

FUZZY TOPSIS IN OCCUPATIONAL RISK MANAGEMENT ASSESSMENT

Joanna TABOR

Częstochowa University of Technology; joanna.tabor@pcz.pl, ORCID: 0000-0002-7746-2970

Purpose: The purpose of this article is to propose and practically verify the use of the fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method for comparing and evaluating occupational risk management in manufacturing companies.

Design/methodology/approach: The adopted approach was verified through a questionnaire survey conducted at four furniture industry companies with similar employment size, product mix and volume. The evaluation criteria were eight detailed occupational risk assessment processes that make up the risk management process. The assessments were carried out by independent experts. Verbal and scoring assessments were used.

Conclusions: With the help of the ordered fuzzy TOPSIS method, the surveyed companies were ranked and the best and worst implemented occupational risk assessment process was identified. The research confirmed the usefulness of the fuzzy TOPSIS method in the area of occupational risk management.

Limitations of the study: The main limitations relate to subjectivity in the selection of experts and subjective expert judgment. This work may inspire the verification of other multi-criteria decision-making methods for their suitability in the field of occupational safety, including their fuzzy counterparts.

Practical implications: The presented approach can be an important tool for improving occupational risk management and, in general, occupational health and safety management in manufacturing companies.

Social implications: In the area of occupational risk management, there is a lack of practically validated tools that decision-makers can use in their decision-making process for shaping safe and healthy working conditions.

Originality/Value: The use of the fuzzy approach in OHS management is particularly beneficial, as it allows experts to evaluate various criteria using the most commonly used linguistic variables. The fuzzy TOPSIS method has already been used for many years to evaluate alternatives in many different areas, while the application, with ordered fuzzy numbers in the field of occupational risk management, is original.

Keywords: occupational risk management, MCDM, fuzzy TOPSIS, manufacturing companies.

Article category: research article.

1. Introduction

Occupational risk management is a key process in ensuring safe and healthy working conditions in all types of organizations, regardless of their size. The implementation of this process is driven by numerous regulations of both local and international nature. Numerous risk analysis and assessment models are available in the literature (Marhavillas et al., 2011; Rausand, Haugen, 2020; Liu et al., 2023). They confirm the continuing need for improved management in this area (Babut, Moraru, 2018; IEC 31010:2019; Pisarczuk, 2021).

According to the basic concept of risk management per se, the process of occupational risk management consists most broadly of two main stages: analyzing and assessing risks and controlling risks (Tixier, 2002, IEC 31010:2019; de Oliveira, et al., 2022).

In the risk analysis and assessment stage, four main activities are carried out: gathering the information needed to assess risks, identifying risks, estimating risks, and determining the level of acceptability. In contrast, five main activities are carried out in the area of risk control: analyzing options for implementing preventive measures, deciding on appropriate measures, implementing these measures, monitoring their implementation, and evaluating their effectiveness. Associated with each of these activities, which can be thought of as sub-processes of risk management, are specific issues that decision-makers must confront during the implementation of each sub-process.

At the stage of risk analysis, the basic problem is the correct selection of information sources for hazard identification and the use of appropriate data collection methods, since the same hazard can cause different consequences (IEC 31010:2019).

The problem at the risk estimation stage is the proper selection of methods in relation to the previously identified risks. Risk estimation methods are plentiful (Tixier, 2002; Rausand, 2013), but not all of them are appropriate for a given risk and in a given situation. The key problem at the risk assessment stage is the correct determination of the level of tolerance, control and non-acceptance of risk. The decision in this regard depends on many different considerations (financial, personnel, organizational, etc.) (Moseman, 2012).

The main problem at the stage of analyzing preventive options is the adoption of an appropriate methodology for selecting preventive and/or protective measures (Hollnagel, 2008; Jensen, 2019; Klimecka-Tatar et al., 2023). These measures of a technical, organizational and/or behavioral nature should be considered in terms of factors such as the effectiveness of the solution, cost-effectiveness, feasibility and implementation time, psychological effect, subjective perception by the employees involved, etc. (Manuelle, 2005; Tabor, Moraru, 2022).

Problems such as appropriate planning of activities, proper allocation of needed resources, identification of responsible persons, and determination of the timing of implementation taking into account the possibility of implementation within the established timeframe are related to decision-making on prevention (Marhavillas et al., 2011).

At the stage of implementation of preventive measures, there are mainly problems related to the practical implementation of planned activities in accordance with the adopted schedule (IEC 31010:2019), while at the stage of monitoring - problems of appropriate selection of the scope and detail of ongoing control of planned activities (Main, 2012).

Problems related to the last (in the sense of analysis) stage in the risk management cycle, i.e. the evaluation of the effectiveness of prevention, concern the correctness of assessing the actual reduction in the level of risk after the application of selected preventive measures.

All of these presented problems mean that the decision-maker may not achieve the goal that the occupational risk management process is supposed to serve, which is the continuous and real improvement of working conditions. Accordingly, systematic efforts are being made to develop methods and tools that will facilitate the resolution of these problems, and the effective management of the occupational risk assessment process.

Nowadays, methods and tools are being sought outside the so-called traditional area of interest (such as AHP) paying attention to advanced methods and tools of multi-criteria decision-making (MCDM) (Nowak et al., 2020). Although multi-criteria decision-making is an integral part of occupational risk management, the use of more advanced tools to support this process (e.g. TOPSIS, VIKOR, PROMETHEE) is still little practiced and rarely described in the H&S literature.

The purpose of this article is to propose and verify the application of the fuzzy TOPSIS method, using directed fuzzy numbers, to compare and evaluate occupational risk management.

The TOPSIS method is a tool used in the decision-making process for linear ordering of alternatives (Hwang, Yoon, 1981; Tzeng, Huang, 2011). The method is based on the use of a measure of relative distance from the best solution, which is the benchmark, and from the worst solution, which is the anti-benchmark. The fundamental objective of TOPSIS is to identify an alternative that would have maximum relative proximity to the pattern and minimum relative proximity to the anti-pattern. Nowadays, the most widely used fuzzy TOPSIS method (Chen, Hwang, 1992) uses fuzzy set theory according to Zadeh (Zadeh, 1965).

In contrast, the directed fuzzy numbers (Ordered Fuzzy Numbers) model was proposed in 2002 (Kosinski et al., 2003). The main advantages of directed fuzzy numbers include the ability to go through multiple operations without losing accuracy and the ability to infer backwards.

The application of the TOPSIS method with directed fuzzy numbers, presented in this article, to the assessment of occupational risk management is original.

2. Methodology

The use of a fuzzy approach in assessing occupational risk management is particularly beneficial, as it allows experts to evaluate various criteria using the most commonly used linguistic variables. The paper uses blurring of grades by extending their ranges with fuzzy uncertainty intervals, which simplifies calculations. The approach is captured in the following calculation procedure:

- 1) Aggregation of criteria scores using the arithmetic mean.
- 2) Create a fuzzy decision matrix X using directed fuzzy numbers:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{M1} & x_{M2} & \dots & x_{MN} \end{bmatrix} \quad (1)$$

where $x_{ij} = (l_{ij} \ 1_{ij}^- \ 1_{ij}^+ \ p_{ij})$ ($i = 1, 2, \dots, M; j = 1, 2, \dots, N$) are directed fuzzy numbers. The fuzzy decision matrix is formed by converting the sharp evaluations x_{ij}^* into evaluations expressed by directed fuzzy numbers x_{ij} .

- 3) Create a normalized fuzzy matrix Z :

$$Z = \begin{bmatrix} z_{11} & z_{12} & \dots & z_{1N} \\ z_{21} & z_{22} & \dots & z_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ z_{M1} & z_{M2} & \dots & z_{MN} \end{bmatrix}, \quad (2)$$

where:

$$z_{ij} = \begin{cases} \left(\frac{l_{ij}}{\max_i p_{ij}} \ \frac{1_{ij}^-}{\max_i p_{ij}} \ \frac{1_{ij}^+}{\max_i p_{ij}} \ \frac{p_{ij}}{\max_i p_{ij}} \right) & \text{when } C_j - \text{"profit"} - \text{type criterion} \\ \left(\frac{\min_i p_{ij}}{l_{ij}} \ \frac{\min_i p_{ij}}{1_{ij}^-} \ \frac{\min_i p_{ij}}{1_{ij}^+} \ \frac{\min_i p_{ij}}{p_{ij}} \right) & \text{when } C_j - \text{"loss"} - \text{type criterion} \end{cases} \quad (3)$$

- 4) Calculation of weights w_j individual criteria, according to the maximum deviation method (Wang, 1998):

$$w_j = \frac{H_j}{\sum_{j=1}^n H_j}, \text{ where: } H_j = \sum_{i=1}^m H_{ij} \quad (4)$$

and

$$H_{ij} = \sum_{k=1}^m d(a_{ij}, a_{kj}), \text{ where: } i \in \{1, 2, \dots, m\}, j \in \{1, 2, \dots, n\} \quad (5)$$

Hence the scalar vector of weights: $w = [w_1, w_2, \dots, w_N]$, where $w_N \in \mathbb{R}$ ($w_N > 0, n = 1, 2, \dots, N$) is the weight of the n^{th} criterion, with $w_1 + w_2 + \dots + w_N = 1$.

- 5) Create a weighted normalized fuzzy matrix V :

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1N} \\ v_{21} & v_{22} & \dots & v_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ v_{M1} & v_{M2} & \dots & v_{MN} \end{bmatrix}, \quad (6)$$

where: $v_{ij} = z_{ij} \times w_j$ ($i = 1, 2, \dots, M; j = 1, 2, \dots, N$).

- 6) Finding the pattern A^+ and anti-pattern A^- for ratings against each criterion, whereby:

$$A^+ = (v_1^+, v_2^+, \dots, v_N^+), \quad (7)$$

where: $v_j^+ = \left(\max_i l_{v_{ij}} \max_i 1_{v_{ij}}^- \max_i 1_{v_{ij}}^+ \max_i p_{v_{ij}} \right), j = 1, 2, \dots, N$

and

$$A^- = (v_1^-, v_2^-, \dots, v_N^-), \quad (8)$$

where: $v_j^- = \left(\min_i l_{v_{ij}} \min_i 1_{v_{ij}}^- \min_i 1_{v_{ij}}^+ \min_i p_{v_{ij}} \right), j = 1, 2, \dots, N$

- 7) Calculation of the distance of each variant's ratings from the pattern and anti-pattern using the following relationships:

$$d_i^+ = \sum_{j=1}^N d(v_{ij}, v_j^+) \text{ and } d_i^- = \sum_{j=1}^N d(v_{ij}, v_j^-) \text{ for } i = 1, 2, \dots, M \quad (9)$$

where:

$$d(A, B) = \sqrt{\frac{1}{4}[(l_A - l_B)^2 + (1_A^- - 1_B^-)^2 + (1_A^+ - 1_B^+)^2 + (p_A - p_B)^2]}, \quad (10)$$

when: $A = (l_A \ 1_A^- \ 1_A^+ \ p_A)$ and $B = (l_B \ 1_B^- \ 1_B^+ \ p_B)$.

- 8) Determination of the synthetic measure of variant evaluations CC_i using the relative proximity of variant evaluations to the pattern and anti-pattern:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \dots, M \quad (11)$$

The shorter the distance of the variant's evaluation from the pattern, and at the same time the greater the distance from the anti-pattern, the closer the value of the measure is to 1.

- 9) Create a ranking for M variants based on linear ordering of synthetic measures CC_i , gdzie $i = 1, 2, \dots, M$.

In structuring the problem, criteria C , for assessing the level of implementation of the occupational risk management process, were defined, which correspond to the following stages of the process: C_1 - Identifying risks, C_2 - Assessing risks, C_3 - Assessing risks, C_4 - Analyzing

preventive options, C₅ - Deciding how to prevent, C₆ - Implementing preventive actions, C₇ - Monitoring preventive actions, C₈ - Evaluating the effectiveness of prevention.

After determining the evaluation criteria, possible alternative A solutions were established on the basis of four furniture industry companies A₁, A₂, A₃ and A₄, with similar product mix, market position and employment size in the range of 50 to 99 people.

At the problem modeling stage, four E experts, using a specially prepared questionnaire, first evaluated the relevance of criteria C₁-C₈, using a seven-point scale from 1 - *not relevant* to 7 - *very relevant* for evaluation.

Then, using a second questionnaire, experts assessed the level of implementation of each sub-process of occupational risk management in each of the surveyed companies separately. The implementation of each sub-process (criterion) was evaluated independently of the results of the evaluation of the other criteria, using a seven-point linguistic scale from *bad* to *excellent*.

The resulting language scores were assigned corresponding fuzzy ratings: *Wrong* (W) – (0.0 0.5 1.5 2.0) *Very poor* (VP) – (1.0 1.5 2.5 3.0), *Poor* (P) – (2.0 2.5 3.5 4.0), *Medium* (M) – (3.0 3.5 4.5 5.0), *Good* (G) – (4.0 4.5 5.5 6.0), *Very good* (VG) – (5.0 5.5 6.5 7.0), *Excellent* (E) – (6.0 6.5 7.5 8.0).

3. Results

Table 1 summarizes the linguistic evaluations of individual criteria C₁-C₈ given by the experts to individual companies A₁, A₂, A₃ and A₄.

Table 1.

Expert linguistic evaluations of criteria C for the surveyed companies A₁, A₂, A₃ and A₄

	A ₁				A ₂				A ₃				A ₄			
	E ₁	E ₂	E ₃	E ₄	E ₁	E ₂	E ₃	E ₄	E ₁	E ₂	E ₃	E ₄	E ₁	E ₂	E ₃	E ₄
C ₁	VP	W	VP	P	P	P	M	VP	P	VP	M	P	VP	VP	P	VP
C ₂	G	G	VG	M	VP	VP	VP	VP	M	M	G	P	G	M	VG	G
C ₃	M	P	M	G	G	M	VG	G	M	P	G	M	VG	M	E	E
C ₄	M	G	M	P	P	VP	M	P	VG	M	E	E	G	M	VG	G
C ₅	P	M	VP	P	G	G	M	VG	VG	E	M	E	M	M	G	P
C ₆	P	M	VP	P	G	G	M	G	VG	G	VG	E	M	M	M	M
C ₇	P	VP	M	P	M	P	G	M	G	G	G	G	M	P	M	G
C ₈	P	P	P	P	P	VP	P	W	P	P	P	P	VP	W	P	VP

Source: own study.

According to the prepared procedure, the obtained assessments were aggregated. The result of the aggregation is shown in Table 2.

Table 2.

Aggregate fuzzy C-criteria ratings for surveyed companies A₁, A₂, A₃ and A₄

	A ₁	A ₂	A ₃	A ₄
C ₁	(1.00 1.50 2.50 3.00)	(2.00 2.50 3.50 4.00)	(2.00 2.50 3.50 4.00)	(1.25 1.75 2.75 3.25)
C ₂	(4.00 4.50 5.50 6.00)	(1.00 1.50 2.50 3.00)	(3.00 3.50 4.50 5.00)	(4.00 4.50 5.50 6.00)
C ₃	(3.00 3.50 4.50 5.00)	(4.00 4.50 5.50 6.00)	(3.00 3.50 4.50 5.00)	(5.00 5.50 6.50 7.00)
C ₄	(3.00 3.50 4.50 5.00)	(2.00 2.50 3.50 4.00)	(5.00 5.50 6.50 7.00)	(4.00 4.50 5.50 6.00)
C ₅	(2.00 2.50 3.50 4.00)	(4.00 4.50 5.50 6.00)	(5.00 5.50 6.50 7.00)	(3.00 3.50 4.50 5.00)
C ₆	(2.00 2.50 3.50 4.00)	(3.75 4.25 5.25 5.75)	(5.00 5.50 6.50 7.00)	(3.00 3.50 4.50 5.00)
C ₇	(2.00 2.50 3.50 4.00)	(3.00 3.50 4.50 5.00)	(4.00 4.50 5.50 6.00)	(3.00 3.50 4.50 5.00)
C ₈	(2.00 2.50 3.50 4.00)	(1.25 1.75 2.75 3.25)	(2.00 2.50 3.50 4.00)	(1.00 1.50 2.50 3.00)

Source: own study.

Using formula (1), a fuzzy decision matrix was created, containing ordered fuzzy aggregate values of the criteria ratings for each alternative.

Then, using formulas (2) and (3), a normalized fuzzy decision matrix was constructed (all evaluation criteria were profit type). Table 3 summarizes the values of normalized fuzzy evaluations of each criterion.

Table 3.

Normalized fuzzy C-criteria scores for surveyed companies A₁, A₂, A₃ and A₄

	A ₁	A ₂	A ₃	A ₄
C ₁	(0.250 0.375 0.625 0.750)	(0.500 0.625 0.875 1.000)	(0.500 0.625 0.875 1.000)	(0.313 0.438 0.688 0.813)
C ₂	(0.667 0.750 0.917 1.000)	(0.167 0.250 0.417 0.500)	(0.500 0.583 0.750 0.833)	(0.667 0.750 0.917 1.000)
C ₃	(0.429 0.500 0.643 0.714)	(0.571 0.643 0.789 0.857)	(0.429 0.500 0.643 0.714)	(0.714 0.789 0.929 1.000)
C ₄	(0.429 0.500 0.643 0.714)	(0.286 0.357 0.500 0.571)	(0.714 0.789 0.929 1.000)	(0.571 0.643 0.789 0.857)
C ₅	(0.289 0.357 0.500 0.571)	(0.571 0.643 0.786 0.857)	(0.714 0.786 0.929 1.000)	(0.429 0.500 0.643 0.714)
C ₆	(0.286 0.357 0.500 0.571)	(0.536 0.607 0.751 0.821)	(0.714 0.786 0.929 1.000)	(0.429 0.500 0.643 0.714)
C ₇	(0.333 0.417 0.583 0.667)	(0.500 0.583 0.750 0.833)	(0.667 0.750 0.917 1.000)	(0.500 0.583 0.750 0.833)
C ₈	(0.500 0.625 0.875 1.000)	(0.313 0.438 0.688 0.813)	(0.500 0.625 0.875 1.000)	(0.250 0.375 0.625 0.750)

Source: own study.

In turn, using formulas (4) and (5), the criteria weights were calculated. Table 4 summarizes the scoring of the criteria by each expert and the corresponding weights.

Table 4.

Expert scoring of each criterion C and corresponding weights

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈
E ₁	7	6	5	3	6	5	5	3
E ₂	5	5	4	3	6	5	3	3
E ₃	6	5	5	4	7	4	3	5
E ₄	7	6	4	4	6	4	4	6
Weights	0.154	0.093	0.093	0.093	0.080	0.093	0.154	0.241

Source: own study.

Hence, the scalar vector of weights took the form: $w = [0.155, 0.093, 0.093, 0.093, 0.093, 0.080, 0.093, 0.154, 0.241]$. Using the normalized fuzzy matrix and the calculated weights, according to formula (6), a weighted normalized fuzzy decision matrix was obtained with the following values - Table 5.

Table 5.*Weighted fuzzy criteria ratings for surveyed companies A₁, A₂, A₃ and A₄*

	A ₁	A ₂	A ₃	A ₄
C ₁	(0.039 0.058 0.096 0.116)	(0.077 0.096 0.135 0.154)	(0.077 0.096 0.135 0.154)	(0.048 0.067 0.106 0.125)
C ₂	(0.062 0.070 0.085 0.093)	(0.016 0.023 0.039 0.047)	(0.047 0.054 0.070 0.078)	(0.062 0.070 0.085 0.093)
C ₃	(0.040 0.047 0.060 0.066)	(0.053 0.060 0.073 0.080)	(0.040 0.047 0.060 0.066)	(0.066 0.073 0.086 0.093)
C ₄	(0.040 0.047 0.060 0.066)	(0.027 0.033 0.047 0.053)	(0.066 0.073 0.086 0.093)	(0.053 0.060 0.073 0.080)
C ₅	(0.023 0.029 0.040 0.046)	(0.046 0.051 0.063 0.069)	(0.057 0.063 0.074 0.080)	(0.034 0.040 0.051 0.057)
C ₆	(0.027 0.033 0.047 0.053)	(0.050 0.056 0.070 0.076)	(0.066 0.073 0.086 0.093)	(0.040 0.047 0.060 0.066)
C ₇	(0.051 0.064 0.090 0.103)	(0.077 0.090 0.116 0.128)	(0.103 0.116 0.141 0.154)	(0.077 0.090 0.116 0.128)
C ₈	(0.121 0.151 0.211 0.241)	(0.075 0.105 0.166 0.196)	(0.121 0.151 0.211 0.241)	(0.060 0.090 0.151 0.181)

Source: own study.

On the basis of the weighted normalized fuzzy decision matrix, using formulas (7) and (8), the pattern and anti-pattern were identified, and then, using formulas (9) and (10), the distances of each evaluation from the pattern and anti-pattern were calculated - Table 6.

Table 6.*Distances from pattern d^+ and anti-pattern d^-*

	A ₁		A ₂		A ₃		A ₄	
	d^+	d^-	d^+	d^-	d^+	d^-	d^+	d^-
C ₁	0.039	0.000	0.000	0.038	0.000	0.038	0.029	0.009
C ₂	0.000	0.046	0.047	0.000	0.016	0.031	0.000	0.046
C ₃	0.026	0.000	0.013	0.013	0.026	0.000	0.000	0.026
C ₄	0.026	0.013	0.040	0.000	0.000	0.040	0.013	0.026
C ₅	0.034	0.000	0.011	0.023	0.000	0.034	0.023	0.011
C ₆	0.040	0.000	0.016	0.023	0.000	0.040	0.026	0.013
C ₇	0.052	0.000	0.026	0.026	0.000	0.051	0.026	0.026
C ₈	0.000	0.060	0.045	0.015	0.000	0.060	0.060	0.000

Source: own study.

Finally, based on formula (11), synthetic measures of CC₁ evaluations were calculated for individual companies A₁, A₂, A₃ and A₄, which amounted to A₁: 0.358, A₂: 0.412, A₃: 0.872 and A₄: 0.472, respectively.

The final ranking (step 9 of the calculation procedure) shows that with such adopted evaluation criteria and such, established relationship of their importance, the company A₃, because A₃ > A₄ > A₂ > A₁, performs the risk assessment process best.

4. Discussion

A key problem within the framework of this study was deciding how to determine the weights of the evaluated criteria. The most common solution is for the decision-maker to set the weights arbitrarily or to use averaged expert opinions, within the framework of procedures available in the literature. In contrast, the present study used a solution based on the maximum deviation method.

In this method, it is assumed that if a certain criterion assumes very different values between alternatives, it plays an important role in the process of selecting the best solution and should have a high weight; while if the values of a criterion differ little between alternatives, such a criterion has little importance and low weight. At the same time, it should be noted that all the adopted evaluation criteria are of the same nature - stimulants (the more, the better), which is due to the adopted process model of occupational risk management, which may also be different.

The specific nature of the various sub-processes of occupational risk management means that verbal terms are most often used to assess the level of their implementation. Obtaining quantitative data (for indicators) is more labor-intensive, and in many cases very difficult. Also problematic is the sharing of some information with others, especially in the form of indicators.

5. Summary

Occupational risk management is a sequence of decision-making processes, many of which are multi-criteria in nature. Therefore, it is important to search for and develop tools to assist decision-makers in their efforts to improve this process, and thus improve occupational health and safety. Since the process of occupational risk management is, by its very nature, complex, and cannot be described by a single parameter, the most desirable approach to assessing the implementation of this process is multivariate analysis, and consequently multivariate (multi-criteria) methods.

This work represents an original application of directed fuzzy numbers and the TOPSIS method to the assessment of occupational risk management. The proposed approach is advantageous in situations of vague and uncertain information, which we face with linguistic expert assessments.

The TOPSIS method used, in the proposed approach, is not the only method of ordering, but it is one of the best known and best described. On the other hand, the use of ordered fuzzy numbers has broadened the scope of the method's application to a hitherto underrepresented area, which is occupational risk management.

With the proposed approach, the occupational risk management processes implemented in four manufacturing companies were compared and ranked, which made it possible to identify the best and worst implemented.

The presented research and analysis confirmed the usefulness of the fuzzy TOPSIS method in the field of occupational safety, to assess, compare and identify the companies with the best and worst implementation of the occupational risk management process.

The approach used in the paper is relatively simple, and any spreadsheet can be used to perform the mathematical operations, which is especially important for small and medium-sized enterprises.

This paper can inspire the search for further applications of the fuzzy TOPSIS method, both in the field of occupational safety and for the application of ordered fuzzy numbers within other numerous multi-criteria decision-making methods.

In the context of the results obtained, further research work is planned, including practical verification of the usefulness of various methods for solving decision-making problems involving other key issues in the field of occupational health and safety management.

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