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APPLICATION ARTICLE

A decision support tool for oil spill response strategy selection: application of LBWA and Z MABAC methods

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Abstract

The high global demand for oil and its derivatives has increased the risk of oil spills associated with the extraction, processing, and transportation of this product. Oil spill emergency management considers that decision-making is a very complex and multi-criteria problem that must be taken into account, given that the effects of these spills include several aspects, the most important of which are the environmental and economic impacts. Oil spill response management decisions are aimed at minimizing these impacts. To solve such a complex problem, this paper is devoted to propose a new multi-criteria model using LBWA-Z MABAC methods. In the first step, the model uses the LBWA method to calculate the criteria weights coefficients. In the second step, the modified MABAC method with Z-numbers was used to select the best contingency strategy to deal with oil spill risks. The calculations were performed on the El Sharara field, which is the second largest oil producing field in Libya. In the case study, six criteria and nine strategies were used, which were selected by a group of experts. The results showed that the type and volume of the oil spill is the most important criterion for selecting the appropriate strategy, and that the best strategy for managing the oil spill in the case study is drain blocking. In order to check the model, a sensitivity analysis was performed by analyzing the effect of changes in the values of the weighting coefficients on the ranking results, as well as by studying the effect of changing the p, q factors. The results obtained were also compared with the fuzzy method and the Z numbers.

Keywords Z number · Level based weight assessment (LBWA) · Multi-attributive border approximation area comparison (MABAC) · Fuzzy logic

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1 Introduction

When comparing the number of oil and chemical spills that occur on water, there are fewer than those that occur on land. The majority of oil spills are less than 7 tons, according to international statistics [31]. This means that small accidents in the oil industry contribute to the higher fraction of polluting oil to the environment. Such a fact may not be surprising considering the number of pipelines extending between oil-producing and consuming countries, pipeline transfers to storage facilities,in addition to road transport, both by rail and road tankers, which are constantly taking place around the world [51]. Due to their effects, media coverage of offshore spills may give a different impression, resulting in higher levels of concern about marine or coastal spills than those on land. This in turn has led to a greater focus on the search for strategies to cope with marine or coastal spills rather than land spills (Krohling and Canpanharo, [38],Davies and Hope, [20]. For example, there are fewer manuals or guidelines for oil spills on the ground than for those on water. Oil spills are large-scale water and soil pollutants that have the potential to destroy organisms in the areas they reach. There are several ways in which oil from spills can return to humans,for example, through fish accumulation, or by consuming contaminated groundwater.

Oil flows and descends, like water, eventually reaching the same outflow points such as streams and rivers. Oil is characterised by the fact that its movement is slower than that of water, and the speed of its movement depends on many factors, including viscosity, surface roughness and condition, permeability, and the degree of surface slope [69]. Given this, movement rates on the ground are slower and flow trends are more pronounced than in aquatic spills and the predictability of motion paths is greater. As a result, it would be possible to focus on response strategies more accurately in the case of landslides.

Most existing studies have focused on offshore or coastal oil spills, and studies on land-based oil spills are still few, although they represent the largest proportion, and are more complex and harder to process [47]. Many techniques have been used to study the problem of oil spills in order to reduce their environmental, social, and economic impacts [80]. For example, multi-criteria methods were used to identify appropriate response strategies. In combination with other approaches, the Analytic Hierarchy Process (AHP) method is most commonly used to calculate weighting coefficients and evaluate alternatives. This method has been used in conjunction with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to determine the best locations for an oil spill action and response center in the Sea of Marmara [37]. Additionally, Zhang et al. [86] elucidate that in the problem of oil-spill response strategy based on linguistic variables, the Analytic Hierarchy Process was used to calculate weighting coefficients. Furthermore, assess the threat level associated with oil spill accidents, estimate the weight of each evaluated index and determine the weight coefficient [36]. The authors used fuzzy logic in various approaches defining the uncertainty connected with this topic. The authors used the fuzzy AHP method to evaluate shoreline sensitivity to oil spills in the study – the Caspian Sea coastal regions in northern Iran. Moreover, the fuzzy AHP method was combined with expert judgment to assess the water pollution risk of mountain industrial parks [73]. Krohlin et al. [40] employed the same strategy and the fuzzy TOmada de Decisao Interativa Multicriterio (TODIM) method to control accidents involving an offshore oil spill. Iakovou et al. [29] used integer linear programming to identify the optimal cleanup equipment capacity and the best cleanup location for oil spill response. Carmody et al. [18] employed the Analytic Network Process method in the example of using organo-clays to clean up oil spills. In the occurrence of oil spills, Analytic Network Process has been utilized to prioritize the managerial tasks of maritime stakeholders in environmental crises [19]. Zafirakou et al. [84] used the Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHE) method to compare different strategies in the case of offshore oil spills. He concluded that floating booms and barriers constitute the best strategy. Ye et al. [81] also used the Fuzzy TOPSIS model to investigate the effects of active operational failure and unsafe latent factors in offshore oil spills. The proposed model contributes to a better understanding of the impact of human factor on oil spills. Wu [75] and Wu & Peng [76] also proposed a grey model to select the best strategy in case of oil spills. In addition, Liu & Wirtz [44] used a hybrid model that integrates the second-order Fuzzy Comprehensive Evaluation (FCE) method and consensus facilitating techniques in the group's computerized decision support system to identify the best strategies for dealing with oil spills.

Optimization models were also used to determine the best alternative given some parameters. Li et al. [43] developed an agent-based simulation optimization approach to provide sound decisions for device integration and customization during fast, dynamic, and cost-effective offshore oil spill recovery under uncertain conditions. The routes of vessels involved in the response process have been improved, as reflected by the model. On the other hand, expert systems were used to formulate spill prediction solutions, provided that Baruque et al. [8] developed a case-based reasoning oil spill prediction model that helps to predict the oil slicks.

Oil exploration, production and transportation companies are responsible for developing oil spill management plans and strategies. It is hard though for such companies to develop a single strategy to address all cases, as these strategies depend upon many criteria. Hence, companies set the goal of developing models that may be used in different situations. In the case of oil spills, the interests of environmental agencies and oil companies involved in the incident tend to conflict in the decision-making method for choosing the best strategy to deal with these spills. It is therefore necessary to evaluate the benefits and drawbacks of different response methods, taking into account social and economic norms as well as environmental factors.

Given the lack of research on terrestrial oil spill response strategies, several strategies were simulated based on a land oil spill in a Libyan oil field. As a result, different response scenarios could be built, which could be selected according to criteria such as the amount of spilled oil and the nature of land. Our research focus is on the development and application of a hybrid decision-making model to a major emergency management problem so as to help select the best available alternatives. To our knowledge, this is the first time this method has been used to manage the oil spill emergency plan, and it is the first study in the oil-rich country of Libya. The aim of this study is to develop a tool to assist decision-makers involved in the emergency plan to manage oil spills and reach the most effective solutions.

In order to solve the presented problem, a hybrid model was selected, based on the crisp LBWA method and the MABAC method which was fuzzified with Z numbers. These methods were selected because of their advantages, which are described later in the paper. The first reason for selecting the LBWA method is its ability of being easily explained to decision-makers/experts (DM/E). Researchers often face the problem of explaining to DM/E what they should do when comparing criteria, because most DM/E have not studied decision-making methods. Additionally, by applying this method the number of comparison of criteria is significantly reduced compared to some traditional methods (for example, the AHP), respectively, brought down to n-1 (where n presents the number of criteria). A small number of criteria comparisons provides better consistency of the DM/E's opinions during criteria evaluation. The simple mathematical algorithm for obtaining weight coefficients of criteria is especially emphasized, including the reliability of the obtained results during the calculation. All these features indicate a simple implementation of the method in practice. The MABAC method also has a number of advantages. The MABAC method provides the stability of the solution in relation to changes in the nature and character of criteria. The next advantage of this method is a well-structured analytical framework for ranking alternatives. The mathematical apparatus used in calculations when applying the MABAC method is very simple, regardless of the number of criteria and alternatives. This method is applicable for both qualitative and quantitative types of criteria and provides the possibility of analyzing the stability of the model when there are changes in the intervals of the weight factors. It can be combined with other areas that that take uncertainty well into account, which is made by applying Z numbers, which provide a much broader framework for considering uncertainty than standard fuzzy numbers.

2 Response strategies and tactics

Typically, after a spill on the ground, the oil remains constant for a short time or moves slowly. This facilitates early detection, allowing recovery to proceed in a more orderly and systematic manner than in open water accidents. The majority of response tactics focus on containing and controlling spills as close to the source as feasible to decrease spillage and, therefore, prevent spills from reaching streams and rivers [47]. The oil movement from land to rivers and open water swiftly expands the impacted area, putting more people, animals, and resources at risk. This is because there are insufficient resources available to protect resources at risk and restore moving oil.

Oil spills at sea or in riverine are more dynamic, and therefore the emergency response methods will be different. These methods will vary for the purpose of containing these spills and reducing their environmental impact. Selecting the appropriate method is a complex process, given that the decision-maker has to consider many factors that may affect the treatment and containment of these spills. These factors include the amount and type of oil spilled, as well as the slope of the terrain; also, the time available to contain the spill is one of the factors influencing appropriate decision making. The decision maker also aims for one of the methods that facilitates the process of recovering some of these quantities. This can be achieved, for example, by constructing dams of sufficient depth to allow the accommodate the use of skimmers. To underscore this point, the same treatment techniques used in coastal spills, such as washing, vacuum removal or on-site treatment, can be used here. Table 2 summarises the most important strategies that can be used to control oil spills [51].

Although progress has been made in accident prevention, this is not the case in all countries, and comprehensive prevention is impossible due to the indiscriminate nature of oil spill. As a result, a significant effort has been undertaken worldwide to establish measures to reduce accidental spills and develop new treatment procedures.

In this study, an initial list of criteria and strategies was prepared based on previous studies. Subsequently, a group of experts working in the Libyan oil sector was contacted to make comments about the suggested criteria and strategies. All of these experts have been working in the oil industry for at least 20 years. After having adopted the criteria and strategies in their final form (Tables 1 and 2), a single questionnaire was prepared to fill out the required data according to the mathematical models used in this research. Four experts from three oil companies were interviewed for the purpose of explaining the model to them and completing those questionnaires. One of these experts works as an operations manager of an oil company, the second is a director of environmental safety department, the third is a director of planning department, and the fourth is a production manager.

3 LBWA–Z MABAC model

Hybrid LBWA–Z MABAC model is defined through three phases as presented in Fig. 1.

The next text follows the description of the applied methods. The methods were applied in group decision making.

3.1 LBWA method

The LBWA method was created in 2019 [88]. Its fundamental characteristic is a simple mathematical apparatus. This is important considering that the DM/E are

Table 1 Criteria used in the study

No	Criterion
C1	Type and volume of the oil spill
C2	Location of the spill point
C3	Sediment type
C4	Terrain slope
C5	Level of impact
C6	Potential of impacts from the candidate cleanup technique

Table 2 List of strategies

No	Strategy	Description
A1	Drain blocking	Any materials that can be used to prevent oil spilled on paved areas like boards, sandbags
A2	Culvert blocking	Any means of oil flow containment can be used for culverts blocking such as sandbags, boards, or earthen materials
A3	Containment berms	The locally available materials are used to construct low barriers for surface oil containment
A4	Diversion berms	The locally available materials are used to construct low barriers to direct surface oil
A5	Sorbent barriers	On relatively flat or gently sloping ground, low-lying sorbent barriers are used to contain oil flows and limit penetration into permeable soils
A6	In-situ burning	The controlled burning of the spilled oil can be used
A7	Blocking dams	This involves the construction of a dam in the drainage stream bed for spilled flow containment
A8	Interceptor trench	Involves constructing trenches across the stream path to block the movement of spilled oil within the subsoil
A9	Slurry walls	Slurry can be used to fill trenches dug to conserve groundwater, as well as to create a barrier for groundwater treatment systems

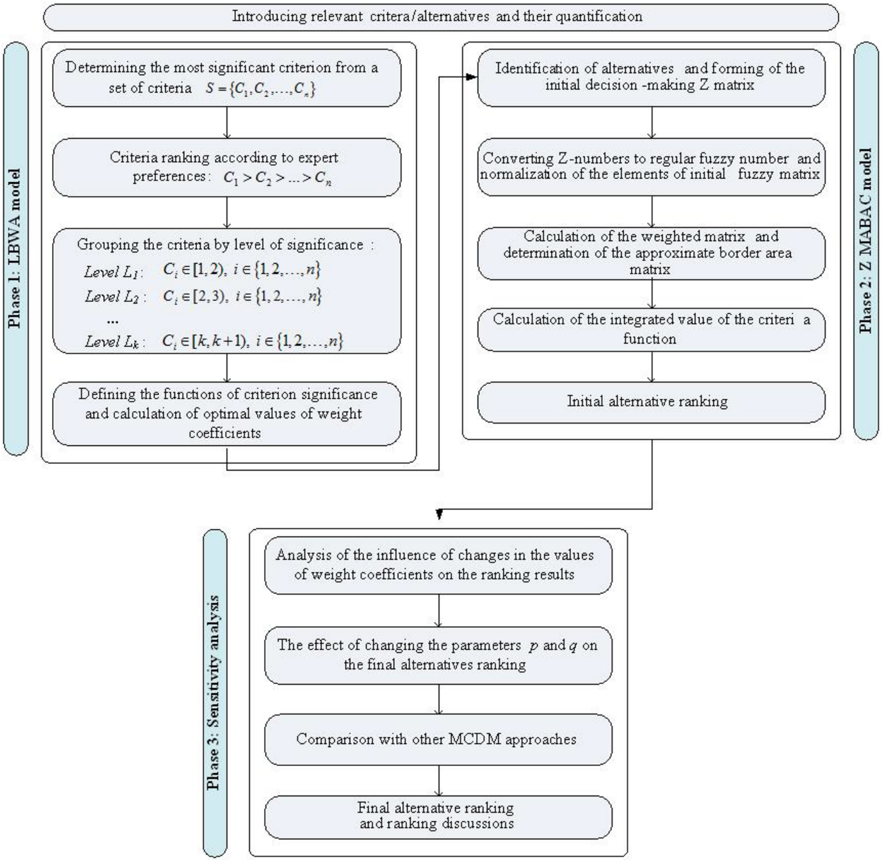

Fig. 1 LBWA-Z-MABAC model

mostly not familiar with the methods although they are supposed to evaluate the criteria accordingly. Although it is a new method, its application has already been found in certain papers. So far, the LBWA method has been applied in the papers Jokić et al. [34], Božanić et al. [11], Božanić et al. [16], Pamučar et al. [57], Deveci et al. [21], etc.

After defining the n criteria, the LBWA method are applied. In this case, the LBWA method is applied through group decision-making. The method consists of seven steps [88]:

Step 1 In the first step, every expert defines the criterion with the largest influence on the final decision.

Step 2 Rough classification of the criteria. Every expert defines the level at which the criteria are positioned. By defining the level of a certain criterion $C_i, i \in \{1, 2...n\}$, the overall relationship to the most influential criterion is defined. The first and last level must have at least one criterion. The number of criteria is not limited.

Step 3 At every level, the criteria are compared according to their significance. To every criterion $C_{i_p} \in S_i$ within the subset $\vartheta_i = \left\{C_{i_1}, C_{i_2,} \dots, C_{i_s}\right\}$ is assigned the value of $I_{i_p} \in \{0, 1, 2, \dots, \varpi\}$. The criterion that is defined as the most influential (C_i) is always assigned a value of $I_i = 0$. If the criterion C_{i_p} is more significant than C_{i_q}, than $I_p < I_q$, also if C_{i_p} is the same as significant as C_{i_q}, than $I_p = I_q$. The comparison scale has values from 0 to ϖ, separately for each problem that is solved. Value ϖ is defined by the use of expressions (1)

$$\varpi = \max\left\{\left|\vartheta_1\right|, \left|\vartheta_2\right|, \dots, \left|\vartheta_{k-1}\right|, \left|\vartheta_k\right|\right\} \tag{1}$$

Step 4
Defining coefficient of elasticity (ϖ_0)- this coefficient should meet the condition where $\varpi_0 > \varpi$.
Step 5
In this step, for each criterion $C_{i_p} \in \vartheta_i$, which is at the i-th level, the function of influence ($f : \vartheta \rightarrow R$) is defined:

$$f(C_{i_p}) = \frac{\varpi_0}{i \cdot \varpi_0 + I_{i_p}} \tag{2}$$

Step 6
The calculation of the weight coefficients is done through two steps:
Step 6.1
For the most influential criterion, expression (3):

$$w_1 = \frac{1}{1 + f(C_2) + \dots + f(C_n)} \tag{3}$$

Step 6.2
For the other criteria, expression (4):

$$w_j = f(C_j) \cdot w_1 \tag{4}$$

Step 7
After calculating the weighting coefficients at the level of each expert, the obtained values are aggregated into one. Aggregation can be done in several ways. In this case, the Bonferroni aggregator was selected [10], according to the expression (5):

$$BM^{p,q}(a_1, a_2, \dots, a_n) = \left(\frac{1}{n(n-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{n} a_i^p a_j^q\right)^{\frac{1}{p+q}} \tag{5}$$

where n presents the number of criteria included and $p,q \geq 0$.

3.2 Z-MABAC method

In the beginning, the creators of the MABAC method (Pamučar & Ćirović, 2015) presented its application with crisp values. The classical MABAC method has found application in many papers [14, 15, 24, 26, 30, 33, 45, 46, 49, 60, 61, 74],). In the available papers, different forms of modifications of the MABAC method can be observed, such as a) by applying for fuzzy numbers [9, 12, 27, 62, 72, 78, 82],b) by applying rough numbers [5, 64, 67],c) in a neutrosophic environment [59]52, 77, 4.

Triangular Z numbers have been used to improve the MABAC method. Figure 2, shows the triangular fuzzy number.

The basics about Z numbers were given by Zadeh [83]. Z-numbers have so far been combined with different methods: with AHP [7], with TOPSIS [79], with Data Envelopment Analysis-DEA [6, 66], with Best Worst Method-BWM [1], with hybrid LBWA- Z-number-MABAC method [11], with hybrid AHP-Z-number-MABAC method Bobar et al. [9], with hybrid FUll COnsistency Method (FUCOM)-Z-number-MABAC method [17], etc.

The Z number ($Z=(\tilde{T},\tilde{B})$) consists of two fuzzy numbers [83]. The first part of the Z number $\tilde{T}$ describes the variable X. The second part, fuzzy number ($\tilde{B}$), presents the reliability of the fuzzy number $\tilde{T}$. Triangular Z-numbers can be presented as follows

$$\tilde{Z} = \left\{ \left(t^l, t^m, t^r \right), (b^l, b^m, b^r) \right\} \tag{6}$$

From Z numbers to classic fuzzy numbers is arrived at by applying expressions [35]:

$$\tilde{Z} = \sqrt{\alpha} * \tilde{T} = (\sqrt{\alpha} * t^l, \sqrt{\alpha} * t^m, \sqrt{\alpha} * t^r) \tag{7}$$

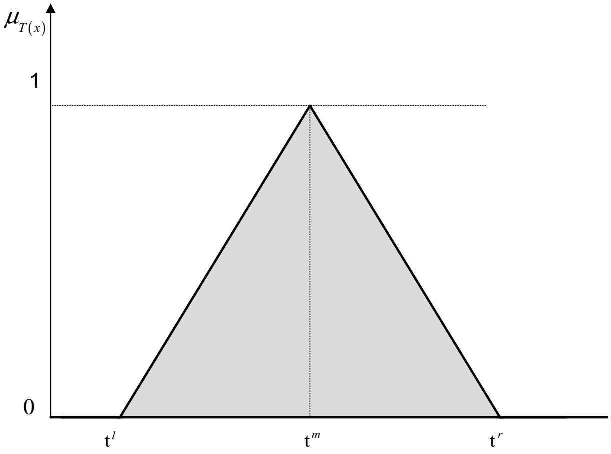

Fig. 2 Standard triangular fuzzy numbers

where the value α presents the crisp number of the fuzzy number ($\tilde{B}$) and it is obtained by using the centered method:

$$\alpha = \frac{b^l + b^m + b^r}{3} \tag{8}$$

The Z-numbers Z=($\tilde{T}_{,\tilde{B}}$) in this paper are applied with the MABAC method, where the first fuzzy number ($\tilde{T}$) presents the data about certain alternative according to certain criterion, and the second fuzzy ($\tilde{B}$) number presents the degree of certainty of the DM/E in the specified data, respectively, in the first fuzzy number ($\tilde{T}$). The fuzzy number $\tilde{B}$ is especially important in the cases when there is some uncertainty, and this is most often when there is not enough data available or the criteria are linguistic. Different scales can be used to define the degree of certainty [42]. The scale applied in the paper has five fuzzy lingustic descriptors (FLD), Fig. 3.

The Hybrid Z-MABAC model has already been presented in Bobar et al. [9] and Božanić et al. [17] but in the context of individual MCDM. The steps of the Z-MABAC model in group decision-making are provided below.

Step 1.

Forming of initial decision-making (IDM) matrix ($\tilde{X}$).

Step 1.1

The IDM matrix is formed for every expert (e_k) separately.

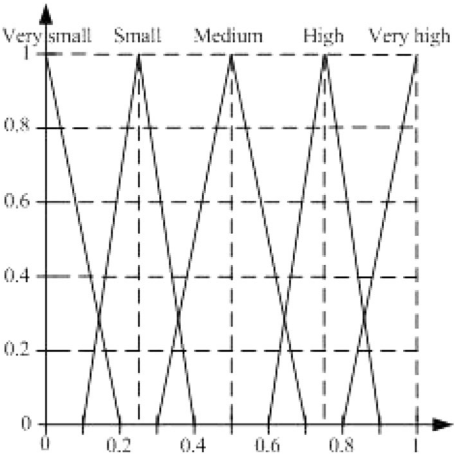

Fig. 3 FLD used to assess the degree of certainty of DM/E [9]

$$\tilde{X}^{e_k} = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \ldots \\ A_s \end{array} & \begin{bmatrix} \tilde{T}_{11};\tilde{B}_{11} & \tilde{T}_{12};\tilde{B}_{12} & \ldots & \tilde{T}_{1n};\tilde{B}_{1n} \\ \tilde{T}_{21};\tilde{B}_{21} & \tilde{T}_{22};\tilde{B}_{22} & & \tilde{T}_{2n};\tilde{B}_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \tilde{T}_{s1};\tilde{B}_{s1} & \tilde{T}_{s2};\tilde{B}_{s2} & \ldots & \tilde{T}_{sn};\tilde{B}_{sn} \end{bmatrix} \end{array}$$

$$= \begin{array}{cc} & \begin{array}{ccc} C_1 & \ldots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \ldots \\ A_s \end{array} & \begin{bmatrix} \left(t_{11}^l, t_{11}^m, t_{11}^r\right);\left(b_{11}^l, b_{11}^m, b_{11}^r\right) & \ldots & \left(t_{1n}^l, t_{1n}^m, t_{1n}^r\right);\left(b_{1n}^l, b_{1n}^m, b_{1n}^r\right) \\ \left(t_{21}^l, t_{21}^m, t_{21}^r\right);\left(b_{21}^l, b_{21}^m, b_{21}^r\right) & \ldots & \left(t_{2n}^l, t_{2n}^m, t_{2n}^r\right);\left(b_{2n}^l, b_{2n}^m, b_{2n}^r\right) \\ \ldots & \ldots & \ldots \\ \left(t_{s1}^l, t_{s1}^m, t_{s1}^r\right);\left(b_{s1}^l, b_{s1}^m, b_{s1}^r\right) & \ldots & \left(t_{sn}^l, t_{sn}^m, t_{sn}^r\right);\left(b_{sn}^l, b_{sn}^m, b_{sn}^r\right) \end{bmatrix} \end{array} \tag{9}$$

Step 1.2

Quantification of IDM matrix. It is used in cases when linguistic expressions are used to evaluate alternatives, as a part of the first step is quantified linguistic expressions.

Step 2.

Converting Z-numbers into regular numbers, using expressions (7) and (8). After the conversion, a new IDM matrix ($\tilde{P}$) is obtained.

$$\tilde{P}^{e_k} = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \ldots \\ A_s \end{array} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & & \tilde{x}_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \tilde{x}_{s1} & \tilde{x}_{s2} & \ldots & \tilde{x}_{sn} \end{bmatrix} \end{array} = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \ldots \\ A_s \end{array} & \begin{bmatrix} (x_{11}^l, x_{11}^m, x_{11}^r) & (x_{12}^l, x_{12}^m, x_{12}^r) & \ldots & (x_{1n}^l, x_{1n}^m, x_{1n}^r) \\ (x_{21}^l, x_{21}^m, x_{21}^r) & (x_{22}^l, x_{22}^m, x_{22}^r) & & (x_{2n}^l, x_{2n}^m, x_{2n}^r) \\ \ldots & \ldots & \ldots & \ldots \\ (x_{s1}^l, x_{s1}^m, x_{s1}^r) & (x_{s2}^l, x_{s2}^m, x_{s2}^r) & \ldots & (x_{sn}^l, x_{sn}^m, x_{sn}^r) \end{bmatrix} \end{array} \tag{10}$$

*Step 3.*where is:

Normalization of new IDM matrix, using expression (11)—for beneficial criteria and, expression (12) for cost criteria:

$$\tilde{n}_{ij} = \left(\frac{x_{ij}^l - x_i^-}{x_i^+ - x_i^-}, \frac{x_{ij}^m - x_i^-}{x_i^+ - x_i^-}, \frac{x_{ij}^r - x_i^-}{x_i^+ - x_i^-} \right) \tag{11}$$

$$\tilde{n}_{ij} = \left(\frac{x_{ij}^l - x_i^+}{x_i^- - x_i^+}, \frac{x_{ij}^m - x_i^+}{x_i^- - x_i^+}, \frac{x_{ij}^r - x_i^+}{x_i^- - x_i^+} \right) \tag{12}$$

- $x_i^+ = \max(x_{1j}^r, x_{2j}^r, \ldots, x_{sj}^r)$—presents maximal values of the right distribution of fuzzy numbers of the observed criteria alternatives and.
- $x_i^- = \min(x_{1j}^l, x_{2j}^l, \ldots, x_{sj}^l)$—presents minimal values of the left distribution of fuzzy numbers of the observed criteria alternatives.

After the normalization, the normalized matrix ($\tilde{N}^{e_k}$) is obtained.

Step 4 The weighted matrix ($\tilde{V}^{e_k}$) is obtained by applying the expression (13):

$$\tilde{v}_{ij} = \left(w_i \cdot \tilde{n}_{ij}^l + w_i, w_i \cdot \tilde{n}_{ij}^m + w_i, w_i \cdot \tilde{n}_{ij}^r + w_i \right) \tag{13}$$

where $\tilde{n}_{ij} \in \tilde{N}^{e_k}$ and w_i is weight coefficients.

Step 5.

The matrix of Border approximate area (BAA) $\tilde{G}^{e_k}$ has a form $n \times 1$:

$$\tilde{G}^{e_k} = \begin{array}{ccc} C_1 & C_2 & \dots & C_n \\ \left[\tilde{g}_1 \right. & \tilde{g}_2 & \dots & \left. \tilde{g}_n \right] \end{array} = \begin{array}{ccc} C_1 & C_2 & \dots & C_n \\ \left[\left(g_1^l, g_1^m, g_1^r\right) \right. & \left(g_2^l, g_2^m, g_2^r\right) & \dots & \left. \left(g_n^l, g_n^m, g_n^r\right) \right] \end{array} \tag{14}$$

The BAA for every criterion is calculated using expression (15):

$$\tilde{g}_i = \left(\prod_{i=1}^{s} \tilde{v}_{ij} \right)^{1/s} = \left(\left(\prod_{i=1}^{s} v_{ij}^l \right)^{1/s}, \left(\prod_{i=1}^{s} v_{ij}^m \right)^{1/s}, \left(\prod_{i=1}^{s} v_{ij}^r \right)^{1/s} \right) \tag{15}$$

Step 6.

Calculation alternatives distance from the BAA ($\tilde{Q}^{e_k}$), using expression (16):

$$\begin{aligned} \tilde{Q}^{ek} &= \tilde{V}^{ek} - \tilde{G}^{ek} \Rightarrow \tilde{q}_{ij}^{ek} = \tilde{v}_{ij}^{ek} - \tilde{g}_j^{ek} \\ &= \left(\left(v_{ij}^{ek(l)} - g_j^{ek(r)} \right), \left(v_{ij}^{ek(m)} - g_j^{ek(m)} \right), \left(v_{ij}^{ek(r)} - g_j^{ek(l)} \right) \right) \end{aligned} \tag{16}$$

Step 7

Ranking of alternatives.

Step 7.1

The calculation of the final values is done by applying expression (17):

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{q}_{ij} = \left(\sum_{j=1}^{n} q_{ij}^l, \sum_{j=1}^{n} q_{ij}^m, \sum_{j=1}^{n} q_{ij}^r, \right) \tag{17}$$

where $\tilde{q}_{ij} \in \tilde{Q}^{e_k}$.

Step 7.2

Defazification of fuzzy value alternatives, using expressions (18) or (19) (Seiford, 1996; Liou and Wang, 1992):

$$S_i = ((t^r - t^l) + (t^m - t^l))/3 + t^l \tag{18}$$

$$S_i = \left[\lambda t^r + t^m + (1 - \lambda) t^l \right] / 2 \tag{19}$$

Step 7.3.

Aggregation of the final values for k experts is performed by applying simple arithmetic mean

$$S_i^G = \frac{\sum_{i=1}^{k} S_i}{k} \tag{20}$$

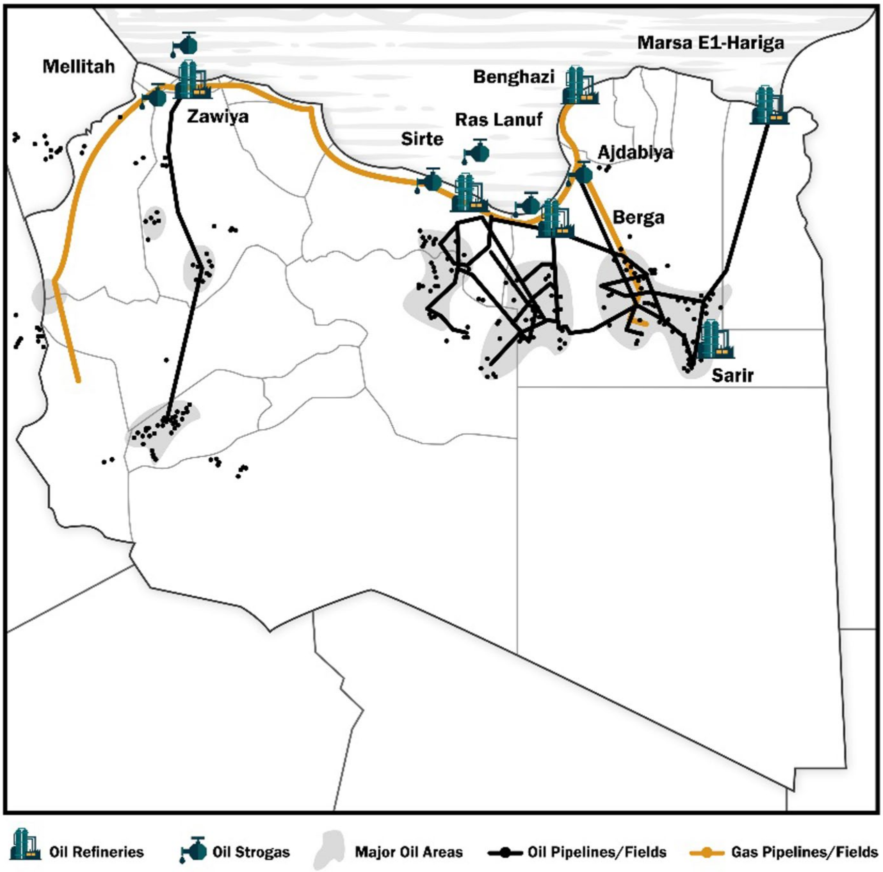

Fig. 4 Oil fields, ports and the pipeline network in Libya

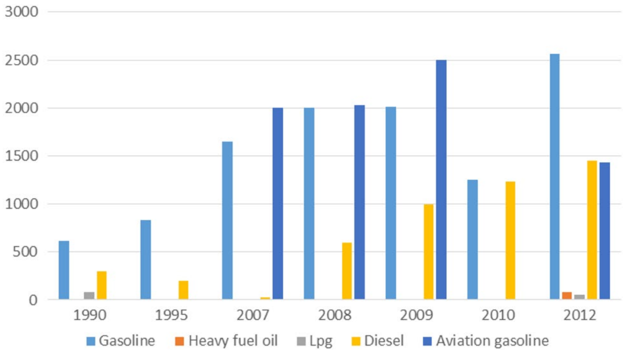

Fig. 5 Libya's import of oil derivatives during the period 1990–2012

Table 3 Distribution of criteria by levels

E1	E2	E3	E4
$\vartheta_1 = \{C_1\}$	$\vartheta_1 = \{C_1, C_3, C_4\}$	$\vartheta_1 = \{C_1\}$	$\vartheta_1 = \{C_1\}$
$\vartheta_2 = \{\emptyset\}$	$\vartheta_2 = \{C_2\}$	$\vartheta_2 = \{C_3, C_2\}$	$\vartheta_2 = \{C_3, C_2\}$
$\vartheta_3 = \{C_4, C_2, C_3\}$	$\vartheta_3 = \{\emptyset\}$	$\vartheta_3 = \{\emptyset\}$	$\vartheta_3 = \{\emptyset\}$
$\vartheta_4 = \{\emptyset\}$	$\vartheta_4 = \{C_5\}$	$\vartheta_4 = \{C_4, C_5\}$	$\vartheta_4 = \{C_4, C_5\}$
$\vartheta_5 = \{C_5, C_6\}$	$\vartheta_5 = \{C_6\}$	$\vartheta_5 = \{\emptyset\}$	$\vartheta_5 = \{\emptyset\}$
		$\vartheta_6 = \{\emptyset\}$	$\vartheta_6 = \{\emptyset\}$
		$\vartheta_7 = \{C_6\}$	$\vartheta_7 = \{C_6\}$

Table 4 Maximum values of the comparison scale

Expert	Maximum values of the comparison scale (r_{max})
E1	$\varpi_{e_1} = \max\{\lvert\vartheta_1\rvert, \lvert\vartheta_2\rvert, \lvert\vartheta_3\rvert, \lvert\vartheta_4\rvert, \lvert\vartheta_5\rvert\} = 3$
E2	$\varpi_{e_2} = \max\{\lvert\vartheta_1\rvert, \lvert\vartheta_2\rvert, \lvert\vartheta_3\rvert, \lvert\vartheta_4\rvert, \lvert\vartheta_5\rvert\} = 3$
E3	$\varpi_{e_3} = \max\{\lvert\vartheta_1\rvert, \lvert\vartheta_2\rvert, \lvert\vartheta_3\rvert, \lvert\vartheta_4\rvert, \lvert\vartheta_5\rvert, \lvert\vartheta_6\rvert, \lvert\vartheta_7\rvert\} = 2$
E4	$\varpi_{e_4} = \max\{\lvert\vartheta_1\rvert, \lvert\vartheta_2\rvert, \lvert\vartheta_3\rvert, \lvert\vartheta_4\rvert, \lvert\vartheta_5\rvert\} = 2$

4 Application of the MCDM model

Libya's economy depends mainly on oil exports, which account for about 95% of the country's total exports. The country has several oil fields and ports, the most important of which are the AMAL field with a daily production capacity of 400,000 barrels per day, SHARARA and AL-PHIL fields with a daily production of more than 300,000 barrels per day each, as well as SIDRA port reaching a daily production of more than 400,000 barrels per day. On the other hand, it imports gasoline, oil, and other oil derivatives (NOC [48]. Figure 4 shows the country's oil fields, ports, and pipeline networks, while Fig. 5 shows the most important oil imports (NOC 2014).

Crude oil is transported through a pipeline network from the fields across the desert to oil ports. Oil derivatives are transported through tanks and distributed to different cities. Due to the age of these carriers, the risk of leakage is increasing; therefore, compelling various oil companies to develop scenarios to counter such risk. A contingency plan is required to reduce the damage caused by oil spills if they occur.

The proposed MCDM model was used to determine the alternative ranking, and for this purpose, a case study was selected for the Sharara oil field, located in the Murzuq desert, discovered in 1980. This field is the second largest oil reservoir supplying heavy oil (API 38) in Libya. Its total proven reserves are estimated at 3 billion barrels. Daily production is concentrated on 300,000 barrels. The length of the pipelines linking the field to the Libyan coast is approximately 750 km. It is worth mentioning that many oil spill accidents have occurred on the field or at the level

Table 5 Evaluation of criteria comparison

E1	E2	E3	E4
$\vartheta_1 : I_1 = 0$	$\vartheta_1 : I_1 = 0, I_3 = 3, I_4 = 3$	$\vartheta_1 : I_1 = 0$	$\vartheta_1 : I_1 = 0$
$\vartheta_3 : I_4 = 1, I_2 = 2.5, I_3 = 3$	$\vartheta_2 : I_2 = 2$	$\vartheta_2 : I_3 = 1, I_2 = 1.7$	$\vartheta_3 : I_4 = 1, I_2 = 2$
$\vartheta_5 : I_5 = 0, I_6 = 3$	$\vartheta_4 : I_5 = 0$	$\vartheta_4 : I_4 = 1, I_5 = 2$	$\vartheta_4 : I_6 = 1, I_5 = 2$
	$\vartheta_5 : I_6 = 3$	$\vartheta_7 : I_6 = 2$	$\vartheta_5 : I_3 = 2$

of these pipelines. In 2019, pipeline erosion resulted in a loss of 1000bbp. The dam reservoir collapse in 2020 also resulted in a loss of 2000bbp.

For use in research, the spilled oil volume has been estimated at 100,000 bbp, which corresponds to the surge tank volume (worst case scenario). A thick sequence continental sediments of Triassic to early Cretaceous continental deposits covers the middle part of the Murzuq Basin. The spill takes place in the surge tank portion of the pipeline. The impact is categorized as medium.

4.1 Calculation of weight coefficients of criteria

The process of the comparison of criteria included four experts. The calculation of weight coefficients is explained in the steps below.

Step 1 In this step, all the experts have defined the criterion C_1 as the most significant, respectively, the most influential.
Step 2 Distribution of the criteria by levels differed from expert to expert, Table 3.
Step 3. Based on the distribution by levels, the ϖ value was also defined,Table 4. For all the distributed criteria, the experts provided their evaluations of the comparison, Table 5.
Step 4 After the criteria had been compared, the calculation of the weight coefficients was started. The example of the calculation was presented in the case of expert 1, while the other experts were provided with final values at the end of the complete method.
The coefficient of elasticity $\varpi_0^{e_1}$, were $\varpi_0^{e_1} > \varpi_{e_1}$, is $\varpi_0^{e_1} = 4$.
Step 5 The functions of the influence were calculated using the expression (2)..

Table 6 Weight coefficient calculated based on expert opinion

Expert	w_1	w_2	w_3	w_4	w_5	w_6
E1	0.449	0.124	0.120	0.139	0.090	0.078
E2	0.337	0.135	0.193	0.193	0.084	0.058
E3	0.418	0.163	0.179	0.096	0.089	0.055
E4	0.456	0.124	0.080	0.137	0.098	0.105

Table 7 Weight coefficients after the aggregation

w_1	w_2	w_3	w_4	w_5	w_6
0.415	0.137	0.142	0.141	0.091	0.074

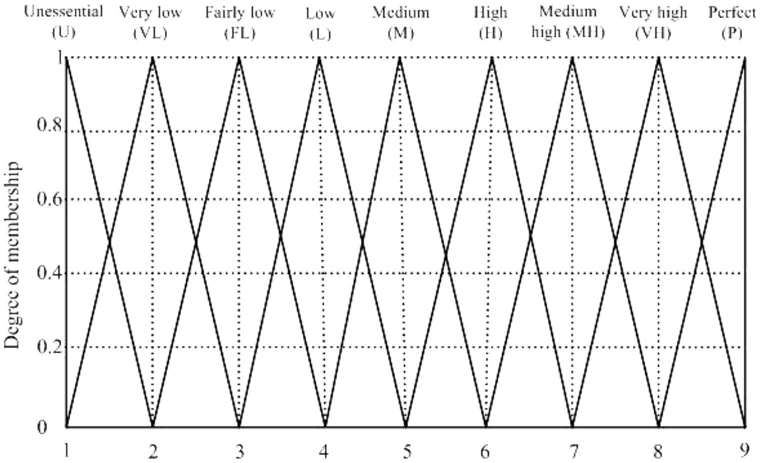

Fig. 6 FLD for the evaluation of alternatives

$$f(C_1)_{e_1} = \frac{4}{1 \cdot 4 + 0} = 1; f(C_4)_{e_1} = \frac{4}{3 \cdot 4 + 1} = 0.308; f(C_2)_{e_1} = \frac{4}{3 \cdot 4 + 2.5} = 0.276;$$
$$f(C_3)_{e_1} = \frac{4}{3 \cdot 4 + 3} = 0.267; f(C_5)_{e_1} = \frac{4}{5 \cdot 4 + 0} = 0.2; f(C_6)_{e_1} = \frac{4}{5 \cdot 4 + 3} = 0.174.$$

Step 6 First, the weight coefficient of criterion C_1 was calculated, according to the expression (3), step 6.1:

$$w_1^{e_1} = \frac{1}{1 + 0.308 + 0.276 + 0.267 + 0.2 + 0.174} = 0.449$$

Further were calculated the weight coefficients according to the expression (4), step 6.2:

$$w_2^{e_1} = 0.276 \cdot 0.449 = 0.124;$$
$$\ldots$$
$$w_6^{e_1} = 0.174 \cdot 0.449 = 0.078.$$

The weight coefficients obtained by applying the LBWA method, by all experts is provided in Table 6.

Step 7. Aggregation of the weight coefficients calculated based on expert opinion is performed by Bonferroni aggregator, as in the expression (5).

Table 8 IDM matrix for the expert 1

Alt	C_1		C_2		C_3		C_4		C_5		C_6	
	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$
A_1	VL	H	P	H	VL	H	VL	S	VL	M	U	H
A_2	U	VH	MH	S	U	VH	MH	H	H	H	FL	H
A_3	VL	S	VL	VS	FL	VS	P	M	M	S	VL	VS
A_4	U	VS	VL	VH	VL	S	U	S	VH	VS	MH	VH
A_5	M	H	U	VS	P	H	U	M	M	H	VL	S
A_6	H	H	MH	M	M	VH	FL	VS	MH	M	U	H
A_7	M	VH	H	VH	H	VS	H	VH	MH	M	FL	H
A_8	VL	H	H	VH	MH	VH	L	VH	FL	VS	L	VS
A_9	U	VS	U	H	FL	M	L	VH	FL	M	U	H

Table 9 Quantified IDM matrix for the expert 1

Alt	C_1		C_2		C_6	
	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$	$\tilde{T}$	$\tilde{B}$
A_1	(1,2,3)	(0.55,0.75,0.95)	(8,9,9)	(0.55,0.75,0.95)	(1,1,2)	(0.55,0.75,0.95)
A_2	(1,1,2)	(0.8,1,1)	(6,7,8)	(0.1,0.25,0.4)	(2,3,4)	(0.55,0.75,0.95)
A_3	(1,2,3)	(0.1,0.25,0.4)	(1,2,3)	(0,0,0.2)	(1,2,3)	(0,0,0.2)
A_4	(1,1,2)	(0,0,0.2)	(1,2,3)	(0.8,1,1)	(6,7,8)	(0.8,1,1)
A_5	(4,5,6)	(0.55,0.75,0.95)	(1,1,2)	(0,0,0.2)	(1,2,3)	(0.1,0.25,0.4)
A_6	(5,6,7)	(0.55,0.75,0.95)	(6,7,8)	(0.3,0.5,0.7)	(1,1,2)	(0.55,0.75,0.95)
A_7	(4,5,6)	(0.8,1,1)	(5,6,7)	(0.8,1,1)	(2,3,4)	(0.55,0.75,0.95)
A_8	(1,2,3)	(0.55,0.75,0.95)	(5,6,7)	(0.8,1,1)	(3,4,5)	(0,0,0.2)
A_9	(1,1,2)	(0,0,0.2)	(1,1,2)	(0.55,0.75,0.95)	(1,1,2)	(0.55,0.75,0.95)

Table 10 New IDM matrix after the conversion into the regular fuzzy numbers for the expert 1

Alt	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(0.87,1.73,2.6)	(6.93,7.79,7.79)	(0.87,1.73,2.6)	(0.5,1,1.5)	(0.71,1.41,2.12)	(0.87,0.87,1.73)
A_2	(0.97,0.97,1.93)	(3,3.5,4)	(0.97,0.97,1.93)	(5.2,6.06,6.93)	(4.33,5.2,6.06)	(1.73,2.6,3.46)
A_3	(0.5,1,1.5)	(0.26,0.52,0.77)	(0.52,0.77,1.03)	(5.66,6.36,6.36)	(2,2.5,3)	(0.26,0.52,0.77)
A_4	(0.26,0.26,0.52)	(0.97,1.93,2.9)	(0.5,1,1.5)	(0.5,0.5,1)	(1.81,2.07,2.32)	(5.8,6.76,7.73)
A_5	(3.46,4.33,5.2)	(0.26,0.26,0.52)	(6.93,7.79,7.79)	(0.71,0.71,1.41)	(3.46,4.33,5.2)	(0.5,1,1.5)
A_6	(4.33,5.2,6.06)	(4.24,4.95,5.66)	(3.86,4.83,5.8)	(0.77,1.03,1.29)	(4.24,4.95,5.66)	(0.87,0.87,1.73)
A_7	(3.86,4.83,5.8)	(4.83,5.8,6.76)	(1.29,1.55,1.81)	(5.8,6.76,7.73)	(4.24,4.95,5.66)	(1.73,2.6,3.46)
A_8	(0.87,1.73,2.6)	(4.83,5.8,6.76)	(5.8,6.76,7.73)	(2.9,3.86,4.83)	(0.52,0.77,1.03)	(0.77,1.03,1.29)
A_9	(0.26,0.26,0.52)	(0.87,0.87,1.73)	(1.41,2.12,2.83)	(2.9,3.86,4.83)	(1.41,2.12,2.83)	(0.87,0.87,1.73)

Table 11 Normalized matrix for the expert 1

Alt	*C₁*	*C₂*	*C₃*	*C₄*	*C₅*	*C₆*
A_1	(0.6,0.75,0.9)	(0.89,1,1)	(0.05,0.17,0.29)	(0.86,0.93,1)	(0.71,0.84,0.97)	(0.8,0.92,0.92)
A_2	(0.71,0.88,0.88)	(0.36,0.43,0.5)	(0.06,0.06,0.2)	(0.11,0.23,0.35)	(0,0.16,0.31)	(0.57,0.69,0.8)
A_3	(0.79,0.87,0.96)	(0,0.03,0.07)	(0,0.04,0.07)	(0.19,0.19,0.29)	(0.55,0.64,0.73)	(0.93,0.97,1)
A_4	(0.96,1,1)	(0.09,0.22,0.35)	(0,0.07,0.14)	(0.93,1,1)	(0.67,0.72,0.77)	(0,0.13,0.26)
A_5	(0.15,0.3,0.45)	(0,0,0.03)	(0.88,1,1)	(0.87,0.97,0.97)	(0.16,0.31,0.47)	(0.83,0.9,0.97)
A_6	(0,0.15,0.3)	(0.53,0.62,0.72)	(0.46,0.59,0.73)	(0.89,0.93,0.96)	(0.07,0.2,0.33)	(0.8,0.92,0.92)
A_7	(0.05,0.21,0.38)	(0.61,0.73,0.86)	(0.11,0.14,0.18)	(0,0.13,0.27)	(0.07,0.2,0.33)	(0.57,0.69,0.8)
A_8	(0.6,0.75,0.9)	(0.61,0.73,0.86)	(0.73,0.86,0.99)	(0.4,0.53,0.67)	(0.91,0.95,1)	(0.86,0.9,0.93)
A_9	(0.96,1,1)	(0.08,0.08,0.2)	(0.13,0.22,0.32)	(0.4,0.53,0.67)	(0.58,0.71,0.84)	(0.8,0.92,0.92)

Table 12 Weighted matrix for the expert 1

Alt	*C₁*	*C₂*	*C₃*	*C₄*	*C₅*	*C₆*
A_1	(0.66,0.72,0.79)	(0.26,0.27,0.27)	(0.15,0.16,0.18)	(0.26,0.27,0.28)	(0.16,0.17,0.18)	(0.13,0.14,0.14)
A_2	(0.71,0.78,0.78)	(0.19,0.2,0.21)	(0.15,0.15,0.17)	(0.16,0.17,0.19)	(0.09,0.11,0.12)	(0.12,0.12,0.13)
A_3	(0.74,0.78,0.81)	(0.14,0.14,0.15)	(0.14,0.15,0.15)	(0.17,0.17,0.18)	(0.14,0.15,0.16)	(0.14,0.15,0.15)
A_4	(0.81,0.83,0.83)	(0.15,0.17,0.18)	(0.14,0.15,0.16)	(0.27,0.28,0.28)	(0.15,0.16,0.16)	(0.07,0.08,0.09)
A_5	(0.48,0.54,0.6)	(0.14,0.14,0.14)	(0.26,0.28,0.28)	(0.26,0.28,0.28)	(0.11,0.12,0.13)	(0.14,0.14,0.15)
A_6	(0.42,0.48,0.54)	(0.21,0.22,0.24)	(0.26,0.27,0.27)	(0.27,0.27,0.28)	(0.1,0.11,0.12)	(0.13,0.14,0.14)
A_7	(0.43,0.5,0.57)	(0.22,0.24,0.26)	(0.14,0.16,0.18)	(0.14,0.16,0.18)	(0.1,0.11,0.12)	(0.12,0.12,0.13)
A_8	(0.66,0.72,0.79)	(0.22,0.24,0.26)	(0.20,0.21,0.23)	(0.2,0.22,0.24)	(0.17,0.18,0.18)	(0.14,0.14,0.14)
A_9	(0.81,0.83,0.83)	(0.15,0.15,0.16)	(0.20,0.21,0.23)	(0.2,0.22,0.24)	(0.14,0.16,0.17)	(0.13,0.14,0.14)

$$BM^{1,1}\left(w_1^{e_1}, w_1^{e_2}, w_1^{e_3}, w_1^{e_4}\right) = \left[\left(\frac{1}{4(4-1)}\right)\begin{pmatrix} 0,449 * 0.337 + 0.449 * 0.418 + 0.449 * 0.456+ \\ 0.337 * 0.449 + 0.337 * 0.418 + 0.337 * 0.456+ \\ 0.418 * 0.449 + 0.418 * 0.337 + 0.418 * 0.456+ \\ 0.456 * 0.449 + 0.456 * 0.337 + 0.456 * 0.418 \end{pmatrix}\right]^{\frac{1}{1+1}} = 0.415$$

In Table 7, the results obtained after the aggregation are presented.

4.2 Application of the Z-MABAC model

Since all the criteria are of linguistic type, a new scale is defined with nine FLD, for evaluating alternatives, Fig. 6.

After defining the FLD, the application of the model follows.

Step 1 In the first step IDM matrices are defined for all the experts. The IDM matrix for expert 1 is provided in Table 8

After defining the IDM matrix, its quantification is performed using value of fuzzy FLD (Fig. 5 and Fig. 6), Table 9.

Step 2 The transition to regular fuzzy numbers were calculated using expressions (7) and (8), Table 10.

Below is an example of the calculation for the alternative A_1 by criterion C_1.

$$\alpha = \frac{0.55 + 0.75 + 0.95}{3} = 0.75$$

$$\begin{aligned}\tilde{Z} &= \sqrt{0.75} * (1, 2, 3)\\ &= (\sqrt{0.75} * 1, \sqrt{0.75} * 2, \sqrt{0.75} * 3) = (0.87, 1.73, 2.6)\end{aligned}$$

Step 3 The normalized values of the new IDM matrix were calculated using expressions (11) and (12). Below is the example of the calculation for the alternative A_1 by the criterion C_1.

$$\tilde{n}^l_{11} = \frac{2.60 - 6.06}{0.26 - 6.06} = 0.6$$
$$\tilde{n}^m_{11} = \frac{1.73 - 6.06}{0.26 - 6.06} = 0.75$$
$$\tilde{n}^r_{11} = \frac{0.87 - 6.06}{0.26 - 6.06} = 0.9$$

Table 11 shows the normalized values.

Step 4 The weighted matrix is calculated using expression (13). Below is the example of the calculation of the alternative A_1 by criterion C_1.

$$\tilde{v}_{11} = 0.415 \cdot (0.6, 0.75, 0.9) + 0.415 = (0.66, 0.72, 0.79)$$

The values of the weighted matrix are provided in Table 12.

Step 5 Applying the expression (15) as the BAA matrix is calculated. The calculation for the criterion C_1 is provided below.

$$\tilde{g}^l_1 = (0.66 * 0.71 * 0.74 * 0.81 * 0.48 * 0.42 * 0.43 * 0.66 * 0.81)^{1/9} = 0.62$$

$$\tilde{g}^m_1 = (0.72 * 0.78 * 0.78 * 0.83 * 0.54 * 0.48 * 0.5 * 0.72 * 0.83)^{1/9} = 0.67$$

Table 13 BAA matrix for the expert 1

C_1	C_2	C_3	C_4	C_5	C_6
(0.62,0.67,0.72)	(0.18,0.19,0.2)	(0.17,0.18,0.20)	(0.21,0.22,0.23)	(0.13,0.14,0.15)	(0.12,0.13,0.13)

Table 14 Matrix of the distance from BAA for the expert 1

Alt	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(−0.06,0.05,0.17)	(0.06,0.08,0.09)	(−0.05,−0.02,0.01)	(0.03,0.05,0.07)	(0.01,0.03,0.05)	(0,0.01,0.02)
A_2	(−0.01,0.11,0.16)	(−0.01,0.01,0.02)	(−0.05,−0.03,−0.01)	(−0.08,−0.05,−0.02)	(−0.06,−0.03,−0.01)	(−0.02,−0.01,0.01)
A_3	(0.02,0.1,0.2)	(−0.06,−0.05,−0.03)	(−0.06,−0.04,−0.02)	(−0.07,−0.05,−0.03)	(−0.01,0.01,0.03)	(0.01,0.02,0.03)
A_4	(0.09,0.16,0.21)	(−0.05,−0.02,0)	(−0.06,−0.03,−0.01)	(0.04,0.06,0.07)	(0.01,0.02,0.04)	(−0.06,−0.05,−0.03)
A_5	(−0.24,−0.13,−0.02)	(−0.06,−0.05,−0.04)	(0.07,0.1,0.11)	(0.03,0.06,0.07)	(−0.04,−0.02,0.01)	(0,0.01,0.02)
A_6	(−0.3,−0.2,−0.08)	(0.01,0.03,0.05)	(0.01,0.04,0.07)	(0.03,0.05,0.07)	(−0.05,−0.03,0)	(0,0.01,0.02)
A_7	(−0.28,−0.17,−0.05)	(0.02,0.05,0.07)	(−0.04,−0.02,−0.01)	(−0.09,−0.06,−0.03)	(−0.05,−0.03,0)	(−0.02,−0.01,0.01)
A_8	(−0.05,0.05,0.17)	(0.02,0.05,0.07)	(0.05,0.08,0.11)	(−0.04,0,0.03)	(0.03,0.04,0.06)	(0,0.01,0.02)
A_9	(0.09,0.16,0.21)	(−0.05,−0.04,−0.02)	(−0.04,−0.01,0.01)	(−0.04,0,0.03)	(0,0.02,0.04)	(0,0.01,0.02)

Table 15 Final values for the expert 1 (e_1)

Alt	$\tilde{S}_i$	S_i
A_1	(−0.01,0.2,0.41)	0.20
A_2	(−0.22,−0.01,0.17)	−0.02
A_3	(−0.16,−0.01,0.17)	0.00
A_4	(−0.03,0.13,0.28)	0.13
A_5	(−0.25,−0.04,0.15)	−0.04
A_6	(−0.3,−0.09,0.13)	−0.09
A_7	(−0.46,−0.24,0)	−0.23
A_8	(0,0.22,0.45)	0.23
A_9	(−0.04,0.13,0.29)	0.13

Table 16 Final ranks of alternatives

Alt	E1	E2	E3	E4	Aggregated values	Rang
A_1	0.204	0.202	0.160	0.176	0.186	1
A_2	−0.019	0.018	0.019	0.086	0.026	5
A_3	0.001	0.055	0.014	0.057	0.032	4
A_4	0.129	0.030	0.099	0.049	0.077	3
A_5	−0.044	−0.043	0.062	−0.123	−0.037	8
A_6	−0.088	0.162	0.018	0.006	0.025	6
A_7	−0.234	0.078	0.105	−0.003	−0.013	7
A_8	0.226	0.096	0.210	0.047	0.145	2
A_9	0.129	−0.358	−0.439	−0.142	−0.203	9

$$\tilde{g}_1^r = (0.79 * 0.78 * 0.81 * 0.83 * 0.6 * 0.54 * 0.57 * 0.79 * 0.83)^{1/9} = 0.72$$

Table 13 shows the values of the BAA matrix for the expert 1.

Step 6 Calculation of the distance from the BAA is performed using the expression (16). Below is the example of the calculation for the alternative A_1 by the criterion C_1.

$$\tilde{q}_{11}^l = 0.66 - 0.72 = -0.6$$

$$\tilde{q}_{11}^m = 0.72 - 0.67 = 0.5$$

$$\tilde{q}_{11}^l = 0.79 - 0.62 = 0.17$$

Table 14 shows the values of distance from the BAA matrix for the expert 1.

Step 7.1 Calculation of the final values is performed by applying the expression (17). Below is an example of the calculation for the alternative A_1.

$$\tilde{S}_1^l = -0.06 + 0.06 - 0.05 + 0.03 + 0.01 + 0 = -0.01$$

$$\tilde{S}_1^m = 0.05 + 0.08 - 0.02 + 0.05 + 0.03 + 0.01 = 0.20$$

$$\tilde{S}_1^r = 0.17 + 0.09 + 0.01 + 0.07 + 0.05 + 0.02 = 0.41$$

Step 7.2 Defuzzification of values obtained in step 7.1. is performed according to expression (18). Below is an example of the calculation for the alternative A_1.

$$S_1 = ((0.41 - (-0.01)) + (0.2 - (-0.01)))/3 + (-0.01) = 0.2$$

.

Table 15 shows the final values of the criteria functions, for the expert 1.

The ranking of alternatives of all four experts is shown in Table 16.

5 Sensitivity analysis

The possibility of certain errors in this process imposes the need for a deeper analysis of the possibilities of the applied methods. For this purpose, sensitivity analysis is usually performed. Sensitivity analysis is performed in several ways, such as changes in

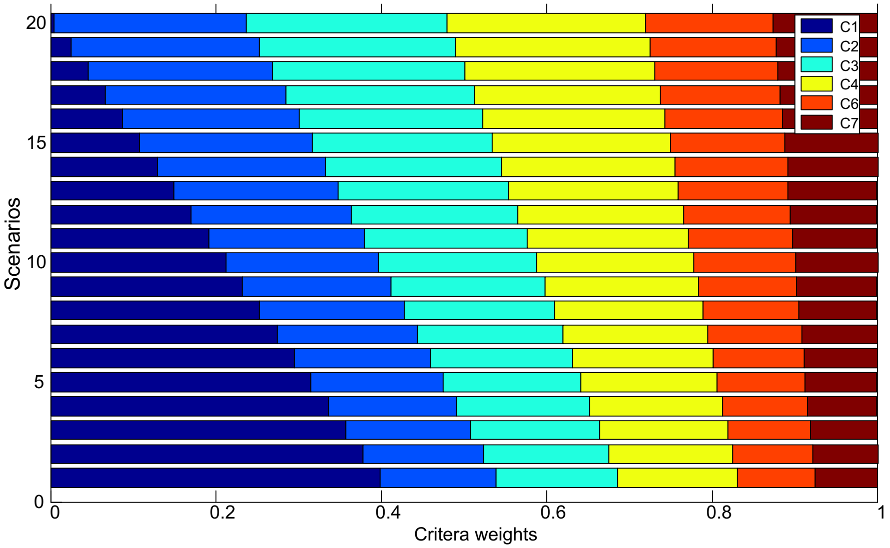

Fig. 7 Values of the weight coefficient by scenarios

Table 17 Ranks of alternatives using different scenarios

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9
S1	1	6	4	3	8	5	7	2	9
S2	1	6	4	3	8	5	7	2	9
S3	1	6	4	3	8	5	7	2	9
S4	1	6	5	3	8	4	7	2	9
S5	1	6	5	3	8	4	7	2	9
S6	1	6	5	3	8	4	7	2	9
S7	1	6	5	3	7	4	8	2	9
S8	1	6	5	3	7	4	8	2	9
S9	1	6	5	4	7	3	8	2	9
S10	1	7	5	4	6	3	8	2	9
S11	1	7	5	4	6	3	8	2	9
S12	1	7	5	4	6	3	8	2	9
S13	1	7	4	5	6	3	8	2	9
S14	1	7	4	5	6	3	8	2	9
S15	1	7	4	5	6	3	8	2	9
S16	1	7	4	5	6	3	8	2	9
S17	1	8	4	6	5	3	7	2	9
S18	1	8	4	6	5	3	7	2	9
S19	1	8	4	6	5	3	7	2	9
S20	1	8	4	6	5	3	7	2	9

weight coefficients, comparison with other methods, changes in units of measurement expressing the values of alternatives, changes in scales presenting linguistic criteria, changes in types of criteria (cost/benefit), and the like [53]. Changing the weighting coefficients is the most common way in which sensitivity analysis is performed (Simanaviciene & Ustinovichius, 2012, [13, 25, 55, 58, 71]. Saati and Ergu [65] point out that this analysis is very important. In his study, Roy (2011) indicated the need to consider vague approximations that are used to make final decisions in the MCDM models. Considering the above recommendations, this paper performed a sensitivity analysis through three phases, which are described below.

5.1 Analysis of the influence of changes in the values of weight coefficients on the ranking results

When analyzing the sensitivity to changes in weighting factors, the influence of the most important criterion is usually measured [55], . This influence was measured through twenty scenarios. In the scenarios, the value of the best criterion within the interval $w_{C_1} \in [0.004, 0.398]$ was simulated. The value of criterion C1 was reduced by 4% in the first scenario, and by 5% in each subsequent one.

The data about the weight coefficients, by twenty scenarios, are presented in Fig. 7.

The ranks of alternatives obtained by the described procedure are shown in Table 17.

As it can be observed from Table 17, there are deviations in the rank of alternatives depending on the scenario, which shows that the LBWA – Z MABAC model is sensitive enough. On the other hand, it can be observed that the alternative A_1 and A8 is the first-ranked and second-ranked in all the scenarios. In all scenarios, alternative A_9 was the last. When applying the scenario on six occasions, the rank of alternatives changes:

In the scenarios S1-S3 (where is $0.357 \le w_1 \le 0.398$) the initial rank was confirmed.

In the scenarios, S4-S6 (where is $0.295 \le w_1 \le 0.336$) the change of the ranks of the alternatives A3 (initially the fourth-ranked) and A6 (initially the fifth-ranked) occurred, which replaced their positions.

In the scenarios S7-S9 (where is $0.253 \le w_1 \le 0.274$) the change of the ranks of the non-dominant alternatives A5 and A7 occurred. In the scenarios S7 and S8, the rank A1 > A8 > A4 > A6 > A3 > A2 > A5 > A7 > A9 was obtained.

In the scenarios S9 (where $w_1 = 0.232$) the change of the ranks of the alternatives A4 and A6 occurred, which replaced their positions, respectively A1 > A8 > A6 > A4 > A3 > A2 > A5 > A7 > A9.

Through the scenarios S10-S12, in which the change of the weight coefficient w_1 within the interval $0.170 \le w_1 \le 0.212$ was simulated, there was a change in the ranks between A4 and A6 alternative, respectively A1 > A8 > A6 > A3 > A4 > A2 > A5 > A7 > A9.

In the following four scenarios (S13-S16) the change of the weight coefficient w_1 within the interval $0.087 \le w_1 \le 0.149$ was simulated. During the changes of the weight coefficients, there was a change in the ranks of alternative A4 and A3. In the scenarios S13-S16 the rank A1 > A8 > A6 > A3 > A4 > A5 > A2 > A7 > A9 was obtained.

In the last four scenarios S17-S20 (where is $0.004 \le w_1 \le 0.066$), the change of the ranks of the non-dominant alternatives A4 and A5 occurred. In the scenarios S17-S20, the rank A1 > A8 > A6 > A3 > A5 > A6 > A2 > A7 > A9 was obtained.

Based on the results presented, it can be concluded that the changes of the weight coefficient of the criterion C1 lead to changes in the values of the criteria functions of the alternatives. However, these changes are not significant for the dominant alternatives (A1 and A8), which maintained the first and the second rank in all scenarios. Other alternatives have undergone significant changes in their ranking. These results are also verified by applying Spearman's coefficient. This coefficient of the ranks of the considered strategies ranges within the interval $K \in [0.7, 1]$, which presents a very high degree of correlation.

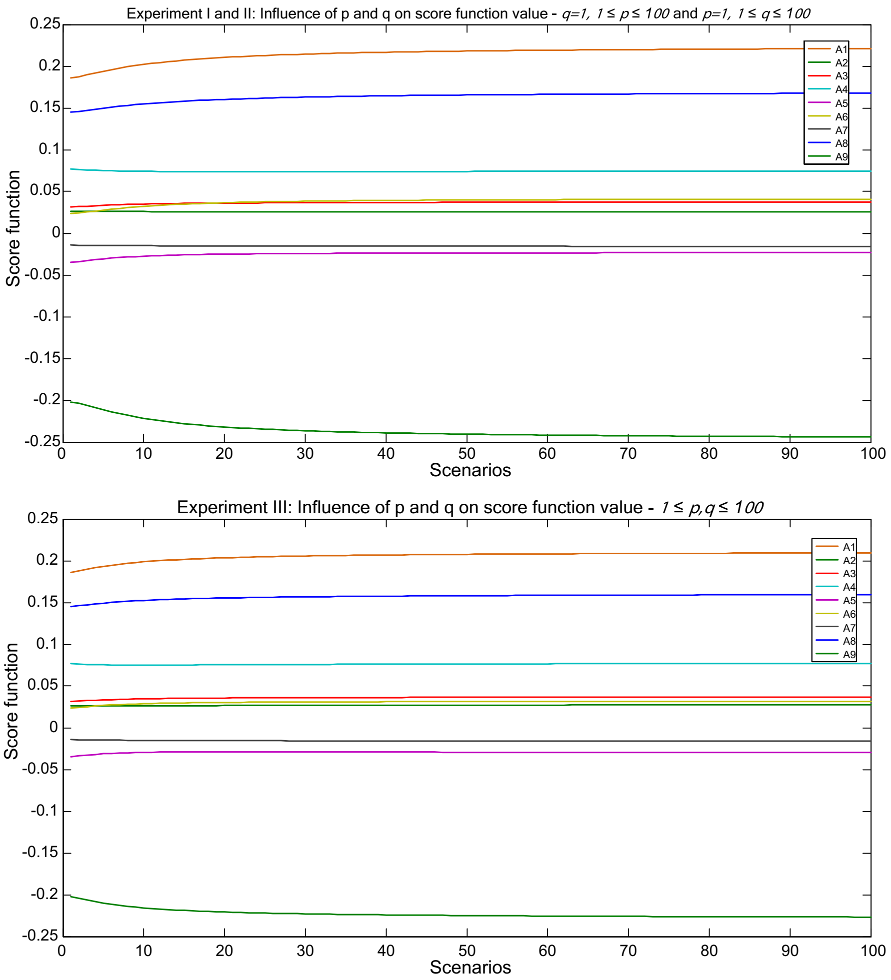

Fig. 8 Influence p and q on the utility function of alternatives

5.2 Influence of the parameters p and q

The fusion of the weight coefficients obtained during the expert comparisons was performed using the Bonferroni aggregator. The change of the parameters p and q can influence the changes in the aggregated values, so this analysis is an indispensable step to validate the obtained values. The change of the mentioned parameters has three experiments where is: (1) $p \in [1, 100]$, $q = 1$; (2) $q \in [1, 100]$, $p = 1$ and (3) $p \in [1, 100]$ and $q \in [1, 100]$.

As it has been stated, three hundred simulations were performed through the three experiments, in which the direct influence p and q on the aggregated values of the weight coefficients were considered. The indirect influence on the utility function of alternatives, was also analyzed as in Fig. 8.

Table 18 Comparative review ranks of alternatives using the MABAC method and its modifications

	S_i			Rank of alternatives		
	MABAC	Fuzzy MABAC	Z MABAC	MABAC	Fuzzy MABAC	Z MABAC
A_1	0.230	0.210	0.185	1	1	1
A_2	-0.016	−0.015	0.026	8	8	5
A_3	0.028	0.017	0.032	5	5	4
A_4	0.133	0.098	0.077	3	3	3
A_5	0.019	0.017	−0.035	6	6	8
A_6	0.004	0.012	0.024	7	7	6
A_7	0.043	0.043	−0.014	4	4	7
A_8	0.194	0.163	0.146	2	2	2
A_9	−0.298	−0.286	−0.203	9	9	9

Table 19 The comparisons of MABAC methods

Characteristic of MCDM method	Z MABAC	Fuzzy MABAC	Crisp MABAC
Flexible fuzzy intervals	Parialy	No	No
Flexible decision making due to decision makers' risk attitude	Yes	No	No
Flexibility in real world applications	Parialy	Parialy	No

In the basic phase of the calculation, a calculation with values of p = k = 1 is recommended, which simplifies the decision-making process. In experiments I and II, where is,$p, q \in [4, 17]$ the alternatives A2 and A6 replaced their places. For the parameter values $p, q \in [18, 100]$, the alternatives A3 and A6 replaced their places, while the remaining alternatives retained their ranks. In experiment III, where is $5 \leq p, q \leq 100$, the sixth (A6) and the fifth-ranked alternative (A2) replaced their positions. In the remaining alternatives, where is $1 \leq p, q \leq 100$, the score functions changed, however, these changes did not lead to the change in their ranks.

The presented simulation showed that the changes in the parameters p and q affected the change in the score function of the alternatives. Based on all three hundred simulations, the rank of alternatives A1 and A8 has not seen a change, indicating that the initial rank is considered verified and credible.

5.3 Comparison with other MCDM approaches

Since the MABAC method was modified with the Z numbers, the question has arisen as to what effect the modification has on the output results [70], 22, 2, 3. In this context, the results are compared using the traditional MABAC method, modified with classic fuzzy numbers and the Z numbers, as in Table 18.

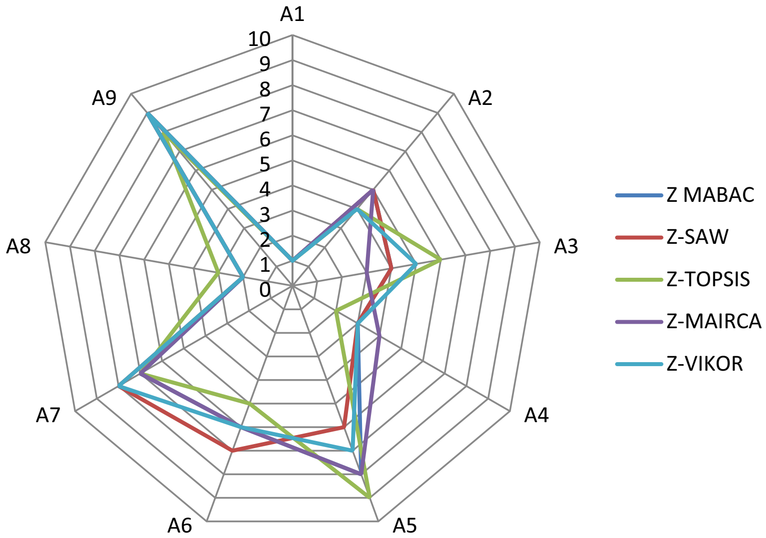

Fig. 9 Rang alternativa primenom različitih metoda

In the following part, a comparison of the used MABAC models was made, Table 19.

Spearman's coefficient within the interval $K \in [0.8, 1]$, respectively, with the MABAC and fuzzy MABAC methods there are no changes in the range, while with the Z MABAC method, the range of some alternatives changes. The rank of the first three (A1, A8, A4) and the last alternative (A9) did not changed. All of the above indicates that the second fuzzy number ($\tilde{B}$) has an impact on the final results, but this impact is not crucial in the ranking of alternatives, respectively, its role is significantly smaller compared to the first fuzzy number ($\tilde{T}$). The very character of the fuzzy number ($\tilde{B}$), as well as the method of conversion into classic fuzzy numbers, have already indicated the greater importance of the fuzzy number $\tilde{T}$. However, in the situations in which the criteria functions of the alternatives are proximate, the fuzzy number $\tilde{B}$ may affect the ranking. On the other hand, sufficient distance between the criteria functions of the alternatives provides a stable solution.

In addition to the comparison with the fuzzy MABAC and crisp MABAC methods, a comparison with other MCMD techniques was performed, namely by the methods TOPSIS [28], Multi-criteria optimization and COMPROMISE Solution—VIKOR [50], MultiAttributive Ideal-Real Comparative Analysis—MAIRCA [23] and Simple Additive Weighting—SAW [87], which are modified by applying Z numbers (Z-TOPSIS, Z-VIKOR, Z- MAIRCA, Z-SAW). The ranking results are shown in Fig. 9.

In the following part, a comparison of the used methods was made, Table 20.

Spearman's coefficient ranges in the interval $K \in [0.81, 0.98]$, which represents a very high correlation. It is particularly emphasized here that alternative A1 is always ranked first. Alternative A2 is ranked second in all methods, except for

Table 20 Comparison of used methods

Characteristic of MCDM method	Z MABAC	Z-SAW	Z-TOPSIS	Z-MAIRCA	Z-VIKOR
Ranking	Complete	Complete	Complete	Complete	Complete
Checking the distance of the dominant alternatives	No	No	No	Yes	Yes
The possibility of determining the preference of DMs according to the choice of alternatives	No	No	No	Yes	No
Flexible fuzzy intervals	Partially	Partially	Partially	Partially	Partially
Flexible decision making due to decision makers' risk attitude	Yes	Yes	Yes	Yes	Yes
Flexibility in real world applications	Partially	Partially	Partially	Partially	Partially

the Z-TOPSIS method, where it is ranked third. Alternative A9 is ranked last in all methods, except for the Z-TOPSIS method, where it is ranked eighth. Also, minor changes in the ranking of other alternatives are observed, which does not significantly affect the choice of the best alternative.

All of the above indicates that the Z MABAC method has provided new quality to the selection process because the selection that the decision-maker should make is verified. According to the presented method, Z MABAC is recommended for solving other problems due to its quality.

6 Research implications

First, we will discuss the theoretical implications of the study. In this research, we focused on appropriate strategies that can be followed when oil spills occur. We primarily focused on onshore oil spills. Most previous research has focused on spills in the water or offshore because of the difficulty in controlling them and their impact on aquatic life. However, terrestrial spills cannot be overlooked, as statistics indicate that most spills occur on land. The proposed methodology was carefully developed and consists of two steps. The first step was to find the weights of the criteria used in the study, and the second step, in which the strategies that can be used to deal with oil spills, were organized.

In practical terms, the El Sharara oil field case study is also an important implication to this research, as Libya has the ninth largest proven oil reserve in the world, but no research has been conducted to compare and select the best oil spill control strategies. Over the past decade, political instability in the country has affected the infrastructure of the oil fields and facilities, which have suffered from oil spills, most notably in the transmission lines and crude oil storage sites, perhaps most recently the leakage from the oil transmission line in the Sharara oil field.The hybrid model developed proved to be easy to use by the experts. Through the sensitivity analysis performed by changing the parameters p and q, as constituent parameters of the Bonferroni aggregator, the initial ranking obtained was upheld, and this confirmed that the result obtained by applying the LBWA method in solving the problem posed is credible. Additionally, using the Z MABAC method to select the best project reinforced many significant facts. More specifically, the experts were allowed to evaluate the alternatives using the FLD rather than a traditional scale, which eliminated some of the doubts the experts had during the evaluation. An additional quality was provided by the second part of the Z-number, which dealt with the certainty of statements made. In overall terms, the model handled uncertainty very well after a large number of decisions. Similarly, the sensitivity analysis comparing the fuzzy MABAC method with the classical MABAC method showed that the modified MABAC Z method provided sound solutions. In other words, in the sensitivity analysis, recalculations confirmed the initial ranking obtained. The same quality was also presented by the fact that the Z MABAC method was applied in group decision making. In fact, further research and innovation in oil spill response is needed to reduce the various impacts of oil spills. For example, research can be pursued in several directions using different methodologies that deal with uncertainty (e.g., fuzzy logic, Grey theory and other methods) in solving MCDM related problems.

7 Conclusion

Accidental oil spills cannot be completely prevented, but the goal of decision makers in managing the response to oil spills is to minimize their consequences, such as environmental and economic impacts. To achieve this, they often make choices from a range of available strategies. Such a management problem is considered here as a multi-criteria decision problem involving a variety of stakeholders. Emergency management of oil spills is a very complex decision-making problem, as it is coupled with vague and incomplete information regarding multiple parameters and complex dynamic environments such as types of oil spills, volume of spills, location of spills, and ground slope.

Most research has focused on spills in water or on the shoreline because of the difficulty of controlling them and their impact on aquatic life. However, spills that occur on land cannot be overlooked, given that statistics indicate that most spills occur on land. The present research developed a hybrid model that was used by a group of oil industry experts and proved to be effective in finding a solution to the onshore oil spill problem that was addressed as a case study. The developed LBWA-Z MABAC hybrid model, used for group decision making, proved its high performance in solving the presented problem. The combination of mathematical models and expert opinions provided consistent results, with the expert opinions ultimately aggregated into a single opinion. Preference ranking of proposed strategies for dealing with accidental oil spills was achieved, with the model selecting the leak plugging strategy as the best strategy for dealing with the spill under study.

Author's contribution Each author has participated and contributed sufficiently to take public responsibility for appropriate portions of the content.

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Declarations

Conflict of interest The authors declare no conflict of interest.

References

Aboutorab, H., Saberi, M., Asadabadi, M.R., Hussain, O., Chang, E.: ZBWM: The Z-number extension of best worst method and its application for supplier development. Exp. Syst. Appl. **107**, 115–125 (2018)

Agarwal, S., Kant, R., Shankar, R.: Evaluating solutions to overcome humanitarian supply chain management barriers: a hybrid fuzzy SWARA - fuzzy WASPAS approach. Int. J. Dis. Risk Reduct. **51**, 101838 (2020)

Agarwal, S., Kant, R., Shankar, R.: Modeling the enablers of humanitarian supply chain management: a hybrid group decision-making approach. Benchmarking An Int. J. **28**(1), 166–204 (2021)

Ali, Z., Mahmood, T., Ullah, K., Khan, Q.: Einstein geometric aggregation operators using a novel complex interval-valued pythagorean fuzzy setting with application in green supplier chain management. Rep. Mech. Eng. **2**(1), 105–134 (2021). https://doi.org/10.31181/rme2001020105t

Alosta, A., Elmansuri, O., Badi, I.: Resolving a location selection problem by means of an integrated AHP-RAFSI approach. Rep. Mech. Eng. **2**(1), 135–142 (2021). https://doi.org/10.31181/rme200102135a

Azadeh, A., Kokabi, R.: Z-number DEA: a new possibilistic DEA in the context of Z-numbers. Adv. Eng. Inform. **30**, 604–617 (2016)

Azadeh, A., Saberi, M. & Pazhoheshfar, P.: Z-AHP: A Z-number Extension of Fuzzy Analytical Hierarchy Process. *Proceedings of the 7th IEEE International Conference on Digital Ecosystems and Technologies (DEST)*, Menlo Park, CA, USA, 141–147. (2013)

Baruque, B., Corchado, E., Mata, A., Corchado, J.M.: A forecasting solution to the oil spill problem based on a hybrid intelligent system. Inf. Sci. **180**(10), 2029–2043 (2010)

Bobar, Z., Božanić, D., Djurić, K.A., Pamučar, D.: Ranking and assessment of the efficieny of social media using the Fuzzy AHP-Z number model – fuzzy MABAC. Acta Polytechnica Hungarika **17**(3), 43–70 (2020)

Bonferroni, C.: Sulle medie multiple di potenze. Bollettino Matematica Italiana **5**, 267–270 (1950)

Božanić, D., Jurišić, D., Erkić, D.: LBWA – Z-MAIRCA model supporting decision making in the army. Operat. Res. Eng. Sci.: Theory and Appl. **3**(2), 87–110 (2020a)

Božanić, D., Kočić, J. & Tešić, D.: Selecting Location for Construction of Single-Span Bailey Bridge by applying fuzzy MABAC method. *Procedings of The 2nd International Conference on Management, Engineering and Environment (ICMNEE)*, Obrenovac, Serbia, 407–416. (2018)

Božanić, D., Milić, A., Tešić, D., Sałabun, W., Pamučar, D.: D numbers – FUCOM – fuzzy RAFSI model for selecting the group of construction machines for enabling mobility. Facta Universitatis Series Mech. Eng. **19**(3), 447–471 (2021)

Božanić, D., Pamučar, D., Karovic, S.: Use of the fuzzy AHP - MABAC hybrid model in ranking potential locations for preparing laying-up positions. Military Tech. Courier **64**(3), 705–729 (2016a)

Božanić, D., Pamučar, D., Karović, S.: Application the MABAC method in support of decision-making on the use of force in a defensive operation. Tehnika **71**(1), 129–137 (2016b)

Božanić, D., Ranđelović, A., Radovanović, M., Tešić, D.: Hybrid LBWA – IR-MAIRCA model of multi-criteria decision making when defining construction elements of weapons. Facta Universitatis Series: Mech. Eng. **18**(3), 399–418 (2020b)

Božanić, D., Tešić, D., Milić, A.: Multicriteria decision making model with z-numbers based on FUCOM and MABAC model. Decision Making: Appl. Manag. Eng. **3**(2), 19–36 (2020c)

Carmody, O., Frost, R., Xi, Y., Kokot, S.: Adsorption of hydrocarbons on organo-clays–Implications for oil spill remediation. J. Colloid Interface Sci. **305**(1), 17–24 (2007)

Celik, M., Topcu, Y.I.: Use of an ANP to prioritize managerial responsibilities of maritime stakeholders in environmental incidents: An oil spill case. Transp. Res. Part d: Transp. Environ. **14**(7), 502–506 (2009)

Davies, A.J., Hope, M.J.: Bayesian inference-based environmental decision support systems for oil spill response strategy selection. Mar. Pollut. Bull. **96**(1–2), 87–102 (2015)

Deveci, M., Özcan, E., John, R., Covrig, C.F., Pamučar, D.: A study on offshore wind farm siting criteria using a novel interval-valued fuzzy-rough based Delphi method. J. Environ. Manage. **270**, 110916 (2020)

El Sayed, M.A., Baky, I.A., Singh, P.: A modified TOPSIS approach for solving stochastic fuzzy multi-level multi-objective fractional decision making problem. Opsearch **57**(4), 1374–1403 (2020)

Gigović, L.J., Pamučar, D., Bajić, Z., Milićević, M.: The combination of expert judgment and GIS-MAIRCA analysis for the selection of sites for ammunition depots. Sustainability **372**(8), 372 (2016)

Gigović, L.J., Pamučar, D., Božanić, D., Ljubojević, S.: Application of the GIS-DANP-MABAC multi-criteria model forselecting the location of wind farms: a case study of Vojvodina, Serbia. Renew. Energy **103**, 501–521 (2017)

Gorcun, O.F., Senthil, S., Küçükönder, H.: Evaluation of tanker vehicle selection using a novel hybrid fuzzy MCDM technique. Decision Making: Appl. Manag. Eng. **4**(2), 140–162 (2021)

Hondro, R.K.: MABAC: pemilihan penerima bantuan rastra menggunakan metode multi- attributive border approximation area comparison. Jurnal Mahajana Informasi **3**(1), 41–52 (2018)

Hu, J., Chen, P., Yang, Y.: An Interval Type-2 fuzzy similarity-based MABAC approach for patient-centered care. Mathematics **7**, 140 (2019)

Hwang, C.L., Yoon, K.: Multiple Attribute Decision Making: A State of the Art Survey: Lecture Notes in Economics and Mathematical Systems. Springer-Verlag, Berlin (1981)

Iakovou, E., Ip, C.M., Douligeris, C., Korde, A.: Optimal location and capacity of emergency cleanup equipment for oil spill response. Eur. J. Oper. Res. **96**(1), 72–80 (1997)

Ibrahimović, F.I., Kojić, S.L., Stević, ŽR., Erceg, ŽJ.: Making an investment decision in a transportation company using an integrated FUCOM-MABAC model. Tehnika **69**(4), 577–584 (2019)

Ivshina, I.B., Kuyukina, M., Krivoruchko, A.V., Elkin, A.A., Makarov, S.O., Cunningham, C., et al.: Oil spill problems and sustainable response strategies through new technologies. Environ Sci Process Impacts **17**(7), 1201–1219 (2015)

Jafari R., Razvarz S., Gegov A. (2020). Applications of Z-Numbers and Neural Networks in Engineering. In: Arai K., Kapoor S., Bhatia R. (eds) *Intelligent Computing*. SAI 2020. Advances in Intelligent Systems and Computing, vol 1230. Springer, Cham. https://doi.org/10.1007/978-3-030-52243-8_2.

Ji, P., Zhang, H.-Y., Wang, J.: Selecting an outsourcing provider based on the combined MABAC–ELECTRE method using single-valued neutrosophic linguistic sets. Comput. Ind. Eng. **120**, 429–441 (2018)

Jokić, Ž, Božanić, D., Pamučar, D.: Selection of fire position of mortar units using LBWA and Fuzzy MABAC model. Operat. Res. Eng. Sci. Theory Appl. **4**(1), 115–135 (2021)

Kang, B., Wei, D., Li, Y., Deng, Y.: A method of converting Z-number to classical fuzzy number. J. Inform. Comput. Sci. **9**(3), 703–709 (2012)

Kang, J., Zhang, J., Bai, Y.: Modeling and evaluation of the oil-spill emergency response capability based on linguistic variables. Mar. Pollut. Bull. **113**(1–2), 293–301 (2016)

Koseoglu, B., Buber, M., Toz, A.C.: Optimum site selection for oil spill response center in the marmara sea using the AHP-TOPSIS method. Archiv. Environ. Protect. **44**(4), 38–49 (2018)

Krohling, R.A., Campanharo, V.C.: Fuzzy TOPSIS for group decision making: a case study for accidents with oil spill in the sea. Exp. Syst. Appl. **38**(4), 4190–4197 (2011)

Krohling, R.A., De Souza, T.T.M.: Combining prospect theory and fuzzy numbers to multi-criteria decision making. Exp. Syst. Appl. **39**(13), 11487–11493 (2012)

Krohling, R.A., Canpanharo, V.C.: Fuzzy TOPSIS for group decision making: a case study for accidents with oil spill in the sea. Exp. Syst. Appl. **38**(4), 4190–4197 (2011)

Krohling, R.A., Pacheco, A.G.C., dos Santos, G.A.: TODIM and TOPSIS with Z-numbers. Front. Inform. Technol. Electron. Eng. **20**, 283–291 (2019)

Kuiri, A., Das, B.: An application of FISM and TOPSIS to a multi-objective multi-item solid transportation problem. Opsearch **57**(4), 1299–1318 (2020)

Li, P., Chen, B., Li, Z.L., Jing, L.: ASOC: a novel agent-based simulation optimization coupling approach-algorithm and application in offshore oil spill responses. J. Environ. Inform **28**(2), 90–100 (2016)

Liu, X., Wirtz, K.W.: Consensus building in oil spill response planning using a fuzzy comprehensive evaluation. Coast. Manag. **35**(2–3), 195–210 (2007)

Luo, S.Z., Xing, L.N.: A hybrid decision making framework for personnel selection using BMW, MABAC. PROMETHEE. Int. J. Fuzzy Syst. **21**(8), 2421–2424 (2019)

Majchrzycka A. & Poniszewska-Maranda A.: Control Operation Flow for Mobile Access Control with the Use of MABAC Model. In Kosiuczenko P., Madeyski L. (eds), *Towards a Synergistic Combination of Research and Practice in Software Engineering*, Studies in Computational Intelligence, vol 733. Cham: Springer. (2018)

Nagkirti, P., Shaikh, A., Vasudevan, G., Paliwal, V., Dhakephalkar, P.: Bioremediation of Terrestrial Oil Spills: Feasibility Assessment. In: Purohit, H.J., Kalia, V.C., Vaidya, A.N., Khardenavis, A.A. (eds.) Optimization and Applicability of Bioprocesses, pp. 141–173. Springer, Singapore (2017)

National Oil Corporation (NOC).: Libyan report. Tenth Arab energy conference. UAE. (2014)

Nunić, Z.: Evaluation and selection of manufacturer PVC carpentry using FUCOM-MABAC model. Operat. Res. Eng. Sci.: Theory and Appl. **1**(1), 13–28 (2018)

Opricović, S., Gwo-Hshiung, T.: The compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. Eur. J. Oper. Res. **156**(2), 445–455 (2004)

Owens, E.H.: Response strategies for spills on land. Spill Sci. Technol. Bull. **7**(3–4), 115–117 (2002)

Pamučar, D., Božanić, D.: Selection of a location for the development of multimodal logistics center: application of single-valued neutrosophic MABAC model. Operat. Res. Eng. Sci.: Theory Appl. **2**(2), 55–71 (2019)

Pamučar, D., Božanić, D., Ranđelović, A.: Multi-criteria decision making: an example of sensitivity analysis. Serbian J. Manag. **12**(1), 1–27 (2017)

Pamučar, D., Božanić, D., Lukovac, V., Komazec, N.: Normalized weighted geometric Bonferroni mean operator of interval rough numbers – application in interval rough DEMATEL-COPRAS model. Facta Universitatis Series: Mech. Eng. **16**(2), 171–191 (2018)

Pamučar, D., Ćirović, G., Božanić, D.: Application of interval valued fuzzy-rough numbers in multi-criteria decision making: the IVFRN-MAIRCA model. Yugoslav J. Operat. Res. **29**(2), 221–247 (2019)

Pamučar, D., Deveci, M., Canitez, F., Božanić, D.: A fuzzy full consistency method-dombi-bonferroni model for prioritizing transportation demand management measures. Appl. Soft Comput. **87**, 105952 (2020). https://doi.org/10.1016/j.asoc.2019.105952

Pamučar, D., Deveci, M., Canitez, F., Lukovac, V.: Selecting an airport ground access mode using novel fuzzy LBWA-WASPAS-H decision making model. Eng. Appl. Artificial Intell. **93**, 103703 (2020). https://doi.org/10.1016/j.engappai.2020b.103703

Pamučar, D., Savin, L.: Multiple-criteria model for optimal off-road vehicle selection for passenger transportation: BWM-COPRAS model. Military Tech. Courier **68**(1), 28–64 (2020)

Peng, X., Dai, J.: Approaches to single-valued neutrosophic MADM based on MABAC, TOPSIS and new similarity measure with score function. Neural Comput. Appl. **29**(10), 939–954 (2018)

Peng, X., Yang, Y.: Pythagorean fuzzy choquet integral based MABAC method for multiple attribute group decision making. Int. J. Intell. Syst. **31**, 989–1020 (2016)

Ramakrishnan, K.R., Chakraborty, S.: A cloud TOPSIS model for green supplier selection. Facta Universitatis, Series: Mech. Eng. **18**(3), 375–397 (2020)

Roy, A., Ranjan, A., Debnath, A., Kar, S.: An extended multi attributive border approximation area comparison using interval type-2 trapezoidal fuzzy numbers. ArXiv ID **1607**, 01254 (2016)

Roy, B.: Robustness for operations research and decision aiding. Wiley Encyclopedia of Operat. Res. Manag. Sci. (2013). https://doi.org/10.1002/9780470400531.eorms1085

Roy, J., Chatterjee, K., Bandhopadhyay, A. & Kar, S.: Evaluation and selection of medical tourism sostes: a rough analytic hierarchy process based multi attributive border approximation area comparison approach. Exp. Syst., e12232. (2017)

Saaty, T.L., Ergu, D.: When is a decision-making method trustworthy? Criteria for evaluating multi-criteria decision-making methods. Int. J. Inf. Technol. Decis. Mak. **14**(06), 1171–1187 (2015)

Sahrom, N.A., & Dom, R.M.: A Z-Number Extension of the Hybrid Analytic Hierarchy Process-Fuzzy Data Envelopment Analysis for Risk Assessment. *Proceedings of the 7th International Conference on Research and Education in Mathematics: Empowering Mathematical Sciences through Research and Education (ICREM7)*, Kuala Lumpur, Malaysia, pp. 19–24. (2015)

Sharma, H.K., Roy, J., Kar, S., Prentkovskis, O.: Multi criteria evaluation framework for prioritizing indian railway stations using modified rough ahp-mabac method. Trans. Telecommun. **19**(2), 113–127 (2018)

Simanaviciene, R., Ustinovicius, L.: A new approach to assessing the biases of decisions based on multiple attribute decision making methods. Elektronika Ir Elektrotechnika **117**(1), 232 (2012)

Simpanen, S., Dahl, M., Gerlach, M., Mikkonen, A., Malk, V., Mikola, J., Romantschuk, M.: Biostimulation proved to be the most efficient method in the comparison of in situ soil remediation treatments after a simulated oil spill accident. Environ. Sci. Pollut. Res. **23**(24), 25024–25038 (2016)

Singh, A., Gupta, A., Mehra, A.: Best criteria selection based PROMETHEE II method. Opsearch **58**(1), 160–180 (2021)

Stewart, T.J., French, S., Rios, J.: Integrating multicriteria decision analysis and scenario planning—Review and extension. Omega **41**(4), 679–688 (2013)

Sun, R., Hu, J., Zhou, J., Chen, X.: A hesitant fuzzy linguistic projection – based MABAC method for patients' priorizitation. Int. J. Fuzzy Syst. **20**(7), 2144–2160 (2018)

Vafai, F., Hadipour, V., Hadipour, A.: Determination of shoreline sensitivity to oil spills by use of GIS and fuzzy model. case study - the coastal areas of caspian sea in north of iran. Ocean Coast. Manag. **71**, 123–130 (2013)

Wei, G., Wei, C., Wu, J., Wang, H.: Supplier selektion of medical products with a probabilistik linguistic MABAC method. Environ. Res. Public Health **16**, 5082 (2019)

Wu, W.: A revised grey relational analysis method for multicriteria group decision-making with expected utility theory for oil spill emergency management. Math. Probl. Eng. **2021**, 1–12 (2021)

Wu, W., Peng, Y.: Extension of grey relational analysis for facilitating group consensus to oil spill emergency management. Ann. Oper. Res. **238**(1), 615–635 (2016)

Xian, H., Xu, D.: A New Single-valued Neutrosophic Distance for MABAC, TOPSIS and New Similarity Measure in Multi-attribute Decision-Making. *Proceedings of the International Conference on Computationand Information Sciences (ICCIS 2019)*, Chengdu, China, pp. 681–688. (2019)

Xue, Y.X., You, J.X., Lai, X.D., Liu, H.C.: An interval-valued intuitionistic fuzzy MABAC approach for materila selection with incomplete weight information. Appl. Soft Comput. **38**, 703–713 (2016)

Yaakob, A.M., & Gegov. A.: Fuzzy Rule-Based Approach with Z-Numbers for Selection of Alternatives using TOPSIS. *Proceedings of the IEEE International Conference on Fuzzy Systems*, Istanbul, Turkey, pp. 1–8. (2015)

Yang, Z., Chen, Z., Lee, K., Owens, E., Boufadel, M.C., An, C., Taylor, E.: Decision support tools for oil spill response (OSR-DSTs): Approaches, challenges, and future research perspectives. Mar. Pollut. Bull. **167**, 112313 (2021)

Ye, X., Chen, B., Lee, K., Storesund, R., Zhang, B.: An integrated offshore oil spill response decision making approach by human factor analysis and fuzzy preference evaluation. Environ. Pollut. **262**, 114294 (2020). https://doi.org/10.1016/j.envpol.2020.114294

Yu, S.-M., Wang, J., Wang, J.-Q.: An interval type-2 fuzzy likelihood-based MABAC approach and its aplication in selecting hotels on a tourism website. Int. J. Fuzzy Syst. **19**(1), 47–61 (2017)

Zadeh, L.A.: A note on Z-number. Inf. Sci. **181**, 2923–2932 (2011)

Zafirakou, A., Themeli, S., Tsami, E., Aretoulis, G.: Multi-criteria analysis of different approaches to protect the marine and coastal environment from oil spills. J. Marine Sci. Eng. **6**(4), 125 (2018). https://doi.org/10.3390/jmse6040125

Zhang, L., Zhang, X., Yang, Y., Wang, W., Zhang, Y., Liu, J.: Risk assessment of water pollution in mountainous industrial parks. Chem. Eng. Trans. **71**, 247–252 (2018)

Zhang, T.T., Zheng, H.B.: Researches of index system and method on marine oil spill threaten degree. Appl. Mech. Mater. **556–562**, 853–856 (2014)

Zionts, S., Wallenius, J.: An interactive multiple objective linear programing method fora a class of underlying nonlinear utility fuctions. Manage. Sci. **29**(5), 519–529 (1983)

Žižović, M., Pamučar, D.: New model for determining criteria weights: level based weight assessment (LBWA) model. Decision Making: Appl. Manag. Eng. **2**(2), 126–137 (2019)

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