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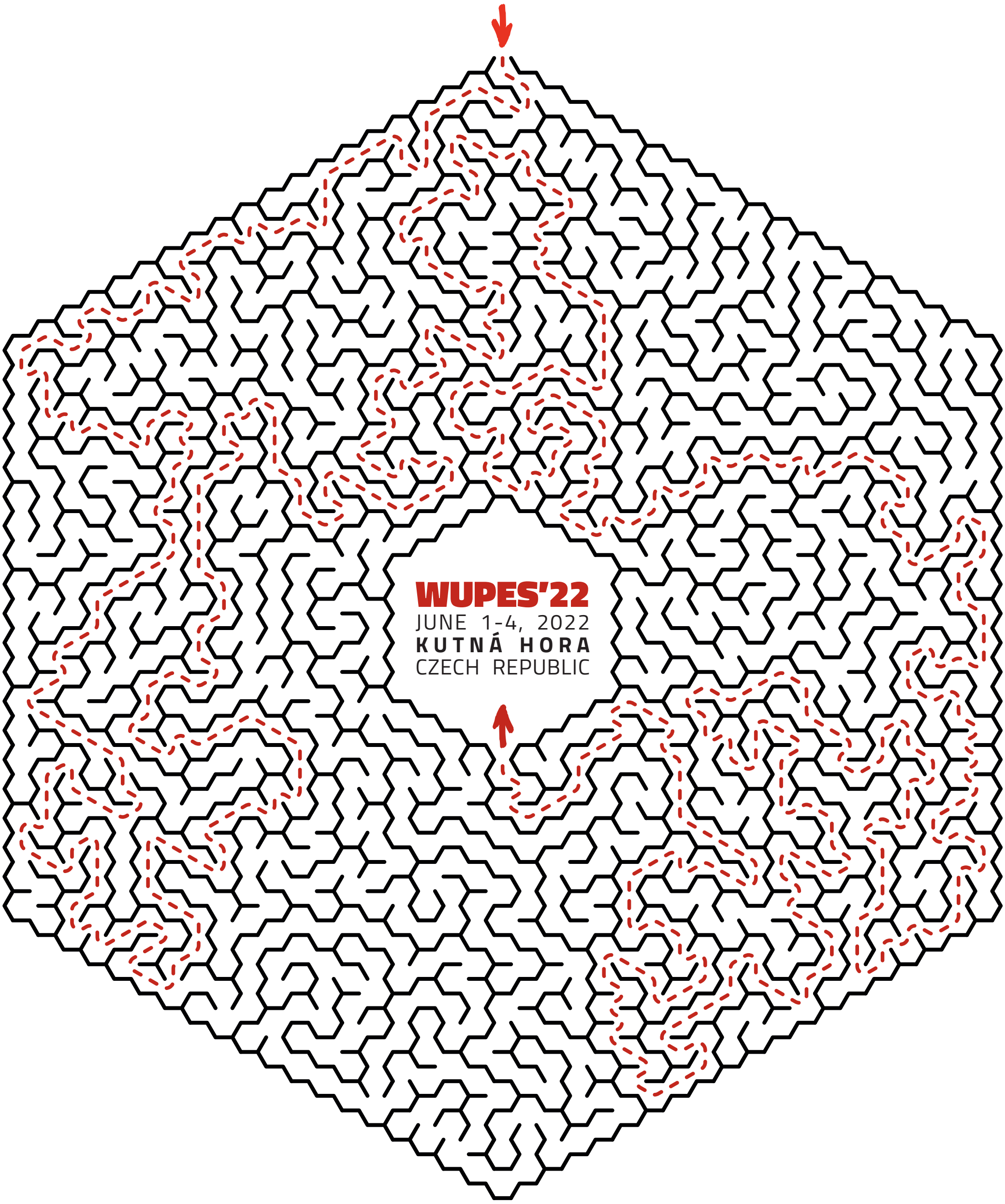

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Characterizing Uncertainty In Decision-Making Models For Maintenance In Industry 4.0

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Abstract

Decision-making involves our daily life at any level, something that entails uncertainty and potential occurrence of risks of varied nature. When dealing with industrial engineering systems, effective decisions are fundamental in terms of maintenance planning and implementation. Specifically, several forms of uncertainty may affect decision-making procedures, for which adopting suitable techniques seems to be a good strategy to attain the main maintenance goals by taking into account system criticality along with decision-maker(s) opinions. A wide variety of factors contributes to uncertainty, being some of them greatly important while other ones less significant. However, all of these factors in synergy can impact the functioning of systems in a positive, neutral, or negative way. In this case, the question is whether obtaining a complete picture of such uncertainty can improve decision-making capabilities and mitigate both through-life costs and unforeseen problems. The fundamental issues include dealing with ambiguity in the maintenance decision-making process by employing numerous evaluation criteria and dealing with real-world scenarios in the maintenance environment. In this study, the Multi-Criteria Decision-Making (MCDM) approach is analysed, with particular reference to the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS), technique capable to effectively rank alternatives while dealing with uncertainty for maintenance decision-making. A final case study is developed to demonstrate the applicability of the method to the field of maintenance in industry 4.0. The proposed study may be useful in supporting intelligent and efficient decisions resulting in favorable maintenance outcomes.

1 Introduction

Enabled by such industry 4.0 technologies as machine learning, big data, and augmented reality, the current digital era is generally characterised by an abundance of information available to aid in decision-making. Assets can be easily and real-time connected via networks of suitable sensors, commonly referred to as the Internet of Things (IoT). The primary problem has shifted from obtaining data to making educated decisions on the basis of the acquired information. The whole maintenance management relies on such information, as well as on how to utilise data and predictive analytic to improve our judgments. As a consequence, new possibilities for data-driven techniques including predictive analytic, artificial intelligence, and machine learning have been developed, with the potential for large efficiency advantages. Everyday life is associated with constant decision-making and each of these decisions involves potential of uncertainty and risk (Van Staden, 2021), something that can directly influence maintenance strategies.

Numerous variables contribute to uncertainty, some of them are extremely significant while other ones may be inconsequential, affecting performance of the system in a favourable, neutral, or negative way (Grenyer et al., 2019). On the whole, two different forms of uncertainty can be distinguished: quantitative, based on recorded statistical data, and qualitative, based on unobserved statistical data consisting of heuristic estimates obtained from expert opinions, supplier specifications, and equipment accuracy. On the one hand, the first category is well-documented and can be simply represented as the standard deviation of a particular data set. On the other hand, the second category is often difficult to be characterised. Additionally, uncertainty can be classified as epistemic and aleatory. The first one stems from model or data accuracy, which is impacted by the available amount of knowledge, and may therefore be alleviated or improved. The other type denotes statistical variables that change continually and so cannot be minimized (Grenyer et al., 2019). Among the several causes of uncertainty, the primary source is the lack of knowledge about engineering phenomena. Indeed, decision-making processes are affected by several types of uncertainty, depending on its own root causes.

Uncertainty manifests itself at several levels in diagnostic problems, particularly when it comes to information and/or system defects. Two primary aspects of uncertainty refers to the available information used to support decision-making problems: fuzziness and stochasticity. The ideal decision-making procedures under situations of uncertainty in order to achieve the maintenance objective vary according to the system's nature and the decision maker's priorities (Borissova et al., 2011). Currently, industrial maintenance decision-making is primarily based on two major categories of data: captured data and subjective expert views. The collected data contains objective facts that are subjected to a degree of uncertainty statistically quantifiable as the standard deviation of the dataset under analysis. Subjective expert opinions assign qualitative uncertainty to individuals based on their characteristics that qualify them as experts and the foundation for their perspective in order to prove its legitimacy. The precision of the equipment employed together with the competence of the maintainer are seldom recognised as contributors to total uncertainty in methods of data collection. However, their roles are fundamental to comprehensively characterise and manage uncertainty, as exemplified in Figure 1.

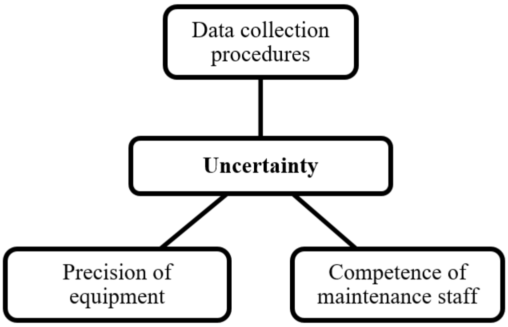

Figure 1: Contributors of uncertainty in maintenance (Grenyer et al., 2019)

A mix of objective data and subjective opinions should be considered to elicit reliable judgments leading to effective maintenance results. Certain instances need indeed further skills while other ones necessitate additional data. The issue is whether taking a comprehensive picture of such uncertainties may help to enhance decision-making capability and mitigate both through-life costs and unanticipated problems (Grenyer et al., 2019).

Reviewing and adapting maintenance policies to the many possibilities available in systems or plants is critical for maintenance managers. Especially when multiple conflicting criteria and methods are taken into account, it is difficult to undertake proper maintenance strategies. The primary problems include dealing with uncertainty in the evaluation of maintenance policies using multiple assessment criteria and dealing with real-world situations in maintenance (Mojtahedi et al., 2020). In this study, we are going to assume a Multi-Criteria Decision-Making (MCDM) perspective and, in particular, an approach based on the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) is going to be applied to rank alternatives relevant to industry 4.0 in order to characterise uncertainty in maintenance decision-making. The proposed study may be useful in supporting companies to make effective decisions optimising business results on the whole.

2 Literature review

MCDM methods are extensively implemented in many domains, e.g. engineering, supply chain management, economics, social sciences, medical sciences, among others. Despite its variety, the MCDM paradigm shares several aims and criteria that are sometimes in conflict with each other. Over the last decades, MCDM methods have grown in importance in such fields as operations research (Nădăban et al., 2016), and their adoption is commonly considered to be a robust scientific strategy to make intelligent and acceptable decisions in complex maintenance contexts (Abdulgader et al., 2018) such as those involved in industry 4.0. Various MCDM methodologies have been largely used by several professionals in different areas of study (Palczewski and Sałabun, 2019).

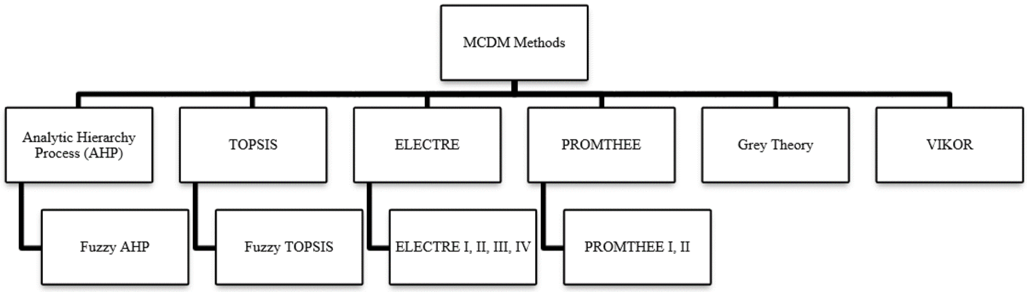

Figure 2: MCDM techniques and types (Aruldoss et al., 2013)

Some of these techniques are summarised by Aruldoss et al. (2013), as recalled in Figure 2, and can be applied in their traditional version or even in their fuzzy developments. In the first case, decision-making elements (i.e. criteria, sub-criteria, alternatives) are evaluated, ranked and/or weighted on the basis of assessments given in the form of crisp numbers. Alternatively, in the second case, linguistic variables to be translated into fuzzy numbers are used in order to better manage the ambiguity as well as the lack of precision and clarity affecting input evaluations (Wang and Lee, 2009).

Among the MCDM methods available in literature, we are going to discuss about the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) along with its fuzzy extension (FTOPSIS). This choice is justified by the fact that these techniques allow extreme flexibility in ranking elements, something that appears to be particularly useful in modern maintenance contexts, greatly impacted by digital transformations.

2.1 Traditional TOPSIS: advantages and limitations

In the vast majority of real-life scenarios, given the ambiguity of human preference behaviour, decision-makers are often unable to produce effectively representative numerical evaluations for discriminating among the main elements of a complex problem. Numerous MCDM approaches have been developed and applied over the years and, among them, TOPSIS is one of the most common methods used in literature to deal with complex decision-making problems (Salih et al., 2019; Palczewski and Sałabun, 2019; Hung and Chen, 2009; Kutlu and Ekmekçioğlu, 2012; Kore et al., 2017), with the ultimate goal of producing a structured ranking of alternatives (Kutlu and Ekmekçioğlu, 2012; Gupta, 2018) on the basis of evaluation criteria, suitably weighted.

TOPSIS was established on the notion that the selected alternative(s) should have the shortest distance to an ideal point, called Positive Ideal Solution (PIS) and, simultaneously, the longest distance to another ideal point, called Negative Ideal Solution (NIS) (Wang and Lee, 2009; Hung and Chen, 2009; Kutlu and Ekmekçioğlu, 2012; Kore et al., 2017; Wang and Elhag, 2006). The output is then based on the calculation, for each alternative, of the positive and negative distances (Solangi et al., 2021). To such an aim, an accommodative aggregation technique may preliminary evaluate a set of alternatives by assigning weights to each criterion (Palczewski and Sałabun, 2019). However, using actual crisp values to score the alternatives under analysis may lead to restrictions in addressing uncertainty (Salih et al., 2019). In any case, TOPSIS includes an easily comprehensible and flexible calculation technique having the capability to take into consideration several criteria with varied units at the same time (Kutlu and Ekmekçioğlu, 2012). Given to its great flexibility of application, TOPSIS is a prominent MCDM method employed by many scholars in a huge variety of sectors (Solangi et al., 2021; Behzadian et al., 2012). Moreover, it has been widely integrated with several other MCDM strategies as an efficient way for prioritizing maintenance decision-making (see Singh et al. (2016); Ighravwe and Oke (2021), among others). TOPSIS is indeed considered to be faster, apart from much more adaptable, comprehensible, and straightforward than many other MCDM methodologies (Haddad et al., 2021).

TOPSIS' strengths comprise transparency, intuitively grasped concepts, improved working efficiency, and capability to evaluate the overall efficiency of each alternative in a simple mathematical format, something that has resulted in the broad acceptance and understanding of this approach from a varied range of industries (Hung and Chen, 2009). The main benefit of employing TOPSIS is that it requires just few data sets from professionals, such as criteria values and linguistic evaluations of alternatives (Gupta, 2018). It accepts contributions in the form of any set of criteria and characteristics. Because of the notion of detachment from flawless patterns, it has actually instinctual physical significance. It is indeed extremely effective in dealing with circumstances in which maintenance managers, due to their specialized knowledge, believe that technical difficulties may be scaled from the most significant to the least critical considerations. The discussed peculiarities of TOPSIS make it a viable choice for dealing with prioritization issues (Ighravwe and Oke, 2021), also considering the possibility to take simultaneously into account optimal and critical solutions by means of an easy mathematical programming procedure (Rani et al., 2020).

Despite its widespread use, TOPSIS has several limitations in its traditional form, since it actually fails to offer precise information when problems are particularly ambiguous and unexplained (Solangi et al., 2021). Additionally, the use of crisp values for evaluating alternatives is generally inefficient in capturing the subjective character of human cognition. This may lead the technique to fail in effectively reflecting decision makers' priorities in real-world scenarios (Haddad et al., 2021). In multi-criteria contexts, variables are usually in discordant proportions, something that generates complex assessment challenges. Furthermore, TOPSIS' weaknesses may originate the following flaws: (1) its simplistic application may produce incorrect findings; (2) its traditional deterministic version may not exhaustively help in considering uncertainty (Abdulgader et al., 2018). As a result, standard TOPSIS can only partially accommodate ambiguous or vague input through expert opinions. To address all of the mentioned shortcomings, various works of research have integrated fuzzy logic ideas within MCDM approaches. In such a direction, the FTOPSIS technique, originally deveoped by Chen (2000), is proposed as a combination of fuzzy set theory and traditional TOPSIS, under which fuzzy values are employed to provide preference ratings by experts (Palczewski and Sałabun, 2019; Salih et al., 2019; Gupta, 2018; Haddad et al., 2021).

2.2 FTOPSIS: effective treatment of uncertainty

In complex decision-making situations related to maintenance management in industry 4.0, analysing the many variables and factors can be a complex task. As we have already explained, extending traditional models to fuzzy logic can significantly help to mitigate this problem, as it has been successfully demonstrated in many industrial applications (Palczewski and Sałabun, 2019). In 1965, Zadeh developed the concept of fuzzy sets for stimulating spontaneous reasoning by taking into account human ambiguity and subjectivity. As the primary goal of fuzzy logic is to grasp the inaccuracy of human thinking and describe it mathematically (Hung and Chen, 2009; Solangi et al., 2021), linguistic variables can be represented by means of fuzzy numbers with an associated degree of membership $\mu(x)$, varying between 0 and 1. Several researchers have been focusing on the possibility to deal with complex uncertain decision-making problems utilizing fuzzy sets theory. Furthermore, in 1993, Gau and Buehrer introduced the concept of ambiguous sets, stressing as a single value cannot testify to its reality (Hung and Chen, 2009).

FTOPSIS is particularly effective in handling ambiguity and uncertainty affecting input data as it results from human perception and evaluation. Given the ambiguity and lack of knowledge in MCDM, linguistic terms used in FTOPSIS can represent inaccurate data so as to better deal with unclear information (Palczewski and Sałabun, 2019; Salih et al., 2019). Indeed, the use of fuzzy numbers for criteria evaluation streamlines the whole assessment process by also making decision-makers more comfortable in expressing their personal opinions when it comes to qualitative criteria. As a result, FTOPSIS represents a simple, practical forecasting and compensatory method to accept or reject potential options based on hard cut-offs (Kore et al., 2017; Wang and Elhag, 2006). However, it is vital to underline that most of the information gathered and used in FTOPSIS derives from human evaluations, something that makes the estimation of values of importance and also strictly dependent on the quantity of data, that hence need to be “dependable, reliable, constant, certain, authentic, real, and respectable”. Despite these drawbacks, FTOPSIS can be regarded as an appropriate method to analyse the values and rank relevant decision-making elements on the basis of linguistic variables and related fuzzy numbers (Solangi et al., 2021).

Numerous studies on FTOPSIS and its integrations are identified in literature. Hwang et al. (2022) assessed maintenance criteria for railroad electrical facility systems based on subjective judgment information of decision-makers by using Design Structure Matrix (DSM) and FTOPSIS approaches. Alshraideh et al. (2021) used a FTOPSIS model to identify the most suitable maintenance contractor under unpredictable conditions, by evaluating proposals’ quality. Momeni et al. (2011) proposed the FTOPSIS as a tool for selecting maintenance plans by translating uncertain and imprecise judgment from the decision makers into fuzzy figures. Selim et al. (2016) created a maintenance planning framework integrating the FTOPSIS and the Failure Mode and Effect Analysis (FMEA) approaches for determining the repair priorities of the machines in order to decrease and stabilize maintenance expenditures. Chen et al. (2020) applied the FTOPSIS technique to rate and prioritize paths to e-waste implementation management solutions in Ghana while accounting for the subjectivity of decision-maker preferences.

FTOPSIS have been developed to deal with any type of problem, examples are: assessing and prioritizing strategies for long-term deployment of renewable energy technologies in Pakistan (Solangi et al., 2021); evaluating many alternatives against subjective criteria and weighting all of the factors for robot selection (Chu and Lin, 2003); evaluating suppliers under Health Safety and Environment (HSE) criteria in the oil and gas sector to prioritize operations and maintenance contracts (Haddad et al., 2021); and so on. As reported by Kutlu and Ekmekçioğlu (2012), FTOPSIS has been used also for dealing with the following problems: selection of plant location, supplier selection, industrial robotic system selection, municipal solid waste disposal method and site selection, selection of the best energy technology alternative, and modeling consumer product adoption processes.

3 Methodological procedure

As mentioned in some previous works (Brentan et al., 2021; Carpitella et al., 2018), the most common types of fuzzy numbers are Triangular Fuzzy Numbers (TFNs) $\tilde{n}$, herein considered, which can be expressed as follows (Klir and Yuan, 1996):

$$\tilde{n} = (a, b, c); \tag{1}$$

where $a \leq b \leq c$. Common algebraic operations involving one or more fuzzy numbers can be easily performed. For instance, one can write the following equations:

$$\tilde{n}_1 \oplus \tilde{n}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2); \tag{2}$$

$$\tilde{n}_1 \odot \tilde{n}_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2); \tag{3}$$

$$\tilde{n}_1^{-1} = (\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}). \tag{4}$$

On the basis of these preliminaries, we now describe the steps needed to implement the FTOPSIS approach (Youssef, 2020; Akram and Arshad, 2019; Ilyas et al., 2021).

- Defining the fuzzy decision matrix $\tilde{X}$ collecting the whole set of input data:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix}. \tag{5}$$

  The generic TFN $\tilde{x}_{ij}$ of matrix $\tilde{X}$ corresponds to the rating of alternative i under criterion j:

$$\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}). \tag{6}$$

- Weighting and normalising matrix $\tilde{X}$ with relation to different criteria, obtaining matrix $\tilde{U}$, whose components are calculated as:

$$\tilde{u}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \times w_{ij}, j \in I'; \tag{7}$$

$$\tilde{u}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \times w_{ij}, j \in I''; \tag{8}$$

$I^{'}$ being the subset of criteria to be maximized, $I^{''}$ the subset of criteria to be minimized, w_j the weight of criterion j and c_j^* and a_j^- calculated as:

$$c_j^* = \max_i c_{ij} \quad if \quad j \in I'; \tag{9}$$

$$a_j^- = \min_i a_{ij} \quad if \quad j \in I''. \tag{10}$$

- Computing distances between each alternative and the fuzzy ideal solutions A^* and A^-:

$$A^* = (\tilde{u}_1^*, \tilde{u}_2^*, \dots, \tilde{u}_n^*); \tag{11}$$

$$A^- = (\tilde{u}_1^-, \tilde{u}_2^-, \dots, \tilde{u}_n^-). \tag{12}$$

where $\tilde{u}_j^* = (1,1,1)$ and $\tilde{u}_j^- = (0,0,0)$, $j = 1 \dots n$. Distances between each alternative and these ideal points can be computed through the vertex method (Chen, 2000), for which the distance $d(\tilde{m}, \tilde{n})$ between two TFNs $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ corresponds to the crisp value:

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}\left[\left(m_1 - n_1\right)^2 + \left(m_2 - n_2\right)^2 + \left(m_3 - n_3\right)^2\right]}. \tag{13}$$

Then, aggregating with respect to the whole set of criteria, the distances of each alternative i from A^* and A^- are, respectively:

$$d_i^* = \sum_{j=1}^{n} d(\tilde{u}_{ij}, \tilde{u}_j^*) \quad i = 1, \dots, n; \tag{14}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{u}_{ij}, \tilde{u}_j^-) \quad i = 1, \dots, n. \tag{15}$$

- Calculating the closeness coefficient CC_i:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \tag{16}$$

To get the final ranking of alternatives it is necessary to order the values of the closeness coefficient related to each alternatives in a decreasing way.

4 Application and discussion

The present case study applies the FTOPSIS technique to rank a set of 13 alternatives, that are the maintenance factors relevant for industry 4.0 identified and formalised in (Ahmed et al., 2022). The considered factors aim to contemplate the role of maintenance digitalization and their final ranking highlights those aspects to be taken primarily into account when planning industrial strategies while considering uncertainty of evaluations. Alternatives have been evaluated under three main criteria, that are safety & security (C_1), process quality (C_2) and cost efficiency (C_3), all of them to be maximised and, in the present application, equally weighted. Linguistic evaluations reported in Table 1 refer to a real company operating in the waste management sector, having been attributed in cooperation with the human resources in charge, respectively, of the maintenance function and of the safety and security system. The used linguistic variables and related TFNs are: VL (1,1,3), very low impact; L (1,3,5), low impact; M (3,5,7), medium impact; H (5,7,9), high impact; VH (7,9,9), very high impact. Table 1 summarises the results of the FTOPSIS application along with the final ranking of maintenance factors.

ID	**Maintenance Factors**	C_1	C_2	C_3	d_i^*	d_i^-	CC_i	**Rank. pos.**
MF_1	Management commitment and support	M	M	M	0.5844	2.4512	0.1925	9^{th}
MF_2	Smart technology development	M	H	M	0.6558	2.3773	0.2162	7^{th}
MF_3	Organizational growth	M	M	H	0.6558	2.3773	0.2162	7^{th}
MF_4	Development of skilled workforce	VH	VH	H	0.8874	2.1277	0.2943	1^{st}
MF_5	Resources required for digitalization	VH	VH	M	0.8160	2.2015	0.2704	3^{rd}
MF_6	Maintenance strategy development	H	H	VH	0.8431	2.1787	0.2790	2^{nd}
MF_7	Corporate culture	M	M	L	0.5161	2.5251	0.1697	10^{th}
MF_8	Change in working practices	M	M	M	0.5161	2.5251	0.1697	10^{th}
MF_9	Effective maintenance system	H	H	H	0.7987	2.2296	0.2637	4^{th}
MF_{10}	Regulatory compliance	M	H	L	0.5875	2.4512	0.1933	8^{th}
MF_{11}	Safety and health awareness	VH	H	M	0.7716	2.2525	0.2552	5^{th}
MF_{12}	Data privacy and security	L	M	M	0.5161	2.5251	0.1697	10^{th}
MF_{13}	Sustainable performance improvement	M	H	H	0.7273	2.3035	0.2400	6^{th}

Table 1: Evaluation of maintenance factors relevant to industry 4.0

By observing Table 1, factor MF_4, that is "development of skilled workforce", has prominent importance in maximising all the considered criteria, according to the perceptions of the involved experts. It can be noticed that also MF_6 ("maintenance strategy development") and MF_5 ("resource required for digitalization") are regarded as priority aspects. On the contrary, factors MF_7, MF_8 and MF_{12} that are, respectively, "corporate culture", "change in working practice" and "data privacy and security" occupy the last position of the ranking, having associated lower impact with respect to the other maintenance factors. Some of the factors occupy the same position in the ranking, e.g. factors MF_2 and MF_3, and the reason of it is that criteria have associated the same weight. If weights varied, so would do the ranking position. For example, again in the case of MF_2 and MF_3, if higher weight was attributed to the quality criterion and lower weight to the cost efficiency, MF_2 would eventually occupy a higher position in the final ranking with respect to MF_3, the last one having associated lower evaluation under C_2.

5 Conclusions

This work discusses how to deal with uncertainty affecting decision-making processes with a special focus on industry 4.0 maintenance management. After a comprehensive review on MCDM approaches implemented in the field under study, we underline the valuable support provided by the integration of such tools as the fuzzy set theory for managing complex real situations in which uncertain human opinions are elicited. Specifically, we analyse the TOPSIS and FTOPSIS techniques on the basis of their high methodological flexibility, by formalising weaknesses and advantages of both approaches. FTOPSIS reveals to be particularly useful for treating uncertainty, as it can be demonstrated by several applications. After describing methodological details, We implement a real case study aimed at providing helpful practical insights for maintenance managers in the complex era of digital transformation. Future lines of research may refer to the integration of other MCDM methods supporting in a more precise calculation of criteria weights along with useful mathematical tools as, for instance, the probability theory.

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