfactory»,
«unsatisfactory»</td><td rowspan="5">«P»,
«N»</td></tr>
<tr><td>α_2 – prospects</td><td>«significant»,
«insignificant»</td><td>«P»,
«N»</td></tr>
<tr><td>α_3 – scientific and technical potential of enterprises</td><td>«enough»,
«not enough»</td><td>«P»,
«N»</td></tr>
<tr><td>α_4 – economic expediency</td><td>«profitable»,
«unprofitable»</td><td>«P»,
«N»</td></tr>
<tr><td>α_5 – efficiency</td><td>«high»,
«low»</td><td>«P»,
«N»</td></tr>
</table>

The rule base is formed after the determination of input, output LV and their term-sets. The general view of each rule in the case of five inputs LV will be as follows:

«IF «Condition 1» AND «Condition 2» AND «Condition 3» AND «Condition 4» AND «Condition 5», THEN «Conclusion», where

«Condition 1» - the value α1 is in the range of N or P;

«Condition 2» - the value α2 is in the range of N or P;

«Condition 3» - the value α3 is in the range of N or P;

«Condition 4» - the value α4 is in the range of N or P;

«Condition 5» - the value α5 is in the range of N or P;

«Conclusion» - the value β is in the range of N or P.

The maximum number of rules is calculated as all possible combinations of "Conditions" and in this case, is determined by the formula:

$$z = u^n \quad , \tag{4}$$

z – number of rules,

u – number of terms for input LV,

n – number of input LV.

After calculations we obtained: $z=u^n=2^5=32$. It should be noted that formula (4) can be used only if the number of terms for each input LV is equal. In our case, we have 2 terms for each LV.

It is possible to reduce the number of rules if it is known certain information about the system. According to previous studies, there were obtained the weight coefficients of criteria for technology criticality. The results are listed in Table 2.

Table 2

Criteria for technology criticality

№	Criterion	Weight coefficient
1	Scope of application	0,14
2	Prospects	0,232
3	Scientific and technical potential of enterprises	0,175
4	Economic expediency	0,208
5	Efficiency	0,245

Experts identified after the survey that the most important criteria for technology selection are “prospects” and “efficiency”. Based on this, we can formulate the first two basic rules.

Rule 1: «IF «Prospects» of technology – significant and «Efficiency» – high, THEN «Criticality» – satisfactory ».

Rule 2: «IF «Prospects» of technology – insignificant and «Efficiency» – low, THEN «Criticality» – unsatisfactory ».

It does not matter which terms the other LV belong to, because only $\alpha 2$ and $\alpha 5$ have a key sense for conclusion forming.

The principle of other rules formulating will be as next. If three or more input LV belong to a positive (negative) term, then the output LV takes a positive (negative) term value. The proposed option contains 18 rules, which greatly simplifies the calculations.

However, the user does not have to do complex calculations if it is used the MATLAB program (Leonenkov, 2005; Shtovba, 2007; Chaira, Ray, 2009; Kyryk, 2019; Dadios, 2012). So for greater accuracy, we will use all 32 rules. The weight coefficients of the criteria have already been taken into account during expert assessment. So, the weights of the rules will be considered the same and equal to one. The estimates for each criterion are equilibrium. The formed base is systematically presented in Table 3.

Let we read, for example, rule 29, for a better understanding: IF «Scope of application – big» AND «Prospects – significant» AND «Scientific and technical potential – enough» AND «Economic expediency – unprofitable» AND «Efficiency – low», THEN «Criticality of technology – satisfactory».

Table 3

Rules base

Linguistic	Rules																															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
	Conformity to the terms																															
α_1	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P	P
α_2	N	N	N	N	N	N	N	N	P	P	P	P	P	P	P	P	N	N	N	N	N	N	N	N	P	P	P	P	P	P	P	P
α_3	N	N	N	N	P	P	P	P	N	N	N	N	P	P	P	P	N	N	N	N	P	P	P	P	N	N	N	N	P	P	P	P
α_4	N	N	P	P	N	N	P	P	N	N	P	P	N	N	P	P	N	N	P	P	N	N	P	P	N	N	P	P	N	N	P	P
α_5	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P	N	P
β	N	N	N	N	N	N	N	P	N	N	N	P	N	P	P	P	N	N	N	P	N	P	P	P	N	P	P	P	P	P	P	P

2.3. Determination of fuzzy inference algorithm (fuzzification, fuzzy inference, defuzzification)

The Mamdani algorithm is the classic and most common (Leonenkov, 2005; Shtovba, 2007; Chaira, Ray, 2009; Dadios, 2012; Iancu, 2012; Kyryk, 2019), so it will be used in this work. The Sugeno algorithm, which is also presented in MATLAB, cannot be used in the proposed model, because the FIS output is a linear function or single set (Leonenkov, 2005; Hamam, Georganas, 2008; Srivastava, et al., 2018).

A concrete criticality value will be obtained for each technology, as a result of defuzzification. The technology will be critical if its criticality exceeds the required satisfactory level β_{CR} (calculated by (2)).

It is offered to consider the developed decision-making model as an example.

3. Results

During the technological foresight, an expert survey was conducted to determine the critical technologies list. Each of the 15 technologies was evaluated according to five criteria. Table 4 shows the generalised and already standardised estimates.

Table 4

Generalised estimates of technologies criticality

Criteria	Generalised and standardised estimates															The sum of evaluations by criterion
	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8	T 9	T 10	T 11	T 12	T 13	T 14	T 15	
Scope of application	0,11	0,07	0,05	0,10	0,04	0,09	0,05	0,02	0,11	0,05	0,02	0,02	0,06	0,10	0,11	*1,00*
Prospects	0,06	0,08	0,10	0,09	0,03	0,04	0,06	0,09	0,05	0,11	0,04	0,08	0,10	0,06	0,03	*1,00*
Scientific and technical potential	0,10	0,07	0,06	0,05	0,10	0,07	0,04	0,07	0,11	0,10	0,09	0,05	0,06	0,01	0,02	*1,00*
Economic expediency	0,09	0,03	0,07	0,10	0,06	0,05	0,09	0,08	0,03	0,02	0,09	0,10	0,03	0,05	0,09	*1,00*
Efficiency	0,10	0,05	0,06	0,03	0,10	0,06	0,08	0,04	0,08	0,11	0,09	0,06	0,03	0,05	0,08	*1,00*

The weight for each criterion is known; Table 5 shows the survey results taking into account the criteria weights. In addition, for convenience, the results are multiplied by 1000.

Table 5

Generalised criticality estimates calculated with weight coefficients

Criteria	Generalised and standardised estimates calculated with weight coefficients															Weight coefficients (*w*1000*)
	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8	T 9	T 10	T 11	T 12	T 13	T 14	T 15	
Scope of application	15,39	10,26	6,84	13,68	5,13	11,97	6,84	3,42	15,39	6,84	3,42	3,42	8,55	13,68	15,39	*140,260*
Prospects	14,53	17,44	23,25	20,34	5,81	8,72	14,53	20,34	11,62	26,16	8,72	17,44	23,25	14,53	5,81	*232,496*
Scientific and technical potential	17,04	12,78	10,65	8,52	17,04	12,78	6,39	12,78	19,18	17,04	14,91	8,52	10,65	2,13	4,26	*174,708*
Economic expediency	19,11	7,17	14,33	21,50	11,94	9,55	19,11	16,72	7,17	4,78	19,11	21,50	7,17	9,55	19,11	*207,810*
Efficiency	24,47	12,24	15,30	6,12	24,47	15,30	18,35	9,18	18,35	27,53	21,41	15,30	6,12	12,24	18,35	*244,726*

After the results are obtained, we can design a fuzzy inference system.

3.1. Determination of membership functions for input and output linguistic variables.

First, it is necessary to obtain the criticality interval (crisp limits). The upper limit of criticality will be determined from the approximate function by the criterion "efficiency", the lower limit – by the criterion "scale of application". These criteria have the highest and lowest weight. Tables 6 and Table 7 show the criticality estimates for these criteria in ascending order.

Table 6

Distribution of technologies in ascending efficiency order

Ranked technologies list in ascending efficiency order															
Ranked numbers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Estimates	6,12	6,12	9,18	12,24	12,24	15,30	15,30	15,30	18,35	18,35	18,35	21,41	24,47	24,47	27,53
Real numbers of technologies	T 4	T 13	T 8	T 2	T 14	T 3	T 6	T 12	T 7	T 9	T 15	T 11	T 1	T 5	T 10

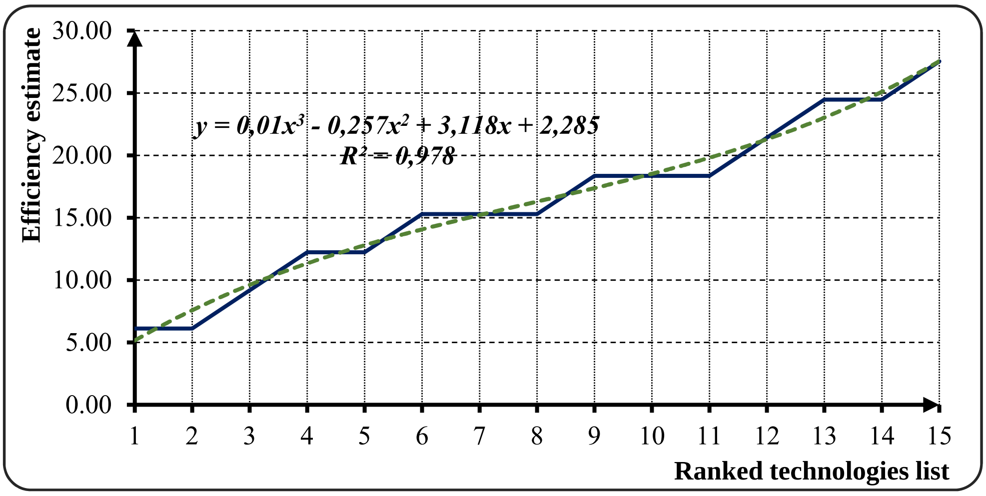
Table 7

Distribution of technologies in ascending scope order

Ranked technologies list in ascending scope order															
Ranked numbers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Estimates	3,42	3,42	3,42	5,13	6,84	6,84	6,84	8,55	10,26	11,97	13,68	13,68	15,39	15,39	15,39
Real numbers of technologies	T 8	T 11	T 12	T 5	T 3	T 7	T 10	T 13	T 2	T 6	T 4	T 14	T 1	T 9	T 15

Figure 6

Approximate function for criterion «Efficiency»



The graph of the technology efficiency growth is shown in Figure 6. After that, an approximation was conducted using the third-degree polynomial function.

The approximation was conducted by the least-squares method. The result is an approximate function with a trustiness of 98% (square of the correlation coefficient):

$$y = 0,01x^3 - 0,257x^2 + 3,118x + 2,285. \quad (5)$$

The next step is the differentiation. Then we equate the derivative to 1 and find the equidistant points:

$$y' = 0,03x^2 - 0,514x + 3,118. \quad (6)$$

$$y' = 1 \Leftrightarrow 0,03x^2 - 0,514x + 3,118 = 1 \Leftrightarrow \begin{cases} x_1 = 6,9 \\ x_2 = 10,2 \end{cases} \Leftrightarrow \begin{cases} y_1 = 14,85 \\ y_2 = 17,96 \end{cases}. \quad (7)$$

From (7) we choose the maximum value that will be the upper criticality limit (17,96).

We calculate the lower criticality limit by a similar principle (Figure 7).

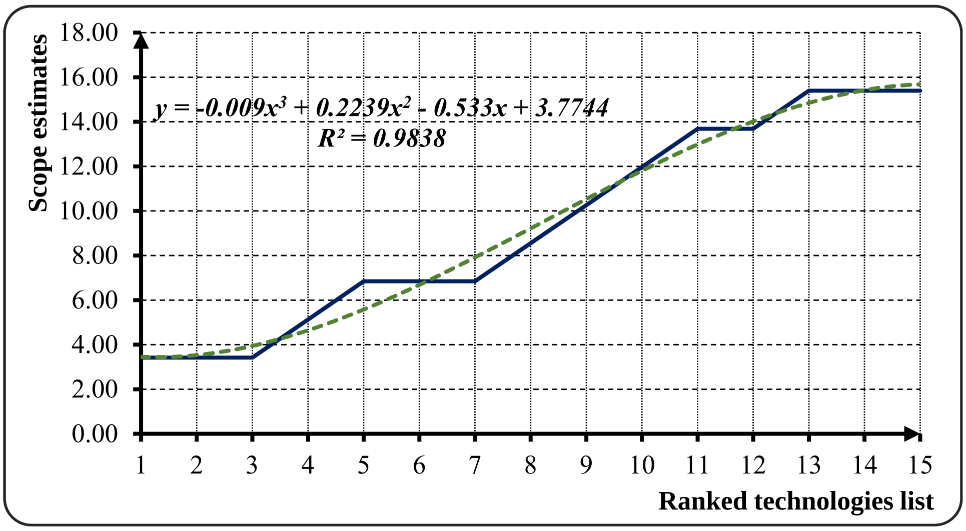
$$y = -0,009x^3 + 0,223x^2 - 0,533x + 3,774. \quad (8)$$

$$y' = -0,027x^2 + 0,446x - 0,533. \quad (9)$$

$$y' = 1 \Leftrightarrow -0,027x^2 + 0,446x - 0,533 = 1 \Leftrightarrow \begin{cases} x_1 = 4,89 \\ x_2 = 11,63 \end{cases} \Leftrightarrow \begin{cases} y_1 = 5,45 \\ y_2 = 13,58 \end{cases}. \qquad (10)$$

Figure 7

Approximate function for criterion «Scope of application»



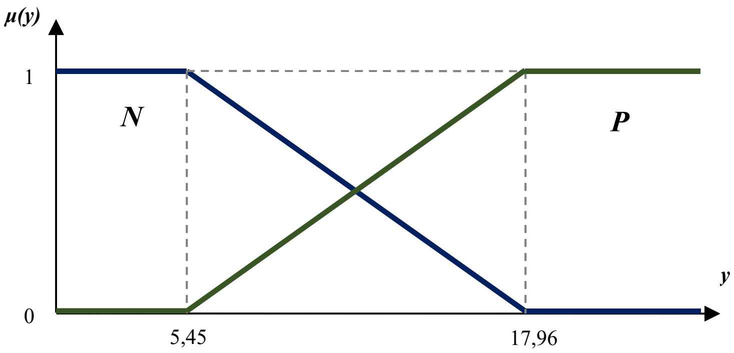
From (10) we choose the minimum value that will be the lower criticality limit (5,45).

Thus, we found the technology criticality limits that will be used for MF construction of input LV:

$$y_{\min} = 5,45; y_{\max} = 17,96. \qquad (11)$$

Figure 8

Membership functions for input linguistic variables



To design the MF of the output LV, we should calculate the minimal satisfactory level of criticality β_{CR} by formula (2). The most important criteria are “prospects” and “efficiency”, their weights are presented in table 2.

The minimal satisfactory criticality level has the next value:

$$\beta_{CR} = \omega_2 + \omega_5 = 0,232 + 0,245 = 0,477\,. \tag{12}$$

Graphically, the MF of the output LV is presented in Figure 5.

3.2. Rule base (knowledge base) forming

Input, output LV and their term-sets were described in the theoretical part of the article and presented in Table 1. The rules were also formulated and presented in Table 3.

3.3. Application of the fuzzy inference system

3.3.1. Fuzzification

It is necessary to calculate the values of input MF for each term for each technology. The results of the calculations are shown in Table 8.

Table 8

Fuzzification results

Input linguistic variables	Terms	Values of input membership function														
		T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8	T 9	T 10	T 11	T 12	T 13	T 14	T 15
Scope of application	*P*	0,79	0,38	0,11	0,66	0	0,52	0,11	0	0,79	0,11	0	0	0,25	0,66	0,79
	N	0,21	0,62	0,89	0,34	1	0,48	0,89	1	0,21	0,89	1	1	0,75	0,34	0,21
Prospects	*P*	0,73	0,96	1	1	0,03	0,26	0,73	1	0,49	1	0,26	0,96	1	0,73	0,03
	N	0,27	0,04	0	0	0,97	0,74	0,27	0	0,51	0	0,74	0,04	0	0,27	0,97
Scientific and technical potential	*P*	0,93	0,59	0,42	0,25	0,93	0,59	0,08	0,59	1	0,93	0,76	0,25	0,42	0	0
	N	0,07	0,41	0,58	0,75	0,07	0,41	0,92	0,41	0	0,07	0,24	0,75	0,58	1	1
Economic expediency	*P*	1	0,14	0,71	1	0,52	0,33	1	0,9	0,14	0	1	1	0,14	0,33	1
	N	0	0,86	0,29	0	0,48	0,67	0	0,1	0,86	1	0	0	0,86	0,67	0
Efficiency	*P*	1	0,54	0,79	0,05	1	0,79	1	0,3	1	1	1	0,79	0,05	0,54	1
	N	0	0,46	0,21	0,95	0	0,21	0	0,7	0	0	0	0,21	0,95	0,46	0

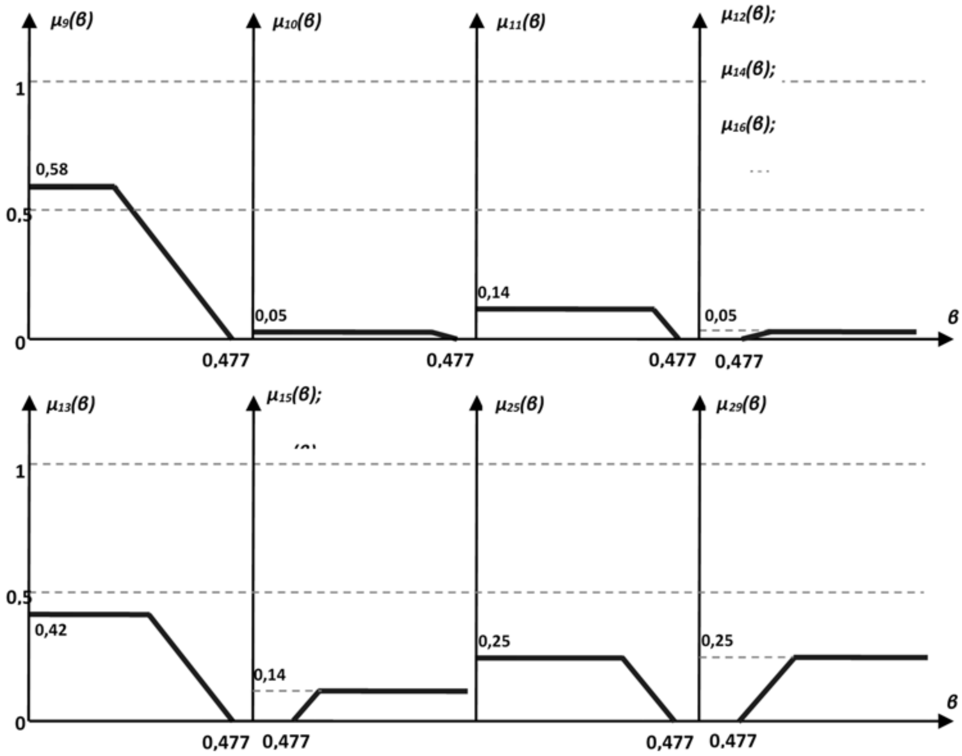
3.3.2. Fuzzy inference

Further calculations should be conducted using the MATLAB and with Mamdani algorithm.

As a clear example, it is offered to consider the technology № 13. In this case, rules 9-16 and 25-32 are applying. All rule weights are equal to 1, so the output MF is cut off to the “Conditions” truthiness degree. There are all the output MF in Figure 9.

Figure 9

Output membership functions for the technology №13 (rules: 9-16 and 25-32)

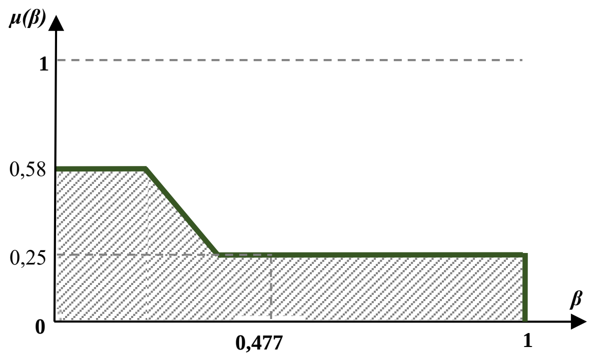


Fuzzy sets are joined by the “max” operation.

The obtained resulting output MF for the technology №13 is shown in Figure 10.

Figure 10

The resulting output membership function for the technology №13

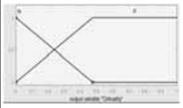
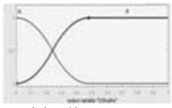


3.3.3. Defuzzification

The defuzzification results are shown in Table 9.

Table 9

Defuzzification results

Technologies No	Criticality assessments with the different types of membership functions for the output linguistic variables			
1.	0,581	0,591	0,698	0,704
2.	0,515	0,515	0,521	0,522
3.	0,547	0,55	0,583	0,585
4.	0,55	0,55	0,578	0,579
5.	0,507	0,507	0,509	0,509
6.	0,508	0,508	0,511	0,511
7.	0,566	0,567	0,611	0,614
8.	0,529	0,529	0,543	0,543
9.	0,547	0,555	0,604	0,606
10.	0,598	0,603	0,705	0,712
11.	0,571	0,573	0,624	0,627
12.	0,576	0,578	0,637	0,641
13.	0,401	0,402	0,396	0,398
13.	0,515	0,515	0,521	0,522
15.	0,58	0,582	0,644	0,648
View of MF	 criticality limit – 0,477	 criticality limit – 0,477	 criticality limit – 0,477	 criticality limit – 0,5

In the proposed example, only one technology is non-critical, because its criticality level is less than the limit 0,477. This is technology №13 (criticality level – 0,401). The other fourteen technologies are critical. The calculations of this example are shown in the first (painted) column of Table 9.

The authors decided to test how the change in the type of the output MF influences the result of the research. Both the calculated (0,477) and the classical (0,5) criticality limits were used. The general view of the output MF can be observed in the bottom row of Table 9 (trapezoidal, S-Z-shaped and rectangular).

The results of defuzzification with different types of MF are shown in Figure 11. The result of calculations has not essential changed when the different types of MF were used. In each of the four cases, the system showed almost identical results. The diagram clearly demonstrates that in the proposed example, the technology №13 is uncritical.

For comparison, in Figure 12 we can observe a diagram with summary estimates of technologies. These values are used in the existing method of forming the Critical Technologies List to create a rating of technologies. Based on the estimates, the expert council decides to include or not a certain technology in the list by voting. In contrast to the proposed in this paper fuzzy inference system, the rating principle of forming a List takes into account only generalised summary estimates of technologies. It is not taken into account the minimal required satisfactory level of criticality or any rules which can be used in the best for the technology.

In the calculated example, the technology №14 has the lowest total summary estimates. Using the existing method, it would probably be decided to exclude the technology №14 from the list. But, table 8 shows that the technology №14 has satisfactory estimates by the three criteria, and the technology №13 has only one. Against this, the existing method looks absurd.

Clarity in this issue is given by the calculations using the other MF. The diagram in Figure 11 shows that the only correct solution is to exclude the technology №13 from the list.

If we are not talking about an example, but about real life, then miscalculations, even with one technology, can lead to millions of unjustified costs budget. And how many such miscalculations can be when the list includes several tens or even hundreds of technologies?!

Figure 11

Criticality assessment of the technologies using different membership functions

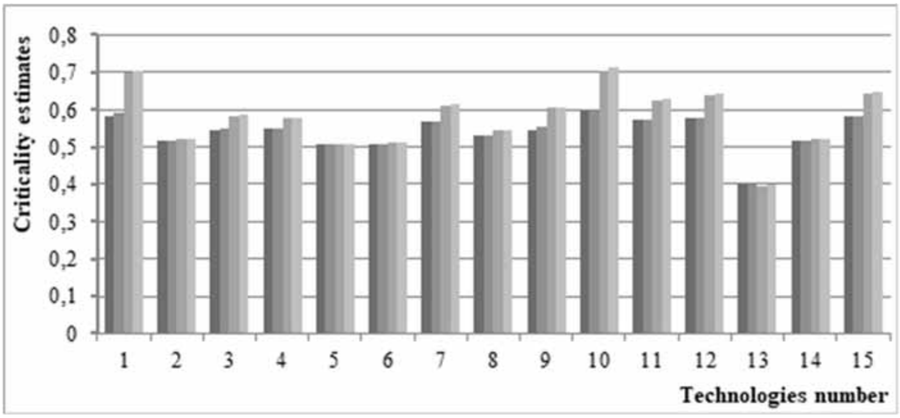
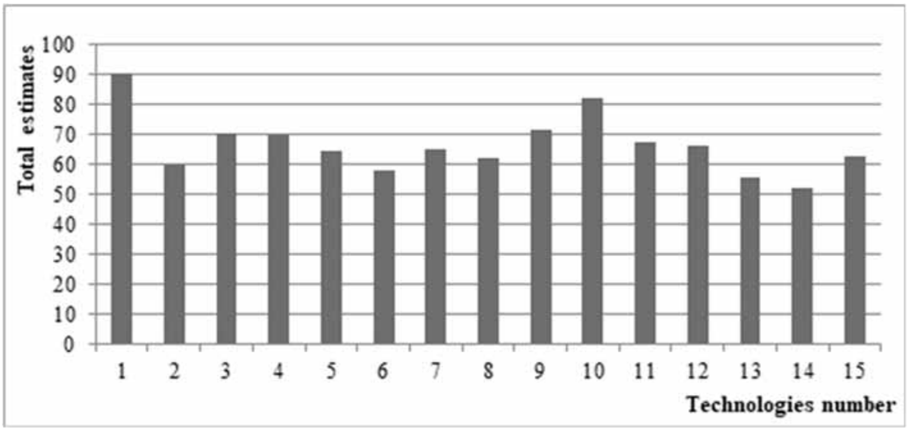


Figure 12

Total summary estimates of technology criticality



4. Conclusions

The proposed decision-making model makes it possible to quickly and efficiently generate a list of critical or disruptive technologies. It is possible to definite a clear line that determines the technology criticality, using fuzzy logic. Not only criterion evaluations are taken into account, but also minimally satisfactory criticality values, which are formulated as the fuzzy inference system rules.

The use of fuzzy logic in the technology foresight allows to remove the subjective expert error. This significantly reduces the time to make a decision, as it does not require an expert council meeting.

The authors propose a new way of finding a mathematically justified minimally satisfactory level of criticality. This makes it possible to determine the membership function based on mathematical calculations rather than the subjective opinion of the experts.

The analysis showed that the application of the model using fuzzy logic is much better than the decision-making model based on summary estimates.

All this makes it possible to prevent the technology forecast miscalculations and identify the most perspective technologies for their long-range development.

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