A novel multi-criteria decision analysis technique incorporating demanding essential characteristics of existing MCDA techniques

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Abstract
This paper has proposed a novel multi-criteria decision analysis (MCDA) technique that considers relationships among the criteria, relationships among the alternatives, relationships among the criteria and the alternatives, the uncertainty or dilemma that the decision makers face in their decision-making, the entropy among the criteria. These characteristics are the essential characteristics of various MCDA techniques as evident from the existing literature. Incorporating all these characteristics in a single algorithm is the novelty and unique contribution of the proposed technique in this paper. The existing MCDA techniques are based on individual characteristics such as distance measurement from the best solution, utility measurement, measuring kind of average values, pair-wise comparison and considerations of relationships among criteria. However, no single research study has considered the prime characteristics of these techniques through a single algorithm. This is the motivation behind the proposed technique. The dilemma of the decision makers has been captured by the use of hesitant fuzzy elements; the information content among the criteria has been captured by applying the concept of entropy through the application of a technique called IDOCRIW. Relationships have been determined by calculating covariances among the criteria and among the alternatives. A kind of sensitivity analysis, rank reversal method has been performed to verify the effectiveness of the proposed technique. The proposed method has also been compared with four different types of already existing MCDA techniques, AHP, MAUT, MACBETH and MOORA. Both the sensitivity analysis and the comparison with other methods establish the effectiveness of the proposed technique. The results of the comparison by these methods establish the superiority of the proposed MCDA technique over the existing techniques.

Keywords Novel MCDA technique · IDOCRIW · Hesitant fuzzy elements · Spearman’s rank correlation

1 Introduction
The existing literature shows vast variety of multi-criteria decision analysis (MCDA) techniques—the benchmark techniques [1–5] and their various modifications, other less frequently applied techniques and the hybridization among various MCDA techniques and with the other techniques [6, 7]. Some of these methods are distance-based techniques (such as TOPSIS), some are pair-wise comparison-based techniques (such as PROMETHEE), some are utility-based techniques (such as MAUT) and so on. Besides, there are techniques for calculating weights of the criteria for a MCDA problem (such as IDOCRIW). The existing literature also shows techniques which endeavored to establish relations among the alternatives and the relationships among the criteria (such as AHP, ANP). Therefore, the existing literature highlights some essential requirements for any MCDA techniques. The most important among these are the relationships among the alternatives, relationships among the criteria, relationships between the alternatives and the criteria, the information content among the criteria, uncertainty and dilemma in assigning the weights to the criteria by the decision makers, and unbiased assignment of the weights to the criteria. In search of the better MCDA techniques over the previously proposed techniques, researchers all over the world are still proposing significant number of techniques. However, each of these techniques addresses one or more particular aspects of MCDA algorithms as mentioned above. But the existing literature is lacking a MCDA technique that considers the most essential characteristics of the MCDA techniques altogether such as relationships
among the criteria, relationships among the alternatives, relationships between the criteria and the alternatives, information content among the criteria, uncertainty and dilemma in assigning the weights to the criteria by the decision makers, and unbiased assignment of the weights to the criteria. This indicates the research gap in the existing literature and the motivation behind the technique as proposed in this paper. The MCDA technique as proposed in this paper addresses this research gap and fills the gap by proposing an MCDA technique which considers all these above-mentioned characteristics of MCDA algorithms. This is the unique contribution and novelty of the proposed MCDA technique as presented in this paper. The proposed technique can be applied to those problems which demand the consideration of the above-mentioned features of the MCDA techniques. Thus, the research question of this paper is—“Is it possible to find a MCDA technique which incorporates the most essential characteristics of MCDA techniques?”.

The proposed MCDA technique applies hesitant fuzzy number in order to deal with uncertainty. However, the proposed technique has been compared with some other relevant MCDA techniques such as AHP, MAUT, MACBETH, MOORA, TODIM and CODAS. The reason for choosing such techniques for comparison is separate characteristics of these techniques—AHP considers relationship among the alternatives for each of the criteria; MAUT ranks the alternatives based on utility score; MACBETH and MOORA are based on a kind of constant values; TODIM ranks the alternatives based on the dominance of each alternative over the other alternatives; and CODAS is a mix of both distance-based and kind of comparison-based technique. The other benchmark MCDA techniques are not being considered for several reasons—some of those techniques have very different approaches or some are very traditional techniques. The comparisons have been performed through Spearman’s rank correlation which has been used for comparing the proposed technique with the four other already existing techniques; and a method as proposed by Bandyopadhyay [8] which is capable of identifying the most suitable technique for a given problem.

2 Preliminaries

Before proceeding to the next section, this section depicts some preliminary concepts which are going to be applied in this paper—the four different MCDA techniques with which the proposed technique has been compared; IDOCRIW technique which has been applied partially in order to determine the weights of the criteria; Spearman’s rank correlation which has been used for comparing the proposed technique with the four other already existing techniques; and a method as proposed by Bandyopadhyay [8] which is capable of identifying the most suitable technique for a given problem.

2.1 Analytic hierarchy process (AHP)

Figure 2 shows the algorithm of AHP (analytic hierarchy process) as proposed by [1]. AHP is based on pair-wise comparison between each pair of alternatives for particular criteria. Thus, for each criterion, a matrix of pair-wise comparisons between each pair of alternatives is obtained. Then, the aggregate rating for each alternative is obtained for each of the matrices of pair-wise comparisons. The ranking of the alternatives is done based on the weighted sum of these average ratings in the descending order of values.

![Fig. 1 Overall approach in this paper](image-url)
2.2 Multi-attribute utility theory (MAUT)

Figure 3 shows the algorithm of MAUT (multi-attribute utility theory) [9] which is based on the calculation of aggregate marginal utility score for each alternative. Marginal utility scores are calculated by certain exponential expression as shown in step 3 of Fig. 3, based on the weighted normalized elements of the decision matrix.

2.3 Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH)

Figure 4 shows the algorithm of MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) [10] which ranks the alternatives based on the aggregate MACBETH score for each alternative. MACBETH score for each alternative is calculated by the expression, as mentioned in step 3 in Fig. 4, for each element of the decision matrix based on a reference value for each criterion.
2.4 Multi-objective optimization ratio analysis (MOORA)

Figure 5 shows the algorithm of MOORA (multi-objective optimization ratio analysis) [11, 12]. MOORA is a very simple method which first identifies a reference point for each criterion based on the weighted normalized decision matrix. Based on this reference point, assessment values are calculated for each element of the decision matrix. The maximum values of these assessment values for each alternative are used to rank the alternatives in descending order.

2.5 TODIM

TODIM [13], an acronym in Portuguese, is based on pairwise comparison following certain mathematical approach and ranks the alternatives based on dominance degree for the alternatives that are calculated from the pair-wise comparisons. Figure 5 shows the algorithm for TODIM. At first, the decision matrix is normalized by the expression given in step 2 of Fig. 6, followed by finding the weighted normalized decision matrix. Then, the maximum of the weights, called reference weight for the criteria is identified. All the criteria are divided by this reference weight in order to get relative weights. The preference index for each the pairs of alternatives is calculated following expression as provided in step 4.

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**MOORA**

1. Get the decision matrix and decided the weight of the criteria
2. Normalize the decision matrix by following the expression, \( a^*_y = \frac{\alpha_y}{\sum \alpha_y} \)
3. Find the weighted normalized decision matrix by following the expression, \( a^*_y = a^*_y \times w_j \)
   where \( w_j \) is the weight of criterion \( j \)
4. Find the reference points for each criterion. The reference point for each of the benefit type of criteria is the maximum \( R_j = \alpha_{j,\text{max}} \) of all the values for that criterion. Similarly, the reference point for each of the cost type of criteria is the minimum \( R_j = \alpha_{j,\text{min}} \) of all the values for that criterion.
5. Calculate the assessment values by following the expression, \( v_y = \frac{a_y - R_j}{n} \)
6. Find the maximum value \( v_{i,\text{max}} \) of \( v_y \) for each alternative
7. Rank the alternatives in the descending order of \( v_{i,\text{max}} \) with the alternative having the highest \( v_{i,\text{max}} \) receiving the highest rank.

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**TODIM**

1. Get the decision matrix and decide the weights of the criteria
2. Normalize the decision matrix by expressions, \( a^*_y = \frac{\alpha_y}{\sum \alpha_y} \) for benefit type of criteria

\[ a^*_y = \frac{1/a_y}{\sum 1/a_y} \] for cost type of criteria
3. Select the reference weight which is the maximum of the weights. Calculate relative weight \( w^*_j \) of each criterion by dividing the current weight by the reference weight
4. Calculate preference index value \( P(A_i, A_j) \) by the following expressions. Here, \( \beta \) is the attenuation factor.

\[ P(A_i, A_j) = \begin{cases} \frac{1}{\beta} \sqrt{\sum w^*_j |a^*_y - a^*_m|} & \text{if } (a^*_y - a^*_m) < 0 \\ 0 & \text{if } (a^*_y - a^*_m) = 0 \\ \frac{\sum w^*_j (a^*_y - a^*_m)}{\sum w^*_j} & \text{if } (a^*_y - a^*_m) > 0 \end{cases} \]
5. Calculate the dominance degree for each alternative by the expression,

\[ d_i = \sum_{j=1}^{n} P(A_i, A_j) \]
6. Calculate the overall dominance degree (ODD) by the expression, \( \text{ODD}_i = \frac{d_i - \min_{i}}{\max_{i} - \min_{i}} \)
7. Rank the alternatives in the descending order of \( \text{ODD}_i \).
Dominance degree is then calculated for each alternative with the help of preference index values, followed by the overall dominance degree for each alternative. The alternatives are finally ranked in the descending order of overall dominance degree.

2.6 Combinative distance-based assessment (CODAS)

CODAS (combinative distance-based assessment)\textsuperscript{[14]} is a combination of both distance-based approach and pair-wise comparison. Euclidian and Taxicab distances are measured for each alternative based on the normalized decision matrix. These distances are used to form a kind of pair-wise comparison between each pair of alternatives. The aggregates of these comparisons are used to rank the alternatives in the descending order of the aggregates. The algorithm of CODAS is presented in Fig. 7.

2.7 Integrated determination of objective criteria weights (IDOCRIW)

IDOCRIW (integrated determination of objective criteria weights)\textsuperscript{[14]} is a type of multiple criteria-based technique that is used to measure the weights of the criteria. A significant number of researchers, as evident from the existing literature, have applied IDOCRIW technique in order to measure weights of criteria. The basic feature of this technique is that this technique captures use of the entropy or the information content among the criteria. This paper has also made partial use of this technique in measuring the weights of the criteria rather than using the random assignment of the weights of the decision makers. The portion of the IDOCRIW technique that has been applied in this paper is depicted below.

\begin{equation}
\bar{a}_{ij} = \frac{a_{ij}}{\sum_{i} a_{ij}}
\end{equation}

\begin{equation}
\text{entropy}_{j} = -\frac{1}{\ln n} \sum_{i} \bar{a}_{ij} \times \ln \bar{a}_{ij}
\end{equation}

\begin{equation}
\text{deviation}_{j} = 1 - \text{entropy}_{j}
\end{equation}

2.8 Spearman’s rank correlation

This paper has made use of Spearman’s rank correlation\textsuperscript{[15]} in order to establish the association among various rankings as obtained from various MCDA techniques as considered in this paper. The expression for Spearman’s rank correlation is shown in expression (4).

\begin{equation}
\tau = 1 - \frac{6 \sum d^2}{n(n^2 - 1)}
\end{equation}

where $d$ is the difference in rankings between MCDA techniques and $n$ is the number of alternatives. Generally, the value of $\tau$ lies between $+1$ and $-1$. The value $\tau = +1$ indicates a perfect positive association between two variables which means if one of those variables increases then the other also increases. The value $\tau = -1$ indicates perfect negative association meaning, if one increases then the other decreases.

Fig. 7 Algorithm of CODAS

\begin{enumerate}
\item Get the decision matrix and the weights of the criteria
\item Normalize the values by following the expressions $\alpha_{q}^* = \frac{a_{q}}{\max_{i} a_{q}}$ for benefit type of criteria and $\alpha_{q}^* = \frac{\min_{i} a_{q}}{a_{q}}$ for the cost type of criteria.
\item Find the weighted normalized matrix by multiplying each normalized element by the corresponding weight of the criterion
\item Calculate the Euclidian distance and Taxicab distance for each alternative based on the minimum element for each criterion
\item Calculate the relative assessment matrix with the help of Euclidian and Taxicab distances for each pair of alternatives. Thus, if the number of alternatives is $m$, then a matrix of order $m \times m$ is formed.
\item Calculate the sum of each row for this matrix
\item The alternatives are ranked in the descending order of these sums.
\end{enumerate}
2.9 A recent performance-based method of comparison

The use of rank correlations and some other methods to compare among the MCDA techniques only establishes the associations and thus is unable to identify the most appropriate MCDA technique for the problem under study. Toward this direction, the method of comparison as proposed by Bandyopadhyay [8] is a performance-based method of comparison, which at first identifies the highest weighted criterion and then identifies the MCDA technique as the most appropriate technique for the problem under study based on the cumulative values of the decision elements up to \( m \) number of sorted alternatives, where \( m \) is the number of best alternatives to be chosen by the decision maker. The method is very simple and identifies the most beneficial MCDA technique for the problem at hand. For the detailed understanding of the method, the work of Bandyopadhyay [8] may be consulted.

3 Literature review

The topic of this paper has several components—multi-criteria decision analysis techniques (MCDA), hesitant fuzzy elements (HFE), IDOCRRIW technique and comparison among MCDA techniques. Therefore, the following subsections review the related existing literature on each of these topics.

3.1 Review on multi-criteria decision analysis techniques (MCDA)

Multi-criteria decision analysis (MCDA) techniques are widely practised among researchers belonging to scientific, technical and management fields of study. These techniques are very popular since real-world decision-making is abundant with complexity. In most cases, decision makers face situations where they are to choose any alternative from among several alternatives, based on certain conditions (criteria). Such decision-making happens both in our everyday lives and in industrial scenarios. Therefore, researchers all over the world have found a significant number of MCDA techniques for several decades [12, 14, 16]. Each of the MCDA techniques has its own characteristics and applicability. Because of the variety in the applicability of these techniques, it becomes difficult to choose the most appropriate technique for a given problem at hand. However, there are some MCDA techniques that are frequently applied and some are not so frequently applied techniques. The basic features of some of these techniques are enlisted in Table 1.

Table 1 shows certain patterns or views toward proposing different MCDA techniques. For example, some techniques are based on distance measurements; some are utility function-based; some are based on pair-wise comparison; and some are based on the relationships among the alternatives and among the criteria. There are also numerous other methods, their modifications and hybrid techniques available in the existing literature [7, 28–30]. Apart from the traditional research studies as mentioned in Table 1, some of the recent research studies are summarized in Table 2. The technique TOPPRA focused on the level of risk aversion for the decision makers, whereas the current simply emphasizes on developing a novel MCDA technique covering all the essential features; RBOP is a distance-based technique, quite different from the technique as proposed in this paper. VIMM is a technique to mainly calculate the weights of criteria through the ranking of the alternative, whereas the approach and focus of the technique as proposed in this paper is quite different. DS-VIKOR is actually the VIKOR technique with the inclusion of Dempster–Shafer evidence theory. CODAS is also a distance-based technique.

The MCDA technique as proposed in this paper considers the most important of these approaches—relationships. There is no single research study that has considered relationships among alternatives, relationships among criteria, along with relationships among the alternatives and the criteria. This paper fills this gap of research by considering the relationships among the alternatives, among the criteria, between the alternatives and the criteria, the uncertainty in deciding the elements and the criteria on the part of the decision makers and the information content in the criteria.

3.2 Review on hesitant fuzzy elements (HFE)

Multiple-criteria decision analysis (MCDA) with HFE is a very demanding topic as evident from the existing literature. In hesitant fuzzy set (HFS), the membership function for an element is defined by multiple values. MCDA with HFE has been applied by many researchers, such as the works by Huchang et al. [37], Sellak et al. [38] and Gou et al. [39]. The primary purpose of HFS and HFE is that it can incorporate the confusion of decision makers. Therefore, HFE has wide applications in the fields of Management and Technology. Recently, the existing literature shows some MCDA techniques based on HFE. Some of the research studies include the research studies of Jibin [40], Wang et al. [41], Wang et al. [42], Chen and Hong [43]. However, each of these research studies has some negativity which will be covered in this paper. Jibin [40] determined priority degrees between each pair of alternatives based on hesitant fuzzy decision matrix and ranked the alternatives based on the aggregate priority degrees for the alternatives. Wang et al. [41] proposed an outranking approach similar to ELECTRE based on HFE and Hausdorff distance which in turn, helped to find the dominance relations for the alternatives and the ranks for
| MCDA technique                        | Authors                      | Feature                                                                                                                                 |
|--------------------------------------|------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| AHP (analytic hierarchy process)     | Saaty [1]                    | This technique is based on comparison matrix containing comparison value among each of the pairs of alternatives for each criterion. The final ranking of the alternatives is done based on some kind of aggregation of the values for each alternative |
| PROMETHEE (preference ranking       | Brans and Mareschal [2]      | This technique is based on pair-wise comparison between each pair of alternatives for each criterion followed by the weighted sum of those comparisons. The final ranking is based on the difference between how each alternative is preferred over other alternatives and how inferior, each alternative is, compared to other alternatives |
| organization method for enrichment of evaluations) |                 |                                                                                                                                       |
| TOPSIS (technique of order preference similarity to the ideal solution) | Behzadian et al. [3]        | This technique is based on the aggregate Euclidian distance measure between the weighted normalized elements of the decision matrix and the best and the worst values for each criterion. The final ranking is based on the ratio of relative aggregate distance from the worst solutions to the sum of distances from the worst and the best solutions |
| ANP (analytic network process)      | Saaty [4]                    | This technique is based on both the relationship among the alternatives and among the criteria. These relationships form the weighted super matrix which is raised to certain power following Markov process, until stable values are obtained. These values are used to rank the alternatives |
| ELECTRE (ELimination Et Choix Traduisant la REalite) | Figueira et al. [5]         | This technique is based on the calculation of domination matrix, concordance matrix and discordance matrix. This technique has several major versions like ELECTRE I, ELECTRE II, ELECTRE III and some more |
| MAUT (multi-attribute utility theory) | Emovon et al. [9]           | This technique calculates marginal utility score for each element of the decision matrix based on the weighted normalized elements. Final ranking of the alternatives is done based on the final utility score of each alternative, which is actually the weighted sum of marginal utility scores for each alternative |
| MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique) | Bana e Costa and Chagas [10] | This technique calculates MACBETH score for each element of the decision matrix based on reference levels for each criterion. The final ranking of the alternatives is done based on the overall MACBETH score for each alternative, which is actually the weighted sum of MACBETH scores of the elements for each alternative |
| SMART (simple multi-attribute rating technique) | Edwards and Barron [18]     | Simple technique based on logarithmic calculation and geometric progression                                                           |
| REGIME                               | Hinloopen and Nijkamp [19]   | This technique is based on the identifying the superior criteria, separate ranking of alternatives based on individual criteria, forming the REGIME matrix based on pair-wise comparison |
| ORESTE                               | Roubens [20]                 | This technique is based on distance measurement. Block distance for each alternative is calculated as a weighted sum based on a position matrix. The weights are termed as succession rate |
| VIKOR                                | Opricovic and Tzeng [21]     | Here, the best and worst values for each criterion are calculated at first. Based on that weighted sum of relative distances of the elements from the best values are calculated for each of the alternatives. This helps in calculating VIKOR index which is used to rank the alternatives |
Table 1 (continued)

| MCDA technique                                      | Authors                | Feature                                                                                           |
|------------------------------------------------------|------------------------|---------------------------------------------------------------------------------------------------|
| EVAMIX (EVAIuation of MIXed data)                    | Voogd [22]             | In this technique, superiority rate for each alternative is calculated, and it helps to determine differential matrix, which in turn helps to determine total dominance for each alternative. The final ranking is done based on this total dominance |
| ARAS (additive ratio assessment)                     | Zavadskas et al. [23]  | This technique calculates optimality function for each alternative based on the weighted normalized decision matrix. The final ranking of alternatives is done based on utility degree for each alternative which is calculated based on optimality function |
| MOORA (multi-objective optimization ratio analysis)   | Brauers et al. [11]    | This is a very simple technique in which final ranking of alternatives are done by calculating the assessment value for each alternative, which is calculated based on the difference between the weighted sums of benefit and cost attributes (criteria) |
| COPRAS (complex proportional assessment)             | Zavadskas et al. [24]  | This technique calculates the sums of weighted normalized elements of decision matrix separately for benefit and cost type of attributes. These values are used to calculate the relative significance values for each of the alternatives and the final ranking is done on this basis |
| WASPAS (weighted aggregates sum product assessment)   | Zavadskas et al. [25]  | This technique calculates additive and multiplicative relative importance for each alternative based on weighted normalized elements of decision matrix. The final ranking of alternatives is done based on joint generalized criterions which are calculated based on additive and multiplicative relative importance |
| TODIM                                                | Gomes [26]             | This technique calculates dominance degree for each alternative followed by overall dominance degree based on relative weights. Final ranking of alternatives is done based on the overall dominance degree of the alternatives |
| EDAS (evaluation based on distance from average solution) | Keshavarz et al. [27]  | This technique first calculates the average solution for each attribute (criterion) and then calculates positive and negative distances for the benefit and cost criteria, respectively. Then the weighted sum of these distances is calculated for each alternative followed by the overall appraisal score for each alternative, which is used to rank the alternatives |
| MABAC (multi-attributive border approximation area comparison) | Bozanic et al. [28]   | This technique calculates Border Approximation Area (BAA) for each criterion-based normalized decision matrix elements. Then the distances of each element from BAA is calculated and aggregated for each alternative, on the basis of which the final ranking of the alternatives is done |

the alternatives. Wang et al. [42] also proposed an outranking MCDA technique combining HFS. Chen and Hong [43] used both HFS and aggregation of normal fuzzy sets and combined these in order to propose an MCDA ranking.

However, the above-proposed techniques did not consider other factors in addition to treating the decision makers’ dilemma with HFS. The other factors include several other required features of MCDA techniques, such as considering the relationships among the alternatives, considering relationships among the criteria, considering the relationships among the alternatives and the criteria, considering the information content in the criteria and a logical reliable method for determining the weights of the criteria instead of receiving random priority values for the criteria for deriving the weights for the criteria. This paper considers all these features in the proposed MCDA technique.

3.3 IDOCRIW MCDA technique

The existing literature is not as abundant with articles dealing with IDOCRIW technique as for other benchmark techniques like TOPSIS, AHP, ANP, PROMETHEE and alike. However, since IDOCRIW technique is basically a technique to determine the weights of criteria, there are some articles
which have endeavored to apply IDOCRIW technique effectively. Some of these research studies are being discussed in this subsection.

Eghbali-Zarch et al. [44] used IDODCIW technique in order to calculate the weights of criteria and used those weights in the application of WASPAS MCDA technique in the managerial decision-making for construction projects. Čereška et al. [45] combined two different techniques—IDODCIW and CILOS (criteria impact loss)—in order to determine weights of criteria and then used these weights to compare screw joints of different diameters and made of different materials based on four MCDA techniques, namely EDAS, SAW, TOPSIS, and COPRAS. Podvezko et al. [46] and Zavadskas and Podvezko [47] gave fuzzy orientation to both CILOS and IDODCIW techniques before combining these techniques with a purpose to consider entropy in determining criteria weights. The weights of the criteria were calculated by the combined techniques. Čereška et al. [48] applied a part of IDODCIW technique just like the current paper in order to consider the information content or entropy in the criteria weights. Vavrek and Bečica [49] mentioned some techniques available in the existing literature for calculating the weights of the criteria, like, ENTROPY, CRITIC, MW, SD, IDODCIW, CV, IDP or SVP. Some of the other research studies applying IDODCIW include the research studies of Zavadskas et al. [50], Dayyani et al. [51]. Therefore, the review of the existing literature on IDODCIW shows the effective application of this technique in different applications. This paper applies a similar approach of Čereška et al. [45] to apply IDODCIW technique partially in determining the weights of the criteria, rather than determining weights based on some random evaluation of criteria by the decision

| MCDA technique             | Authors                        | Feature                                                                 |
|----------------------------|--------------------------------|------------------------------------------------------------------------|
| TOPPRA                     | Golpîra [32]                   | TOPPRA (technique for order of preference using pattern mining based on dms level of risk aversion) was based on the decision makers’ extent of risk aversion. Decision is made either at the individual decision maker’s level based on the decision maker’s risk aversion or in an integrated fashion considering all the decision makers’ risk aversion levels with the help of linear assignment problem. U2P-Miner algorithm was used to rank the alternatives. The basic contribution and focus of this paper was the consideration of the level of risk aversion. The risk factor is an important consideration for MCDM or MCDA techniques. The author of this paper basically has focused on finding the rank of the attributes. The alternatives had been ranked first and this rank had been used to rank the attributes later. However, in order to avoid or reduce risk, different aspects of criteria, alternatives and uncertainty need to be considered. The current paper not only considers the various aspects of MCDA techniques, but also handles risk through the consideration of uncertainty which has been dealt with hesitant fuzzy number. Since the approaches and focus of the MCDA technique by Golpîra (2018) and the current paper are quite different; thus, the current paper is not being experimentally compared with the technique as proposed by Golpîra (2018) |
| RBOP                       | Zakeri [33]                    | The proposed technique RBOP (ranking based on optimal points) has a unique approach to rank the alternatives. The authors took the view that each alternative may have optimal values from which the distances of the real alternatives should be calculated and ranking should be done based on these distances. Thus, RBOP is a distance-based technique. The method also considers entropy for the criteria while calculating their weights. The authors had applied Grey theory in order to deal with uncertainty. Although a very unique approach, but this method does not consider the other aspects of MCDA techniques as mentioned previously in this paper |
| An MCDA technique with z-number application | Shen et al. [34] | The authors had proposed the use of z-number to deal with uncertainty in decision-making. A multi-criteria decision-making method with z-number application had been proposed |
| VIMM                       | Zakeri et al. [35]             | Zakeri et al. (2021) proposed a MCDM method called vital-immaterial-mediocre method (VIMM) which is a method to calculate the weights of criteria that are conflicting in nature. The approaches taken for proposing the method are pair-wise comparison, vector-based procedure and a scoring approach. The criteria are divided into categories, vital, immaterial and mediocre. The alternatives are compared based on these criteria. The effects of the criteria on the alternatives decrease from the vital criteria, to mediocre criteria to immaterial criteria. the proposed method is compared with AHP and BWM |
| DS-VIKOR                   | Fei et al. [36]                | Fei et al. (2019) proposed a MCDA technique called DS-VIKOR, which had modified the MCDA technique, VIKOR by Dempster–Shafer evidence theory, which can model uncertainty effectively |
| CODAS                      | Ghorabaee, Mehdi, et al. [37]  | Ghorabaee, Mehdi, et al. (2016) proposed a new CODAS (combinative distance-based assessment) method. The procedure has been depicted in details in this paper |
makers. The partial application considers the entropy of the criteria just like it was considered by Čereška et al. [45].

### 3.4 Comparison among MCDA techniques

The existing literature shows some methods of comparison among MCDA techniques. Some of these research studies are mentioned in this subsection. Triantaphyllou [52] performed comparisons among some MCDA techniques based on the methods adopted to calculate the criteria weights. Ishizaka and Nemery [14] classified some MCDA techniques based on the applications of the techniques in to different kinds of problems. Such a comparison was not very effective in comparing the algorithms of the techniques. Ishizaka and Siraj [53] compared three benchmark MCDA techniques based on the opinions of 146 participants, and thus, such comparison is a survey-based comparison techniques in which there are always chances of biased opinions and such method of comparison cannot be taken as a universal one. However, the existing literature basically applied different methods of rank correlation measurements in order to compare among different MCDA techniques.

For example, Moradian et al. [54] applied both graphical method and Spearman’s rank correlation to compare the rankings as obtained from applying MOORA, TOPSIS and VIKOR. Zamani-Sabzi et al. [55] applied both Kendall’s tau-b and Spearman’s rank correlation to perform comparisons among different MCDA techniques, namely SAW, WPM, CP, TOPSIS, VIKOR and four different versions of AHP. They also compared the results through bar diagrams. Moghassem [56] compared TOPSIS with VIKOR by performing sensitivity analysis in terms of the changing of ranking order of the alternatives. Javaid et al. [57] compared some MCDA techniques by performing sensitivity analysis by varying weights of the criteria. Ceballos et al. [58] applied Spearman’s rank correlation to compare among multi-MOORA, TOPSIS and VIKOR. Özcan et al. [59] compared AHP, TOPSIS, ELECTRE and Grey theory by explaining the difference in terms of the characteristics of these techniques. Hodgett [60] compared among MARE, AHP and ELECTRE III in terms of various characteristics of the techniques along with the time taken in execution. Hajkowicz and Higgins [61] applied Spearman’s rank correlation and Kendall’s coefficient of correlation to compare among weighted summation, compromise programming, PROMETHEE II and EVAMIX. Selmi et al. [62] had applied Gini Index, a concept borrowed from Economics, in order to perform comparisons among MCDA techniques.

The existing literature shows that the most common methods of comparison among all the methods are the methods of rank correlation. Some other articles applying rank correlations include the research studies of Athawale and Chakraborty [63], Chitsaz and Banihabib [64], Mathew and Sahu [65]. However, many of these research studies have also acknowledged the fact that such rank correlations cannot identify the most suitable technique for a problem at hand [66–70].

However, the thorough review of the existing literature on the comparison among MCDA techniques revealed the fact that the existing literature basically emphasized on comparing the MCDA techniques in terms of characteristics or in terms of establishing associations through various rank correlations or through various types of sensitivity analysis like rank reversal method, varying the weights of the criteria, addition or deleting alternatives and so on. None of these methods is capable of identifying the most suitable MCDA technique for a particular problem. However, recently Bandyopadhyay [8] have proposed a performance-based method of comparison in which for a particular problem, decision maker can choose the most beneficial ranking which will maximize the benefit since that is the primary purpose of all the ranking techniques. Therefore, this paper applies both Spearman’s rank correlation which is a traditional method of comparison and the method by Bandyopadhyay [8] to compare the ranking by the proposed MCDA technique with those of the other MCDA techniques as considered in this paper. However, some recent research studies have emphasized some other aspects of MCDA techniques. Some significant ones of these are enlisted in Table 3.

#### 4 Proposed algorithm

The proposed multi-criteria decision analysis technique is depicted in Fig. 8. Here, the decision matrix is the normalized matrix as calculated from HFEs as shown in Table 5. Next, instead of receiving random preference values from the decision makers, this paper has applied IDOCRiW (integrated determination of objective criteria weights) partially, in order to calculate the weights of the criteria. The procedure for calculating the weights is shown in Fig. 9. Figure 9 shows method to consider the entropy in calculating the weights of the criteria as depicted previously in this paper. Next, the hesitant fuzzy elements (HFEs) are calculated for each criterion for each alternative as depicted in the Case Study section. These HFEs are aggregated by calculating median values following the work of Wang et al. [78] who had calculated means instead of medians. Now, the weighted normalized matrix $D_{m \times n}$ is calculated by multiplying the calculated weights of the criteria by the aggregate values of the HFEs.

Next, following the idea as adopted in correspondence analysis (CA) which is frequently used in social research studies, this paper calculates both $D_{m \times n}^T D_{n \times m}$ and $D_{n \times n}^T D_{m \times n}$ matrices in order to get two square matrices of sizes $m \times m$ and $n \times n$, respectively. Now, a covariance matrix is calculated from the $m \times m$ matrix in order to get
Table 3 Latest research trends on MCDA techniques

| Authors               | Research topic                                                                                                                                 |
|-----------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| Pelegrina et al. [68] | Proposed a method based on weighted average method in order to get rid of redundancy among criteria                                         |
| Juanpera et al. [69]  | Proposed a novel MCDA technique using fuzzy rating scale in order to deal with uncertainty. The new technique has been termed as MIMDU (methodology for integrated multi-criteria decision-making with uncertainty) |
| Zhang et al. [71]     | Proposed a novel MCDA technique based on stochastic multi-criteria acceptability analysis—evidential reasoning (SMAA-ER) approach in order to “aggregate the interval cross-efficiency” |
| Li et al. [72]        | Proposed a novel method for multi-criteria group decision-making based on preference, indifference and incomparability                        |
| García-Cáceres [73]  | Proposed a MCDA technique by introducing stochastic multi-criteria acceptability analysis—matching (SMAA-M)                                    |
| Jia et al. [74]       | Proposed a new multi-criteria group decision-making method with uncertainty based on “Atanassov’s interval-valued intuitionistic fuzzy sets (AVIFSs), Z-numbers and trapezium clouds” |
| Tavares and Arruda [75]| Proposed a MCDA technique for based on OPTIONCARDS method                                                                                     |
| Hussain et al. [76]   | Proposed a MCDA technique FTBWA considering uncertainty and is based on the fuzzy reference comparison                                         |
| Stoilova and Munier [77]| Proposed a novel fuzzy-based MCDA technique in order to deal with uncertainty                                                                       |
| Harju et al. [78]     | Proposed a multi-criteria decision-making method based on additive spatial value function                                                        |

Fig. 8 Overview of the proposed technique

Fig. 9 Procedure to calculate weights of criteria

1. Normalize each element of the decision matrix by dividing each element under each criterion by the sum of values for that criterion. The normalized element is represented by $X^*_y$
2. For each element in the decision matrix, calculate $\bar{X}_y = \ln X^*_y$
3. Perform the multiplication $\bar{X}_y = X^*_y \times \bar{X}_y$ for each element of the matrix
4. Calculate the sum $Entropy_j = -\frac{1}{\ln n} \sum_{i=1}^{n} X^*_y$ for each of criteria. So, a total of J number of weights for J number of criteria is calculated. Each of these J values I normalized by dividing each value by the total of all the J values
5. Calculate the deviation rate by the expression $deviation_j = 1 - Entropy_j$
6. The deviations are now normalized by dividing each value by the total of all the J deviation values
7. The resultant normalized J number of values is the weights of the criteria
the covariances among the alternatives. Similarly, covariance matrix is calculated from the $n \times n$ matrix in order to get the covariances among the criteria. For each alternative, we have $d_{1 \times n}$ matrix, and thus, the multiplication $d^T_{n \times 1} d_{1 \times n}$ can be performed, from where variances for each of the criteria for the particular alternatives can be calculated. Similarly, the multiplication $d^T_{m \times 1} d_{1 \times m}$ provides a matrix from which the variances for each of the alternatives for the particular criteria can be calculated. Next, a bigger matrix of size $(m + n) \times (m + n)$, with the help of covariance matrix for $D_{m \times n} D^T_{n \times m}$, covariance matrix for $D^T_{n \times m} D_{m \times n}$, variances calculated from $d^T_{n \times 1} d_{1 \times n}$ matrix, variances calculated from $d^T_{m \times 1} d_{1 \times m}$ matrix, is formed. Such formation of bigger matrix is similar to ANP technique except the fact that in the proposed MCDA technique, the relations among the criteria, relations among the alternatives and the relations among each criterion with the alternatives and the relations among each alternative with the criteria are all being considered. Finally, following Markov process, equilibrium values of this $(m + n) \times (m + n)$ matrix by raising to the powers until stable values are obtained. The first $m$ values are taken for ranking the alternatives in the descending order of the values. This entire method is depicted through the numerical example on case study in the following section.

5 Case study

A small company is taking a decision on purchasing two cars for official purposes. A total of 11 different cars have been chosen. The determining factors (criteria) for selecting the two cars, as decided by the management are: price (cost criterion), mileage (benefit criterion), fuel tank capacity (benefit criterion) and maximum torque (benefit criterion). The benefit criteria are to be maximized and the cost criterion is to be minimized. The values as collected from six different web-sites against 11 different types of cars from various car websites are shown in Table 4. The data have been collected from six different websites sources. Thus, the

| Car       | Price (lakhs) | Mileage (Kmpl) |
|-----------|---------------|----------------|
| Car 1     | 22.58         | 15.38          |
| Car 2     | 96.3          | 11.13          |
| Car 3     | 5.35          | 6.19           |
| Car 4     | 8.13          | 8.72           |
| Car 5     | 32            | 30.87          |
| Car 6     | 38.82         | 16.5           |
| Car 7     | 43.06         | 14.82          |
| Car 8     | 13.8          | 14.82          |
| Car 9     | 19.81         | 25.35          |
| Car 10    | 8.6           | 20.45          |
| Car 11    | 12.58         | 13.83          |

| Car       | Fuel tank capacity | Maximum torque (nm@rpm) |
|-----------|-------------------|-------------------------|
| Car 1     | 62                | 392                     |
| Car 2     | 87                | 400                     |
| Car 3     | 32                | 90                      |
| Car 4     | 42                | 215                     |
| Car 5     | 71                | 340                     |
| Car 6     | 64                | 380                     |
| Car 7     | 51                | 400                     |
| Car 8     | 60                | 319                     |
| Car 9     | 50                | 300                     |
| Car 10    | 50                | 245                     |
| Car 11    | 63                | 320                     |

Table 4 Raw data collected from different websites

(a) (b) (c) (d)
missing value in Table 4 indicates that particular website did not have the required data for the required model of the car.

Each of the values in the above tables is normalized by either dividing the values by the minimum of that row (for criterion, price) or by the maximum of that row (for all other criteria). These normalized values are taken as hesitant fuzzy elements (HFEs). Table 5 shows the resultant HFEs. Some of the values in this table have been approximated to the nearest fractional values. Wang et al. [78] approximated the HFEs for each alternative and each criterion by calculating the means. In this paper, the median value for each set of HFEs has been calculated. These values have been used as the elements of the normalized decision matrix (see Table 6).

### 6 Application of Proposed MCDA Technique on the Case Study

In this section, the proposed MCDA technique has been applied on the case study, on the HFE-based decision matrix as shown in Table 6 in previous section. All the calculations in this paper have been done in MS-Excel. At first, the weights of the criteria are calculated by the partial application of IDOCRIW (integrated determination of objective criteria weights) technique as mentioned in the previous sections. Based on IDOCRIW method, each of the elements of the decision matrix in Table 6 is divided by the aggregate of the respective criterion (or column) (as shown in expression (1) to get the normalized decision matrix (see Table 7). For example, the aggregate of the first column (criterion) in Table 6 is 9.073. Thus, the first value in cell (A1, price) in Table 7
Table 9 Weights of the criteria

| Price     | Mileage    | Fuel tank capacity | Maximum torque |
|-----------|------------|--------------------|----------------|
| 0.170189  | 0.211279   | 0.009927           | 0.608606       |

Table 10 Weighted decision matrix

| Price     | Mileage    | Fuel tank capacity | Maximum torque |
|-----------|------------|--------------------|----------------|
| 0.142278  | 0.147895   | 0.00982728         | 0.44428211     |
| 0.163211  | 0.164798   | 0.00982728         | 0.60251957     |
| 0.137342  | 0.203884   | 0.00943022         | 0.4868845      |
| 0.147299  | 0.175361   | 0.00962875         | 0.3347331      |
| 0.148915  | 0.180643   | 0.00908279         | 0.57208929     |
| 0.158276  | 0.192264   | 0.00982728         | 0.60251957     |
| 0.147213  | 0.152121   | 0.00962875         | 0.42602394     |
| 0.1353    | 0.209166   | 0.00947985         | 0.49297056     |
| 0.129344  | 0.172192   | 0.00957912         | 0.35299127     |
| 0.120834  | 0.200715   | 0.00982728         | 0.49905662     |
| 0.114027  | 0.159516   | 0.00883463         | 0.60251957     |

is calculated as: $0.836/9.073 = 0.092147$. The other values of Table 7 are calculated in the similar way.

Next, the degree of entropy for each criterion is calculated by expression (2) as depicted before and also mentioned in Fig. 6[12], and the resultant degree of entropies for the criterion is shown in Table 8. For example, the entropy for price is calculated as: $\sum_{i=1}^{n} \frac{D_i}{\ln(11)} - \frac{\ln(0.092147)}{\ln(11)} = -0.21973$. Next, these values are now aggregated for criterion price. Thus, the aggregated value will be $= (0.2973) + (-0.23755) + ... + (-0.19245) = -2.393$. The total number of dataset, $n = 11$. Thus, the entropy value as calculated for criterion price is $= -(1/\ln(11)) * (-2.393) = 0.99715$. In this way, the degrees of entropy for other criteria are also calculated as shown in Table 8. Next the deviation rates are calculated by expression (3) and normalized as depicted in Fig. 6, in order to get the weights of the criteria (see Table 9).

For example, the degrees of entropy for the criteria as calculated are: 0.997915, 0.997412, 0.999878 and 0.992545. The deviation of the first degree of entropy is $1 - 0.997915 = 0.002085$. Similarly, the other deviations for the other criteria are calculated. The total of all the deviations is 0.01225. The final weights are obtained by normalizing these deviations. For example, the first normalized value is calculated as: $0.002085/0.01225 = 0.170189$. These weights are now multiplied with the elements of the HFE-based decision matrix in order to get a weighted decision matrix $D$ of size $m \times n$ as shown in Table 10.

Next, following the Markov theory, the matrix in Table 15 is raised to the power until the stable values are obtained. The first $m$ numbers of such values for $m$ alternatives are taken and are ranked in the descending order of values. Thus, the final values along with the respective ranks of the alternatives are shown in Table 16.
Table 11 Covariance matrix for the alternatives

|     | A1   | A2   | A3   | A4   | A5   | A6   | A7   | A8   | A9   | A10  | A11  |
|-----|------|------|------|------|------|------|------|------|------|------|------|
| A1  | 0.0018 | 0.0024 | 0.0019 | 0.0013 | 0.0022 | 0.0024 | 0.0017 | 0.0019 | 0.0014 | 0.00197 | 0.0024 |
| A2  | 0.0024 | 0.0032 | 0.0026 | 0.0018 | 0.0032 | 0.0023 | 0.0026 | 0.0019 | 0.00266 | 0.0032 |
| A3  | 0.0019 | 0.0026 | 0.0021 | 0.0015 | 0.0025 | 0.0026 | 0.0018 | 0.0021 | 0.0015 | 0.00216 | 0.0026 |
| A4  | 0.0013 | 0.0018 | 0.0015 | 0.001 | 0.0017 | 0.0018 | 0.0013 | 0.0015 | 0.0011 | 0.0015 | 0.0018 |
| A5  | 0.0022 | 0.003 | 0.0025 | 0.0017 | 0.0029 | 0.003 | 0.0022 | 0.0025 | 0.0018 | 0.00253 | 0.003 |
| A6  | 0.0024 | 0.0032 | 0.0026 | 0.0018 | 0.0032 | 0.0023 | 0.0026 | 0.0019 | 0.00266 | 0.0032 |
| A7  | 0.0017 | 0.0023 | 0.0018 | 0.0013 | 0.0022 | 0.0023 | 0.0016 | 0.0019 | 0.0013 | 0.00189 | 0.0023 |
| A8  | 0.0019 | 0.0026 | 0.0021 | 0.0015 | 0.0025 | 0.0026 | 0.0019 | 0.0022 | 0.0016 | 0.00219 | 0.0026 |
| A9  | 0.0014 | 0.0019 | 0.0015 | 0.0011 | 0.0018 | 0.0019 | 0.0013 | 0.0016 | 0.0011 | 0.00158 | 0.0019 |
| A10 | 0.002 | 0.0027 | 0.0022 | 0.0015 | 0.0025 | 0.0027 | 0.0019 | 0.0022 | 0.0016 | 0.00221 | 0.0027 |
| A11 | 0.0024 | 0.0032 | 0.0026 | 0.0018 | 0.0032 | 0.0023 | 0.0026 | 0.0019 | 0.00265 | 0.0032 |

Table 12 Covariance matrix for the criteria

|          | Price         | Mileage       | Fuel tank capacity | Maximum torque |
|----------|---------------|---------------|-------------------|----------------|
| Price    | 0.07527722    | 0.095526768   | 0.0050955         | 0.2738205      |
| Mileage  | 0.09552677    | 0.121232147   | 0.00646638        | 0.3474754      |
| Fuel tank capacity | 0.0050955    | 0.006466376   | 0.00034492        | 0.0185348      |
| Maximum torque | 0.27382047   | 0.347475415   | 0.01853478        | 0.9961993      |

Table 13 Vector of elements for A1 and results of multiplication $d^T_{n \times 1} d_{1 \times n}$

|          | A1           | 0.142278    | 0.147895 | 0.009827 | 0.444282 |
|----------|--------------|-------------|----------|----------|----------|
| Price    | 0.020243     | 0.021042    | 0.001398 | 0.063212 | 0.000682 |
| Mileage  | 0.021042     | 0.021873    | 0.001453 | 0.065707 | 0.000737 |
| Capacity | 0.001398     | 0.001453    | 9.66E−05 | 0.004366 | 3.2E−06  |
| Torque   | 0.063212     | 0.065707    | 0.004366 | 0.197387 | 0.006653 |

Table 14 Vector of elements for “Price” and results of multiplication $d^T_{m \times 1} d_{1 \times m}$

|          | 0.142277952 | 0.1632 | 0.137 | 0.1473 | 0.1489 | 0.158 | 0.147 | 0.135 | 0.129 | 0.121 | 0.114 |
|----------|--------------|--------|-------|--------|--------|-------|--------|-------|-------|-------|-------|
| Price    | 0.0202       | 0.023  | 0.0195 | 0.021  | 0.021  | 0.023 | 0.021  | 0.019  | 0.018  | 0.017  | 0.016  |
| Variance | 4.55E−06     | 5.98E−06 | 4.24E−06 | 4.87E−06 | 4.98E−06 | 5.63E−06 | 4.87E−06 | 4.11E−06 | 3.76E−06 | 3.28E−06 | 2.92E−06 |
7 Analysis of the proposed MCDA technique

The existing literature shows research studies which have performed sensitivity analysis for proposed MCDA techniques. In general, sensitivity analysis defines how robust a solution is. However, for MCDA techniques, there is "no consensus" about what should be the most appropriate sensitivity analysis for MCDA techniques [79]. The reason lies in the fact that any change in criteria or alternatives or decision matrix is definitely going to have influence on the final ranking. Therefore, the concept of robustness is not applicable to the ranking obtained from MCDA techniques. Based on the requirements of the MCDA techniques, the best MCDA ranking for a particular problem is required to be found. But before the application of such a technique to verify the effectiveness of the proposed MCDA technique in a later section, this section applies traditional sensitivity analysis in the form of rank reversal in order to establish the validity of the proposed technique.

Among the various sensitivity analysis as proposed in the existing literature, Mukhametzyanov and Pamačar [79] checked the consistency among ten different MCDA techniques under a total of eleven criteria. The authors performed statistical analysis of simulation experimentation, in terms of means and variances. Verification of consistency has also been considered by most of the researchers [80, 81]. Yu et al. [82] performed sensitivity analysis for the weightages of the attributes and for the uncertainty for the attributes. The application area for the sensitivity analysis is the selection of onshore environmentally friendly drilling systems. This paper applied a popular method called rank reversal. Li et al. [84] also applied rank reversal by varying weights of the attributes for TOPSIS MCDA technique. However, there is a significant number of articles on sensitivity analysis, among which the most popular technique is rank reversal technique. However, most of the rank reversal techniques have been applied on the already existing MCDA techniques as evident from the review of the existing literature. In this paper, sensitivity analysis for the proposed MCDA technique has been applied—1) by varying the weights of the criteria and 2) by varying some of the elements of the decision matrix. The following subsections depict these sensitivity analyses.

7.1 Ranks as obtained by varying weights of criteria

The randomly modified weights for the criteria are shown in Table 17. After applying the same proposed MCDA technique on the same decision matrix by the same calculated
as shown above, based on the modified weights of the criteria, the ranks of the alternatives are obtained as shown in the second column of Table 19.

### 7.2 Ranks as obtained by varying some elements of decision matrix

In this case, some of the elements of the decision matrix have been modified randomly, as shown in Table 18. The modified values are indicated by bold and italic font. The resultant ranks of the alternatives are shown in the third column of Table 19.

Two different methods of rank correlations have been applied in order to verify the association between the ranking as obtained from the proposed MCDA technique and each of the rankings as obtained by the first and second sensitivity analysis techniques. The rank correlation methods as obtained are Spearman’s rank correlation and Pearson’s rank correlation. The results are shown in Table 20. Table 20 shows a low but positive association between the rankings obtained from the proposed technique and each of the rankings obtained from the two sensitivity analyses. The positive value of the rank correlation value indicates that the ranks of the proposed technique are positively associated with the rankings as obtained from each of the two types of modifications as applied. The low positive association can be justified by the fact that such drastic changes in the weights of the criteria and the randomly modified values are certainly going to have negative influences on the resultant rankings. However, the validity and guarantee of sensitivity analysis techniques have never been verified for MCDA techniques, as commented by several research studies [75].

### 8 Ranking of the alternatives by AHP, MAUT, MACBETH, MOORA, TODIM and CODAS

In this paper, a total of six different types of MCDA techniques (AHP, MAUT, MACBETH, MOORA, TODIM and CODAS) have been considered for comparison with the proposed MCDA technique. Among these techniques, AHP is based on the comparison among the alternative for each criterion; MAUT is based on the utility scores of the alternatives; MACBETH is based on the relative distances of the elements of decision matrix from the best and worst values for each criterion; MOORA is a simple technique which is also based on some kind of distances of the elements from a reference point. TODIM is based on pair-wise comparison; and CODAS is based on both distances and the pair-wise comparison among alternatives for each criterion. These techniques have been chosen for comparison because of the varying natures of these methods. These methods have been applied to the data as obtained from the case study, after considering the hesitant fuzzy elements.
| Alternatives | Price     | Mileage   | Fuel tank capacity | Maximum torque | Rank |
|--------------|-----------|-----------|--------------------|----------------|------|
| CAR 1        | 0.167903  | 0.254358  | 0.009639           | 0.674544       | 4    |
| CAR 2        | 0.146368  | 0.22827   | 0.009639           | 0.497391       | 10   |
| CAR 3        | 0.173937  | 0.184508  | 0.010045           | 0.615522       | 6    |
| CAR 4        | 0.16218   | 0.214519  | 0.009838           | 0.895304       | 1    |
| CAR 5        | 0.16042   | 0.208246  | 0.01043            | 0.523848       | 9    |
| CAR 6        | 0.150932  | 0.19566   | 0.009639           | 0.497391       | 11   |
| CAR 7        | 0.162274  | 0.247292  | 0.009838           | 0.703453       | 3    |
| CAR 8        | 0.176563  | 0.179849  | 0.009993           | 0.607923       | 7    |
| CAR 9        | 0.184694  | 0.218467  | 0.009889           | 0.848955       | 2    |
| CAR 10       | 0.1977    | 0.187422  | 0.009639           | 0.600509       | 5    |
| CAR 11       | 0.209503  | 0.235828  | 0.010722           | 0.497391       | 8    |

| Alternatives | Price     | Mileage   | Fuel tank capacity | Maximum torque | Rank |
|--------------|-----------|-----------|--------------------|----------------|------|
| CAR 1        | 6.389453  | 31.34395  | 1.004843           | 6.763721       | 3    |
| CAR 2        | 31.34395  | 10.84425  | 1.004843           | 1.004843       | 5    |
| CAR 3        | 4.551466  | 1.318053  | 3.566858           | 3.958306       | 9    |
| CAR 4        | 9.133986  | 5.91295   | 1.883448           | 31.34395       | 1    |
| CAR 5        | 10.27816  | 4.42426   | 11.91868           | 1.436407       | 8    |
| CAR 6        | 21.00438  | 2.393439  | 1.004843           | 1.004843       | 6    |
| CAR 7        | 9.0778    | 23.76201  | 1.883448           | 8.586599       | 4    |
| CAR 8        | 3.967526  | 1.004843  | 3.033513           | 3.674245       | 10   |
| CAR 9        | 2.68042   | 7.064037  | 2.205107           | 23.83583       | 2    |
| CAR 10       | 1.552369  | 1.550049  | 1.004843           | 3.412072       | 11   |
| CAR 11       | 1.004843  | 14.91544  | 31.34395           | 1.004843       | 7    |

| Alternatives | Aggregate MACBETH score | Rank | Final values for MOORA | Rank |
|--------------|--------------------------|------|------------------------|------|
| CAR 1        | 64.33428402              | 4    | 0.001407               | 6    |
| CAR 2        | 15.29950557              | 10   | 0.002649               | 1    |
| CAR 3        | 37.45024288              | 6    | 0.001239               | 7    |
| CAR 4        | 78.2219728               | 2    | 0.001689               | 4    |
| CAR 5        | 22.44252852              | 9    | 0.001782               | 3    |
| CAR 6        | 7.536161335              | 11   | 0.002341               | 2    |
| CAR 7        | 65.51752475              | 3    | 0.001684               | 5    |
| CAR 8        | 34.90271269              | 8    | 0.00103                | 8    |
| CAR 9        | 81.42762305              | 1    | 0.000724               | 9    |
| CAR 10       | 41.09183749              | 5    | 0.000311               | 10   |
| CAR 11       | 35.13242358              | 7    | 0                      | 11   |
At first, AHP has been applied and some of the results and the ranks are provided in Table 21. Next, the relevant calculations based on the algorithms as depicted in the Introduction section of this paper, are provided in Table 22, Table 23, for the techniques MAUT, MACBETH and MOORA, respectively. Table 24 shows the final calculations for TODIM and CODAS. The ranks as obtained from these four MCDA techniques are going to be compared with that for the proposed MCDA technique in the following section.

9 Comparison between proposed MCDA technique and other techniques

The proposed MCDA technique has been compared by different methods of comparison with other six MCDA techniques, AHP, MAUT, MACBETH, MOORA, TODIM and CODAS. The existing literature has shown various methods of comparison. All of these methods are basically based on establishing the association between different rankings as depicted in Literature Review section of this paper. Some of these techniques are Spearman’s rank correlation, Kendall’s tau and Kendall’s coefficient of correlation [15]. However, since the applications of these techniques provide similar results, this paper has only applied Spearman’s rank correlation technique, instead of applying all these techniques. Table 25 shows the rankings as obtained by applying the proposed MCDA techniques and that for AHP, MAUT, MACBETH, MOORA, TODIM and CODAS.

Next, Spearman’s rank correlations have been calculated between the proposed MCDA technique and each of the other four MCDA techniques as considered in this paper. Table 26 shows the results of the application of Spearman’s rank correlation. Table 26 shows positive associations between the proposed MCDA technique and all the other six techniques through Table 26a, b, c, d, e and f for AHP, MAUT, MACBETH, MOORA, TODIM and CODAS, respectively. The highest positive association is observed for MAUT followed by MOORA, TODIM, CODAS, AHP and MACBETH. Except for MAUT, all the other associations show low values of correlation, although all the positive associations. Such positive associations indicate that there is some similarity (although, low) between the proposed MCDA technique and the other six MCDA techniques. However, the low values for the associations can be explained by the application of a completely different method in the proposed MCDA technique. In general, a positive rank correlation between two variables indicates that the increase in the value of one variable leads to the increase in the value of the other one.

However, the authors applying various rank correlations to compare among various MCDA techniques also acknowledged the fact that such methods for establishing associations among the various MCDA techniques are unable to identify the most appropriate technique for a problem under study as indicated by the review of existing literature as presented in the Literature Review section. Therefore, Bandyopadhyay [8] has proposed a method of comparison in order to identify the most appropriate technique among several techniques for the problem under study. Bandyopadhyay [8] has simply identified the most profitable technique for a problem at hand. The method as proposed by Bandyopadhyay [8] has compared the best cumulative value for the highest weighted criterion for each of the MCDA techniques. For example, for the case study presented in this paper, the highest weighted criterion is “maximum torque.” Tables 27, 28, 29 and 30 show the cumulative values for different MCDA techniques considered in this paper, for the criterion “maximum torque” as considered and proposed in this paper. Based on the current case study, the best two cars will have to be selected. Thus, the second cumulative values for the highest rated criterion (maximum torque) for each of the MCDA techniques are to
### Table 25  Rankings as obtained

| Original Rank | AHP | MAUT | MACBETH | MOORA | TODIM | CODAS |
|---------------|-----|------|---------|-------|-------|-------|
| 3             | 4   | 3    | 4       | 6     | 4     | 9     |
| 2             | 10  | 5    | 10      | 1     | 7     | 4     |
| 11            | 6   | 9    | 6       | 7     | 11    | 8     |
| 1             | 1   | 1    | 2       | 4     | 2     | 1     |
| 8             | 9   | 8    | 9       | 3     | 6     | 5     |
| 5             | 11  | 6    | 11      | 2     | 8     | 3     |
| 7             | 3   | 4    | 3       | 5     | 1     | 10    |
| 10            | 7   | 10   | 8       | 8     | 5     | 7     |
| 6             | 2   | 2    | 1       | 9     | 3     | 11    |
| 4             | 5   | 11   | 5       | 10    | 10    | 6     |
| 9             | 8   | 7    | 7       | 11    | 9     | 2     |

### Table 26  Application of Spearman’s rank correlation

| Original rank AHP | Original rank MAUT |
|-------------------|-------------------|
| AHP 0.24 1        | MAUT 0.58 1       |
| MACBETH 0.19 1    | MOORA 0.43       |
| TODIM 0.336364 1  | CODAS 0.281818 1 |

### Table 27  Cumulative maximum torque for proposed technique and AHP

| Proposed technique | Maximum torque | Cumulative torque | AHP | Maximum torque | Cumulative torque |
|--------------------|----------------|-------------------|-----|----------------|-------------------|
| 3                  | 0.8            | 0.8               | 4   | 0.55           | 0.55              |
| 2                  | 0.99           | 1.79              | 10  | 0.82           | 1.37              |
| 11                 | 0.99           | 2.78              | 6   | 0.99           | 2.36              |
| 1                  | 0.73           | 3.51              | 1   | 0.73           | 3.09              |
| 8                  | 0.81           | 4.32              | 9   | 0.58           | 3.67              |
| 5                  | 0.94           | 5.26              | 11  | 0.99           | 4.66              |
| 7                  | 0.7            | 5.96              | 3   | 0.8            | 5.46              |
| 10                 | 0.82           | 6.78              | 7   | 0.7            | 6.16              |
| 6                  | 0.99           | 7.77              | 2   | 0.99           | 7.15              |
| 4                  | 0.55           | 8.32              | 5   | 0.94           | 8.09              |
| 9                  | 0.58           | 8.9               | 8   | 0.81           | 8.9               |
be considered. Tables 27, 28, 29 and 30 show that the cumulative values for the proposed MCDA technique, AHP, MAUT, MACBETH, MOORA, TODIM and CODAS are 1.79, 1.37, 1.74, 1.37, 1.72, 1.25 and 1.13, respectively. Thus, the highest value among these cumulative values is 1.79 for the proposed MCDA technique. This indicates that the most appropriate MCDA technique for the current case study is the proposed MCDA technique as it outperforms all the other six techniques. Therefore, the comparison of the proposed MCDA technique establishes its superiority over the other MCDA techniques as considered in this paper. Therefore, such results indicate that the proposed MCDA technique is capable of competing with the other existing MCDA techniques.

### 10 Conclusion

This paper proposes a novel multi-criteria decision analysis (MCDA) technique which considers various characteristics of MCDA techniques which have been considered till now,
as evident from the existing literature. Such characteristics include considering relationships among the alternatives; relationships among the criteria; relationships among the criteria and the alternatives; the uncertainty or dilemma among the decision makers; and the consideration of entropy of the criteria while calculating the weights of the criteria. For calculating the weights of the criteria, this paper has applied IDOCRIW method which also considers the entropy in the criteria while calculating the weights; the uncertainty of the decision makers has been dealt with the hesitant fuzzy elements. Both a kind of sensitivity analysis in the form of rank reversal and the comparison with six other different types of MCDA techniques have been performed in order to establish the effectiveness of the proposed MCDA technique.

Authorship contributions The author contributes the following through this paper: A novel multi-criteria decision analysis (MCDA) technique has been proposed. The proposed MCDA technique has considered relationships among the alternatives, relationships among the criteria, relationships between the criteria and the alternatives, the dilemma in decision-making for the decision makers, consideration of information content in the criteria. The proposed MCDA technique has been analyzed by sensitivity analysis. The proposed technique has also been compared with other six different MCDA techniques in order to establish its effectiveness and validity.

Data availability I confirm that the data for my manuscript may be available if the data is required by the journal.

Declarations

Ethical approval (1) No content from the manuscript has been copyrighted, published, or accepted for publication elsewhere; (2) No content is or will be under review by another journal while under consideration by this journal; (3) The manuscript uses appropriate citations for the reproduction of someone else’s original words or expression of ideas; (4) The manuscript has not been submitted to any journal before; (5) No working paper, prior draft, and final version of the manuscript were posted online and will not be posted during the review process.

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