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A comparison study of fuzzy-based multiple-criteria decision-making methods to evaluating green concept alternatives in a new product development environment

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Abstract

Purpose – In this paper, the four popular multiple-criteria decision-making (MCDM) methods in fuzzy environment are utilized to reflect the vagueness and uncertainty on the judgments of decision-makers (DMs), because the crisp pairwise comparison in these conventional MCDM methods seems to be insufficient and imprecise to capture the right judgments of DMs. Of these methods, as Fuzzy analytic hierarchy process (F-AHP) is used to calculate criteria weights, the other methods; Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (F-TOPSIS), Fuzzy Grey relational analysis (F-GRA) and Fuzzy Preference Ranking Organization METhod for Enrichment of Evaluations (F- PROMETHEE II) are used to rank alternatives in the three different ways for a comparative study.

Design/methodology/approach – The demand for green products has dramatically increased because the importance and public awareness of the preservation of natural environment was taken into consideration much more in the last two decades. As a result of this, especially manufacturing companies have been forced to design more green products, resulting in a problem of how they incorporate environmental issues into their design and evaluate concept options. The need for the practical decision-making tools to address this problem is rapidly evolving since the problem turns into an MCDM problem in the presence of a set of green concept alternatives and criteria.

Findings – The incorporation of fuzzy set theory into these methods is discussed on a real-life case study, and a comparative analysis is done by using its numerical results in which the three fuzzy-based methods reveal the same outcomes (or rankings), while F-GRA requires less computational steps. Moreover, more detailed analyses on the numerical results of the case study are completed on the normalization methods, distance metrics, aggregation functions, defuzzification methods and other issues.

Research limitations/implications – The designing and manufacturing environmental-friendly products in a product design process has been a vital issue for many companies which take care of reflecting environmental issues into their product design and meeting standards of recent green guidelines. These companies have utilized these guidelines by following special procedures at the design phase. Along the design process consisting of various steps, the environmental issues have been considered an important factor in the end-of-life of products since it can reduce the impact on the nature. In the stage of developing a new product with the aim of environmental-friendly design, the green thinking should be incorporated as early as possible in the process.

Practical implications – The case study was inspired from the previous work of the author, which was realized in a hot runner systems manufacturer, used in injection molding systems in a Canada. In a new product development process, the back- and front-ends of development efforts mainly determine the following criteria: cost, risk, quality and green used in this paper. The case study showed that the three fuzzy MCDM methods come to the same ranking outcomes. F-GRA has a better time complexity compared to the other two methods and uses a smaller number of computational steps. Moreover, a comparative analysis of the three F-MCDM methods; F-PROMETHEE II, F-TOPSIS and F-GRA used in ranking for green concept alternatives using the numerical results of the case study. For the case study; as seen in table 20, the three F-MCDM methods produced the numerical results on the rankings of the green concept alternatives as follows; {Concept A-Concept C–Concept B–Concept D}.

Social implications – Inclusion of environmental-related criteria into concept selection problem has been gaining increasing importance in the last decade. Therefore, to facilitate necessary calculations in applying each method especially with its fuzzy extension, it can be developed a knowledge-based (KB) or an expert system (ES) to help the DMs make the required calculations of each method, and interpret its results with detailed analysis.

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Originality/value – The objective of the research was to propose a F-AHP based F-MCDM approach to green concept selection problem through F-PROMETHEE II, F-TOPSIS and F-GRA methods. As the F-AHP is used to weight evaluation criteria, the other methods are respectively used for ranking the concept alternatives and determine the best concept alternative.

Keywords New product development, Green concept selection, Multiple-criteria decision making, Fuzzy logic, AHP, TOPSIS, GRA, PROMETHEE II

Paper type Research paper

1. Introduction

Designing green products as a result of increasing public awareness about the preservation of natural environment has become a critical concern for companies, incorporating environmental issues in their product design in order to meet recent green guidelines. For companies to follow these guidelines in their new product development environment, special procedures must be carried out. The bill-of-material or content of a product is an important factor at its end-of-life since it can reduce the impact on the environment. At the design stage of a new product, the aim of design, i.e. green thinking must be incorporated as early as possible in the product development process. At the design process, there are several factors to be taken into consideration. For example, material selection for different components will be part of the final product. On the other hand, for the product assembly, the used method and assembly sequences are the other two critical factors that should be taken into consideration in the design process (Chu *et al.*, 2009). Furthermore, today's companies give more attention to environment-friendly technologies and design applications to minimize waste, and in turn, transform waste into a profitable product (Zhang *et al.*, 1997; Srivastava, 2007). Environmentally conscious design and manufacturing is a proactive approach toward minimizing the impact of products on the environment during all stages of a new product development (NPD); that is, the sequence of steps or activities which an enterprise employs to conceive, design and commercialize a product (Ulrich and Eppinger, 2000). This process has the following activities with environmental issues from raw materials, production, transportation and distribution to re-use, remanufacturing and recycling to final disposal (Zhang *et al.*, 1997): (1) identifying customer needs, (2) establishing target specifications, (3) concept generation, (4) concept selection, (5) concept testing, (6) setting final specifications, (7) project planning, (8) economic analysis, (9) benchmarking of competitive products, (10) modeling and (11) prototyping.

Among these activities, *the concept selection* is a process of evaluating a set of concept alternatives in terms of the criteria (i. e. quality level and unit cost) to find out the best option (Ayag, 2005a, b). It is also critical because the selected concept plays an important role at the phase of generating a set of the design alternatives. On the other hand, it is pointed out in literature that around 70% of the unit cost of a product is committed at this phase (Duffy *et al.*, 1993). After this, the development process will lead to a more detailed solution. Therefore, the concept selection is shortly defined to evaluate a set of design alternatives in a new product environment and a critical element to improve design productivity. In addition, during the development process, a company's product engineers (or designers) must consider an increased number of design options to meet the needs of customers. The activity of judging and selecting from a set of competing design options is referred to as *evaluation*. As the number of design options to evaluate increases and the time available decreases, designers or product engineers need more help with evaluating the possible concept alternatives and determining the most satisfying one. So, the evaluation process can be defined as a multiple-criteria decision making (MCDM) problem as there are a set of alternatives which should be evaluated in terms of evaluation criteria, and a decision-maker(s) (DM) will need at least one of the MCDM methods in current literature. Therefore, in this paper, the four popular MCDM methods are chosen for the evaluation design alternatives, such as analytic hierarchy process (AHP) invented by Saaty (1981); TOPSIS (the Technique for Order of Preference by Similarity to Ideal Solution) originally developed by Hwang and Yoon (1981); GRA (Grey relational analysis) first invented by Deng (1982); and PROMETHEE II (Preference Ranking Organization METhod for Enrichment of Evaluations) by Jean-Pierre Brans (Brans *et al.*, 1986).

On the other hand, these conventional MCDM methods use a crisp scale to reach the best satisfying alternative. As result of this, some shortcomings are observed as follows: it causes an unbalanced scale of the judgments of a DM; does not model uncertainty by mapping of DM's judgment to a number; and the subjective judgment of a DM has great influence on the ranking. Due to the vagueness and uncertainty on the judgments of a DM, the crisp comparison in these conventional methods seems to be insufficient and imprecise to capture the right judgments of DMs. That is why, in this study, fuzzy logic is utilized to make up for this deficiency in the conventional methods.

Shortly, the objective of this paper is to propose a fuzzy AHP (F-AHP) based approach to the green concept evaluation problem through Fuzzy PROMETHEE II (F-PROMETHEE II), Fuzzy TOPSIS (F-TOPSIS) and Fuzzy GRA (F-GRA) methods. Of these methods, as F-AHP is used to calculate criteria weights, the others, F-TOPSIS, F-GRA and F- PROMETHEE II are used to rank alternatives in three different ways for a comparative study. The integration of fuzzy set theory into the three methods is discussed on a real-life case study; and a comparative analysis is done by using its numerical results in which the F-AHP based three F-MCDM methods reveal the same rankings, while F-GRA requires fewer computational steps. Moreover, more detailed analyses on the numerical results of the case study are completed on the following issues: normalization methods, distance metrics, aggregation functions, defuzzification methods and others.

The remaining part of this paper is organized as follows: Section 2 presents a brief review of the MCDM methods and their fuzzy extensions, used in green concept selection and other types of MCDM problems. Section 3 presents an introduction to fuzzy set theory and its incorporation into four popular MCDM methods: AHP, TOPSIS, GRA and PROMETHEE II. In Section 4, a real-life case study is presented inspired by a study previously done by Ayag (2016). Section 5 presents a detailed comparative analysis using the numerical results of the case study in which the F-AHP based three F-MCDM methods are used; and Section 6 presents conclusions, research limitations and directions for future work.

2. Literature review

This section covers a concise review of literature on the related topic as follows: To the best of our knowledge, a number of studies on concept evaluation have been done in various fields using the MCDM methods with/out their fuzzy extensions; some of them are given as follows: Thurston and Carnahan (1992) utilized fuzzy logic and utility analysis in early design evaluation in terms of a group of criteria. Carnahan *et al.* (1994) also used fuzzy logic integrated with an MCDM method to rank alternatives based on evaluation criteria. Buyukozkan *et al.* (2004) used fuzzy integrated ANP to prioritize design requirements by taking into consideration the degree of the interdependence between the customer needs and design requirements. Kwong *et al.* (2007) proposed an approach through the quality function deployment (QFD) by considering the fuzzy relation measures between customer requirements and engineering characteristics to determine the weights of engineering characteristics. Hu and Zhang (2007) utilized the AHP method to determine the HoQ (House of Quality) parameters, and the method of fuzzy clustering dynamic sort to classify customer requirements for product design features. Buyukozkan *et al.* (2007) proposed a fuzzy QFD to fuse multiple preference styles to respond to customer needs in a product development process. Chen and Weng (2006) developed a fuzzy-based Gaussian process (GP) model to evaluate engineering design alternatives by considering business competition by specifying the pre-emptive priorities between goals and the minimum meeting levels of design requirements. Huang and Gu (2006) developed a reasoning scheme to infer the relationships between the requirements and information, and the feedback control mechanism by analyzing the conflicting or cooperative relationships among the process requirements. Karsak (2004) proposed the QFD with the aim of developing new and modifying existing products to improve the level of customer satisfaction by integrating the business functions of an organization. Vinodh *et al.* (2010) proposed a fuzzy ANP for concept evaluation in total agile design systems. Ng and Chuah (2014) used the AHP and evidential reasoning (ER) approaches in the environmental performance evaluation and prioritization of different design options with a case study. Kahraman *et al.* (2007) developed a systematic decision process for finding more rational new product ideas using both, a fuzzy heuristic multi-attributive utility theory (MAUT) for the identification of non-dominated new product candidates and a hierarchical F-TOPSIS method for the selection of the best design option. Lin *et al.* (2008) proposed a framework using the AHP and TOPSIS methods to help designers to determine customer requirements and design characteristics and achieve an effective evaluation of the ultimate design solution. Chan (2008) used the GRA method for the product end-of-life decisions of manufacturing companies. Vinodh and Girubha (2012) developed an approach using the PROMETHEE method to solve the sustainable concept selection problem that is vital for manufacturing organizations. Vinodh *et al.* (2014) also used the AHP and PROMETHEE for agile concept selection problem. Later, Vinodh *et al.* (2015) also proposed an integrated grey system rough set theory to evaluate agile concept options for the automotive sector. On the other hand, Le Teno and Mareschal (1998) proposed an interval version of PROMETHEE I in order to deal with interval criteria and evaluated the environmental quality of building products' design through life cycle assessment. Geldermann *et al.* (2000) also used the PROMETHEE method with trapezoidal fuzzy numbers for specification of fuzzy preferences, scores and weights.

On the other hand, to the best of our knowledge, there are a limited number of studies on the comparisons of the MCDM methods for concept selection problem, some of which are summarized here as follows: Lakshmi and Venkatesan (2014) did a comparison study to determine the effects of various normalization methods on the results of the TOPSIS method and found out the best method in terms of time and space complexity. Naaz *et al.* (2011) analyzed the effect of five different defuzzification methods in a fuzzy-based load balancing problem and compared their results to determine the best method. Zavadskas *et al.* (2006) used the TOPSIS with vector and linear normalization methods for the ranking accuracy in construction management problem and compared them to each other. Honkala *et al.* (2007) compared existing MCDM methods for concept selection, to identify possible differences in the methods, and to give recommendations for their use in concept selection under variable situations. The comparison primarily showed parallel results between compared methods, but certain noticeable differences also occurred. These differences are pointed out and clarified, and five suggestions for the general use of MCDM methods were made. Velasquez and Hester (2013) performed a literature review of common MCDM methods and examined their advantages and disadvantages. They also explained how their common applications relate to their relative strengths and weaknesses in order to provide a clear guide for how MCDM methods should be used for particular problems.

Also, there are many works on the fuzzy based hesitant fuzzy linguistic term sets; and some of them recently published are summarized as follows: Lin *et al.* (2020a) proposed a TODIM-based MCDM approach with hesitant fuzzy linguistic term sets, and applied for the evaluation and ranking of several satellite launching centers in order to illustrate the validity and applicability of the proposed method. Lin *et al.* (2020b) developed a model for site selection of car sharing station under picture fuzzy environment using MULTIMOORA.

Can and Demirok (2019) used an integrated fuzzy MCDM approach for universal usability evaluation. Li *et al.* (2020) presented a novel approach to emergency risk assessment using failure mode and effects analysis (FMEA) with extended MULTIMOORA method under interval-valued Pythagorean fuzzy environment. Chen *et al.* (2019) developed a grey clustering evaluation based on AHP and interval grey number. Wang *et al.* (2019) proposed an MCDM approach based on improved cosine similarity measure with interval neutrosophic sets. Lin *et al.* (2020) presented an approach to evaluate Internet of things (IoT) platforms using integrated probabilistic linguistic MCDM method. Xiuqin *et al.* (2021) developed a probabilistic uncertain linguistic TODIM method based on the generalized Choquet integral and its application. Qiyas *et al.* (2020) present an approach for emergency problem selection issue using the concept of Yager operators with the picture fuzzy set environment.

To the best of our knowledge, in current literature, there is a research gap on the exploration of different MCDM methods for green concept evaluation; therefore, in this paper, a F-AHP based methodology through the three popular MCDM methods in fuzzy environment, F-TOPSIS, F-GRA and F-PROMETHEE II are presented for a comparative work using the numerical results of a case study in terms of the normalization methods, distance metrics, aggregation functions, defuzzification methods, time complexity and other issues, as F-AHP is only used for weighting evaluation criteria.

3. Green concept selection using fuzzy decision-making

Designing a green product or components in an NPD environment is a comprehensive process because the process is progressively detailed through a series of phases. The end of each phase is generally called "the gate;" a design review is held to approve the design and release it to the next level. In this paper, as one of the critical phases of the NPD process, the phase of concept selection is taken into consideration to evaluate the green concept alternatives in order to find out the most appropriate green concept for further development activities. On the other hand, the selecting process for the best concept becomes vital and complicated for companies. As the development progresses on a selected concept, it becomes more difficult to make any design modifications because of quality, cost and schedule implications. Therefore, to find out the best green concept alternative among a set of alternatives, in this paper, as illustrated in Figure 1, a F-AHP-based F-MCDM approach through F-TOPSIS, F-GRA and F-PROMETHEE II is proposed to firstly weight the evaluation criteria though F-AHP and rank concept alternatives using each of the three F-MCDM methods. Finally, also a comparative study of the three F-MCDM methods is presented using the numerical results of a case study. Moreover, more detailed analyses on the numerical results of the case study are completed on the normalization methods, distance metrics, aggregation functions, defuzzification methods, time complexity and other issues.

As seen in Figure 1, the approach has three main sections, one of which is the F-AHP section that includes the steps of determining the relative weights of the evaluation criteria; another is the section including necessary steps to rank competing concept alternatives to reach the best one using each of the three F-MCDM methods, as the final section is about a comparative study of the three ranking methods using the numerical results of a case study. Next, this approach with three sections is explained in more detail.

3.1 Criteria weighting through F-AHP

The main idea of fuzzy set theory developed by Zadeh is based on an element with a degree of membership in a fuzzy set (Zadeh, 1965), which is defined by a membership function mapping elements in the universe of discourse to elements in a certain interval of [0, 1].

In the first section, the AHP is used for weighting a set of criteria using a nine-point scale and based on a hierarchy considering the distribution of a goal amongst the elements being compared, and judges which element has a greater influence on that goal. It is one of the most

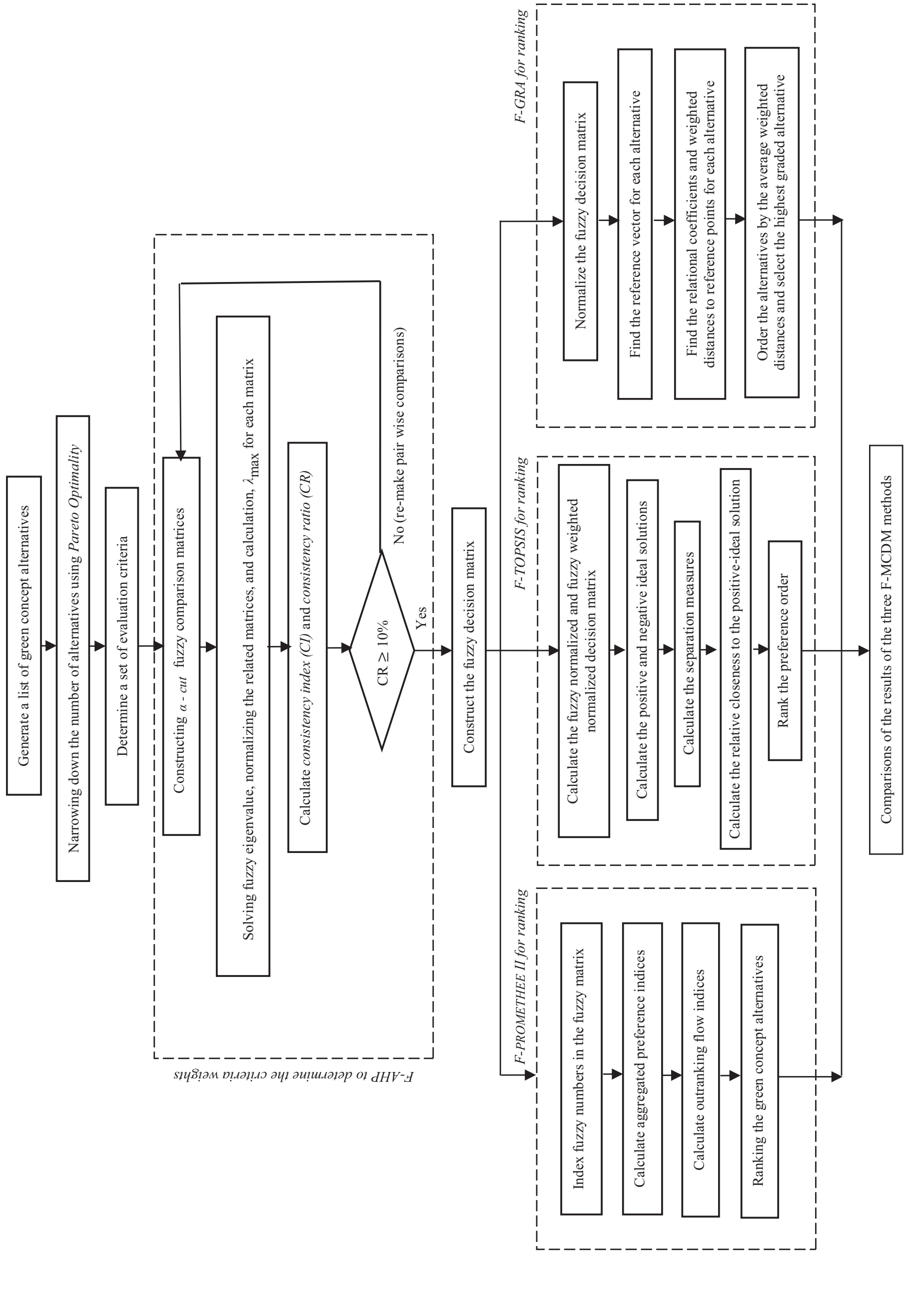

Figure 1.
Comparative analysis of F-AHP based F-MCDM methods for green concept selection problem

commonly used MCDM methods in literature and has been widely used for different kinds of MCDM problems (Ayag and Ozdemir, 2007). For weighting the evaluation criteria for green concept selection problem using F-AHP, triangular fuzzy numbers (TFNs), $\tilde{1}$ to $\tilde{9}$, are utilized to make the required pairwise comparisons of the selection process to capture the vagueness of a DM as seen in Table 1.

A fuzzy number is a special fuzzy set $F = \{(x, \mu_F(x)), x \in R\}$, where x takes it values on the real line; R: $-\infty < x < +\infty$ and $\mu_F(x)$ is a continuous mapping from R to the closed interval [0, 1]. A TFN denoted as $\tilde{M} = (l, m, u)$, where $l \leq m \leq u$, has the following triangular type of membership function:

$$\mu_F(x) = \begin{cases} 0 & x < l \\ x - l/m - 1 & l \leq x \leq m \\ u - x/u - m & m \leq x \leq u \\ 0 & x > u \end{cases}$$

The TFNs are used to improve the traditional the nine-point scaling scheme of Saaty's to take the imprecision and vagueness of DM judgments into consideration. In this scale, the five TFNs ($\tilde{1}$, $\tilde{3}$,$\tilde{5}$,$\tilde{7}$,$\tilde{9}$) are defined with their membership function. All evaluation criteria and alternatives are linguistically depicted by Figure 2. The shape and position of linguistic elements are chosen to illustrate the fuzzy extension of the method.

Later, the DM is asked to compare the elements at a given level on a pairwise basis to estimate their relative importance in relation to the element at the immediate proceeding level. In traditional AHP of Saaty, the required pairwise comparisons, also as seen in Table 1, are done by using a nine-point ratio scale (Saaty, 1989). Unfortunately, although this scale has the advantages of simplicity and easiness, it is not enough to reflect the uncertainty associated with the mapping of DM's judgment to a number. Therefore, the fuzzy logic is integrated to the conventional AHP to overcome this difficulty, *called F-AHP*. Next, the steps of this method are concisely given:

Step 1. Comparing the performance scores: the TFNs are used to indicate the relative strength of each pair of elements in the same hierarchy.

Numerical rating	Judgment or preference	Remarks	TFNs
1	Equally important	Two attributes contribute equally to the attribute at the higher decision level	(1, 1, 2)
3	Moderately more important	Experience and judgment slightly favor one attribute over another	(2, 3, 4)
5	Strongly more important	Experience and judgment strongly favor one attribute over another	(4, 5, 6)
7	Very strongly more important	Experience and judgment strongly favor one attribute over another; its dominance has been demonstrated in practice	(6, 7, 8)
9	Extremely more important	Experience and judgment extremely favor one attribute over another; the evidence favoring one attribute over another is of the highest possible order of affirmation	(8, 9, 10)

Table 1. Nine-point fundamental scale used in pairwise comparisons (Saaty, 1989)

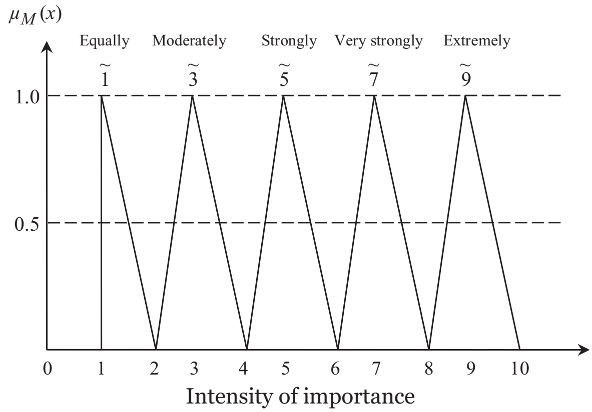

Figure 2.
Fuzzy membership function for linguistic values for evaluation criteria

Step 2. Constructing the fuzzy comparison matrix: the fuzzy judgment matrix $\tilde{A}$ (a_{ij}) is constructed via pairwise comparison using TFNs as given below;

$$\tilde{A} = \begin{bmatrix} 1 & \widetilde{a_{12}} & .. & .. & \widetilde{a_{1n}} \\ \widetilde{a_{21}} & 1 & .. & .. & \widetilde{a_{2n}} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \widetilde{a_{n1}} & \widetilde{a_{n2}} & .. & .. & 1 \end{bmatrix}$$

where, $\widetilde{a_{ij}^{\alpha}} = 1$, if i is equal j, and $\widetilde{a_{ij}^{\alpha}} = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$ or $\tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1}$, if i is not equal j

Step 3. Solving fuzzy eigenvalue: A fuzzy eigenvalue, $\tilde{\lambda}$ is a fuzzy number solution to

$$\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x} \tag{Eq. 1}$$

where nxn is the fuzzy matrix containing fuzzy numbers $\tilde{a_{ij}}$ and $\tilde{x}$ is a non-zero $nx1$, fuzzy vector containing fuzzy number $\tilde{x}_i$. To perform fuzzy multiplications and additions by using the interval arithmetic and $\alpha - cut$, the equation $\tilde{A}\tilde{x}=\tilde{\lambda}\tilde{x}$ is equivalent to

$$\left\lfloor a_{i1l}^{\alpha}x_{1l}^{\alpha}, a_{i1u}^{\alpha}x_{1u}^{\alpha} \right\rfloor \oplus \ldots\ldots \oplus \left\lfloor a_{inl}^{\alpha}x_{nl}^{\alpha}, a_{inu}^{\alpha}x_{nu}^{\alpha} \right\rfloor = \left\lfloor \lambda x_{il}^{\alpha}, \lambda x_{iu}^{\alpha} \right\rfloor$$

where

$$\tilde{A} = [\tilde{a}_{ij}], \widetilde{x^t} = (\widetilde{x_1}, \ldots, \widetilde{x_n}),$$

$$\tilde{a}_{ij}^{\alpha} = \left[a_{ijl}^{\alpha}, a_{iju}^{\alpha}\right], \tilde{x}_i^{\alpha} = \left[x_{il}^{\alpha}, x_{iu}^{\alpha}\right], \tilde{\lambda}^{\alpha} = \left[\lambda_l^{\alpha}, \lambda_u^{\alpha}\right] \tag{Eq. 2}$$

for $0 < \alpha \leq 1$ and all i, j, where $i = 1, 2 \ldots n, j = 1, 2 \ldots n$

$\alpha - cut$ is commonly known to incorporate a DM confidence over his/her judgments. The degree of satisfaction for a judgment matrix, $\tilde{A}$ is estimated by using the index of optimism μ. A larger value of index μ indicates a higher degree of optimism. The index of optimism is a linear convex combination defined by Lee (1999) and given as in the following equation:

$$\widetilde{a_{ij}^{\alpha}} = \mu a_{iju}^{\alpha} + (1 - \mu)a_{ijl}^{\alpha}, \quad \forall \mu \in [0, 1] \tag{Eq. 3}$$

while α is fixed, the following matrix is obtained after setting the value of μ , to estimate the degree of satisfaction.

$$\tilde{A} = \begin{bmatrix} 1 & \widetilde{a_{12}} & .. & .. & \widetilde{a^{\alpha}_{1n}} \\ \tilde{a}^{\alpha}_{21} & 1 & .. & .. & \widetilde{a^{\alpha}_{2n}} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \widetilde{a^{\alpha}_{n1}} & \widetilde{a^{\alpha}_{n2}} & .. & .. & 1 \end{bmatrix}$$

The eigenvector is calculated by fixing the μ value and identifying the maximal eigenvalue. Then, the matrix is normalized, and the priority weights of the concept alternatives are determined.

Step 4. Consistency analysis: To make sure that the result is based on the consistent on the judgments of the DM, first $\lambda_{\max}$ calculated by Eq. (1), then the consistency index (CI) is calculated for the matrix by Eq. (4). The deviations from the consistency are expressed by the CI, the measure of inconsistency.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad \text{(Eq. 4)}$$

Later, the consistency ratio (CR) is calculated by Eq. (5) by dividing the value of CI by the value from the Table of *Random Consistency Index (RI)*, the average index for randomly generated weights based on the matrix size (Saaty, 1981).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \quad \text{(Eq. 5)}$$

For consistency of a matrix, the value of CR should be less than 0.10; and it means that the pairwise comparisons of the DM are consistent and acceptable, otherwise not.

3.2 Ranking alternatives through three F-MCDM methods

In the second section, it is presented one-by-one on how the three F-MCDM methods, F-TOPSIS, F-GRA and F-PROMETHEE II, are utilized respectively for ranking green product alternatives. In these methods, the same linguistic variables and membership functions, as given in Table 2 and Figure 3, are used for ranking green concept alternatives.

F- TOPSIS for ranking: The TOPSIS method helps us select the best alternative with a set of criteria. It has been used in various application areas to solve different MCDM problems. The method is based on the idea that the best alternative should have the shortest distance

Numerical rating	Linguistic variables (degree of importance)	TFNs
1	Very poor (VP)	(0, 1, 2)
2	Poor (P)	(1, 2, 3)
3	Medium poor (MP)	(2, 3.5, 5)
4	Fair (F)	(4, 5, 6)
5	Medium good (MG)	(5, 6.5, 8)
6	Good (G)	(7, 8, 9)
7	Very good (VG)	(8, 9, 10)

Table 2. Linguistic variables for green concept ratings (Banaeian *et al.*, 2018)

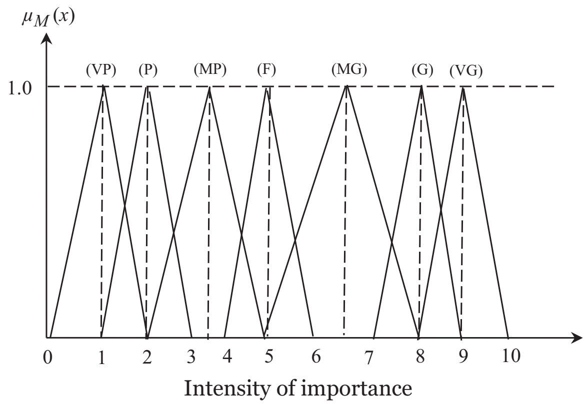

Figure 3.
Fuzzy membership function for linguistic values for alternatives

from the positive-ideal solution and the farthest distance from the negative-ideal solution. Although its concept is rational and easy to use, and the number of computational steps are uncomplicated, the inherent difficulty of assigning reliable subjective preferences to the criteria is noteworthy as a well-known classical MCDM method. It has received much interest from researchers and practitioners, and the global interest in the method has exponentially grown (Behzadian *et al.*, 2010). The approach uses weighted *Euclidean distances* to ensure a meaningful interpretation of the comparison result. Next, the steps of the TOPSIS method are given (Triantaphyllou 2000);

Step 1. Construct the fuzzy and fuzzy normalized fuzzy decision matrices: First, the following fuzzy decision matrix ($\tilde{X}$) using the TFNs based on Table 2 and Figure 3 is constructed, where m and n indicate alternatives and criteria, as $\tilde{x}_{ij}$ indicates the jugdments of the DM (i = 1, 2, 3,. . ., n; j = 1, 2, 3,. . ., m).

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & . & . & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & . & . & \tilde{x}_{2n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{m3} & . & . & \tilde{x}_{mn} \end{bmatrix}$$

Then, it converts various criteria in different dimensions into non-dimensional ones. An element $\tilde{r}_{ij}$ of the normalized fuzzy decision matrix ($\tilde{R}$) is thus calculated as follows:

$$\tilde{r}_{ij} = \frac{\tilde{x}_{ij}}{\sqrt{\sum_{j=1}^{n} \tilde{x}_{ij}^2}} \Rightarrow \tilde{r}_{ij} = \frac{l_{ij}}{\sqrt{\sum_{j=1}^{n} u_{ij}^2}}, \frac{m_{ij}}{\sqrt{\sum_{j=1}^{n} u_{ij}^2}}, \frac{u_{ij}}{\sqrt{\sum_{j=1}^{n} u_{ij}^2}} \quad \text{(Eq. 6)}$$

Step 2. Construct the fuzzy weighted normalized decision matrix: In Section 3.2, the criteria weights $W = (w_1, w_2, w_3, ..., w_n)$, where $\sum w_i = 1\,(i = 1,\ 2, \ldots, n)$ have been calculated through the F-AHP. In ranking alternatives, first these weights are converted to the crisp values after defuzzification; and later, the weighted normalized fuzzy decision matrix $\tilde{V}$ ($\tilde{v}_{ij} = w_j \tilde{r}_{ij}$) is obtained as follows:

$$\tilde{V} = \begin{bmatrix} w_1\tilde{r}_{11} & w_2\tilde{r}_{12} & w_3\tilde{r}_{13} & . & . & w_n\tilde{r}_{1n} \\ w_1\tilde{r}_{21} & w_2\tilde{r}_{22} & w_3\tilde{r}_{23} & . & . & w_n\tilde{r}_{2n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ w_1\tilde{r}_{m1} & w_2\tilde{r}_{m2} & w_3\tilde{r}_{m3} & . & . & w_n\tilde{r}_{mn} \end{bmatrix}$$

where $w_j\tilde{r}_{ij}$ is the fuzzy weighted normalized matrix obtained by multiplying decision matrix $\tilde{r}_{ij}$ by the weights of criteria w_j.

Step 3. Determine the positive-ideal and the negative-ideal solutions: The positive-ideal solution, denoted as $\tilde{A}^*$ is calculated by selecting the largest normalized and weighted score for each criterion by Eq. (7). Similarly, the negative-ideal solution, denoted as $\tilde{A}^-$ is calculated by selecting the least normalized and weighted score for each criterion by Eq. (8).

$$\tilde{A}^* = \{(\max_i \tilde{v}_{ij} | j \in J), (\min \tilde{v}_{ij} | j \in J'_i), i = 1, 2, 3, ..., m\} \qquad \text{(Eq. 7)}$$

$$\tilde{A}^* = \{\tilde{v}_{1*}, \tilde{v}_{2*}, ..., \tilde{v}_{n*}\}$$

$$\tilde{A}^- = \{(\min_i \tilde{v}_{ij} | j \in J), (\max \tilde{v}_{ij} | j \in J'_i), i = 1, 2, 3, ..., m\} \qquad \text{(Eq. 8)}$$

$$\tilde{A}^- = \{\tilde{v}_{1-}, \tilde{v}_{2-}, ..., \tilde{v}_{n-}\}, \text{where}, J = \{j = 1, 2, 3, ..., n\} \text{ and } J' = \{j = 1, 2, 3, ..., n\}$$

Step 4. Calculate the separation measures: The *n-dimensional Euclidean distance* method is used to measure the separation distances of each concept alternative from the positive-ideal solution and the negative-ideal solution. Thus, the distances are obtained using the following equations:

$$d_{i*} = \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - \tilde{v}_{j*})^2} \text{ for } i = 1, 2, 3, ...m \qquad \text{(Eq. 9)}$$

where d_{i*} is the distance of each alternative from the positive-ideal solution.

$$d_{i-} = \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - \tilde{v}_{j-})^2} \text{ for } i = 1, 2, 3, ...m \qquad \text{(Eq. 10)}$$

where d_{i-} is the distance of each alternative from the negative-ideal solution.

Step 5. Calculate the relative closeness to the ideal solution: The relative closeness of an alternative $\tilde{A}_i$ with respect to the ideal solution $\tilde{A}^*$ is defined as follows:

$$\text{Closeness index: } CI_i = \frac{d_{i-}}{d_{i*} + d_{i-}} \qquad \text{(Eq. 11)}$$

where $1 \geq CI_i \geq 0$, and $i = 1, 2, 3, ..., m$ (m: number of alternatives, apparently, $CI_i = 1$, if $\tilde{A}_i = \tilde{A}^*$, and $CI_i = 0$, if $\tilde{A}_i = \tilde{A}^-$

Step 6. Rank the preference orders: After determining the values of CI_i for the alternatives, it is said that the best alternative is the one with the highest preference order (a.k.a. the one with the shortest distance to the ideal solution).

F-GRA for ranking: The GRA method has found a significant place in literature for cases in which there is uncertainty of information and a decision with multiple criteria. The goal of the

GRA method is to show the degree of difference of development trends between two elements: an alternative and the ideal alternative. If the trend of change between two elements is consistent, it is said that they have a stronger relationship; otherwise, the relational grade is smaller. Shortly, the GRA method is used to measure the relationship between reference and comparison series. Furthermore, to overcome the vagueness of a DM, the fuzzy logic is integrated with the GRA, called *F-GRA*. Next, the steps of the F-GRA method are presented.

Step 1. Construct the fuzzy decision matrix ($\tilde{X}$) using the TFNs, specified in Table 2 and Figure 2, as it is done in the F-TOPSIS.

Step 2. Convert the fuzzy matrix into the fuzzy normalized decision matrix ($\tilde{R}$). Given an element $\tilde{r}_{ij}$ of the fuzzy normalized decision matrix ($\tilde{R}$) is thus calculated as follows:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_{j*}}, \frac{m_{ij}}{u_{j*}}, \frac{u_{ij}}{u_{j*}}\right) i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \quad \text{(Eq. 12)}$$

where

$$u_{j*} = \max_i\{u_{ij}\} \forall ii = 1, 2, \ldots, m \quad \text{(Eq. 13)}$$

Step 3. Determine the vector of reference series; the reference number for each criterion is found as in the following equation:

$$\tilde{R}_0 = [\tilde{r}_{01}, \tilde{r}_{02}, \ldots., \tilde{r}_{0n} = \max(\tilde{r}_{ij})] \quad i = 1, 2, \ldots, n \quad \text{(Eq. 14)}$$

Step 4. Find the distance matrix; the distance δ_{ij} between the reference value and each comparison value is calculated using the equations:

$$d(\tilde{A},\ \tilde{B}) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]} \quad \text{(Eq. 15)}$$

where the distance between $\tilde{A}$ and $\tilde{B}$ is calculated using TFNs.
The grey relational coefficient (ξ_{ij}) is also calculated as in the following equation.

$$\xi_{ij} = \frac{\delta_{\min} + \rho\delta_{\max}}{\delta_{ij} + \rho\delta_{\max}},\ \delta_{\max} = \max(\delta_{ij}),\ \delta_{\min} = \min(\delta_{ij}) \text{ and } \rho \text{ resolving coefficient } \rho\epsilon[0,\ 1] \quad \text{(Eq. 16)}$$

Step 5. The grey relational grade (γ_i) is estimated by the following relation.

$$\gamma_i = \sum_{j=1}^{n} w_j\xi_{ij},\ j = 1,\ 2,\ \ldots,\ n \quad \text{(Eq. 17)}$$

where w_j is the weight of the jth criterion, and $\sum_{j=1}^{n} w_j = 1$.

Finally, the alternatives are ranked in accordance with the value of ξ_{ij}. The higher the grade, the better the alternatives would be.

F-PROMETHEE II for ranking: In literature, it is reported that the PROMETHEE II has been used with success to solve various MCDM problems (Samanlioglu and Ayag, 2016). It is based on a comparison pair per pair of possible decisions along each criterion. Possible decisions are evaluated according to different criteria, which have to be maximized or minimized. It also requires two additional types of information for each criterion; *a weight* and *a preference function*. The preference function characterizes the difference for a criterion between the evaluations obtained by two possible decisions into a preference degree in the interval of [0, 1]. To facilitate the definition of these functions, six basic preference functions were proposed by Figueira *et al.* (2004). Next, the four steps of F-PROMETHEE II are presented (Samanlioglu and Ayağ, 2016).

Step 1. Construct a fuzzy decision-making matrix together with the results of the F-AHP method; $W = (w_1, w_2, w_3, \ldots, w_n)$, where $\sum w_i = 1\,(i = 1,\ 2, \ldots, n)$, and a typical m by n fuzzy decision matrix is shown as below:

$$\begin{array}{c c} & \begin{array}{c}(w_1 \ldots\ w_j \ldots\ w_n)\\ (\widehat{c}_1 \ldots\ \widehat{c}_j \ldots\ \widehat{c}_n)\end{array} \\ \begin{array}{c}\widehat{A}_1\\ .\\ .\\ \widehat{A}_i\\ .\\ .\\ \widehat{A}_m\end{array} & \begin{bmatrix} 1 & \widetilde{r_{12}} & .. & .. & \widetilde{r_{1n}} \\ \widetilde{r_{21}} & 1 & .. & .. & \widetilde{r_{2n}} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \widetilde{r_{m1}} & \widetilde{r_{m2}} & .. & .. & 1 \end{bmatrix} \end{array}$$

Here, $\widehat{c_j} \in \widehat{C}$ is a fuzzy positive criterion. The criterion is a maximum criterion if the DM prefers more value for it. Otherwise, it is a minimum. $\widehat{A_i} \in \widehat{A}$ is fuzzy alternative. $\widehat{A^*}$ is the fuzzy alternative from $\widehat{A}$. $\widehat{r_{ij}} \in \widehat{r}$ is the utility value. $w_j \in W$ is the weight of $\widehat{c_j}$.

Step 2. Index fuzzy numbers in the fuzzy decision matrix: the fuzzy number in the fuzzy matrix is defuzzified with *centroid defuzzification approach* (Wang, 2009) to the crisp number by Eq. (18);

$$(l, m, u) = (l + m + u)/3 \qquad \text{(Eq. 18)}$$

In other words, the above process converts a fuzzy decision matrix into a crisp decision matrix as follows:

$$\begin{array}{c c} & \begin{array}{c}(w_1 \ldots\ w_j \ldots\ w_n)\\ (c_1 \ldots\ c_j \ldots\ c_n)\end{array} \\ \begin{array}{c}A_1\\ .\\ .\\ A_i\\ .\\ .\\ A_m\end{array} & \begin{bmatrix} 1 & r_{12} & .. & .. & r_{1n} \\ r_{21} & 1 & .. & .. & r_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ r_{m1} & r_{m2} & .. & .. & 1 \end{bmatrix} \end{array}$$

where $c_j \in C$ is the positive criterion, $A_i \in A$ is the alternative, A^* is the ideal alternative from A, $r_{ij} \in r$ is the utility value, $w_j \in W$ is the weight of c_j. The cap removal from the notations is crisp value.

Step 3. Calculate aggregated preference indices: $P_j(A_i, A_k) = P_j(d(A_i, A_k)) = P_j(r_{ij} - r_{kj})$ is a preference function showing how much A_i prefers to A_k with respect to c_j. Brans *et al.* (1986) defined the six types of generalized functions and also pointed out that the *Gaussian criterion* rather than the others was mostly preferred by users for practical applications especially in the case of continuing data. As the evaluation criteria contain continuing data, the *Gaussian criterion* preference function was chosen here for the evaluation process given below:

$$P(d) = \begin{Bmatrix} 0 & d \leq 0 \\ 1 - e^{-\frac{d^2}{2s^2}} & d > 0 \end{Bmatrix}, \tag{Eq. 19}$$

if the criterion is a maximum and

$$P(d) = \begin{Bmatrix} 0 & d \geq 0 \\ 1 - e^{-\frac{d^2}{2s^2}} & d < 0 \end{Bmatrix} \tag{Eq. 20}$$

if the criterion is a minimum.

Aggregated preference index $\pi(A_i,\ A_k)$ expresses the degree of how much A_i is preferred to A_k over all the criteria. The aggregated preference indices are of the form:

$$\pi(A_i,\ A_k) = \frac{\sum_{j=1}^{n} P_j(A_i,\ A_k).w_j}{\sum_{j=1}^{n} w_j},\ \forall A_i,\ A_k \in A \text{ and } i \neq k \tag{Eq. 21}$$

Step 4. Calculate outranking flow. Each alternative A_i faces (m-1) other alternatives in A. In order to rank the alternatives, the outranking flows are defined as follows:

The positive outranking flow is of the form:

$$\varnothing^{+}(A_i) = \sum_{k=1}^{m} \pi(A_i,\ A_k) \tag{Eq. 22}$$

The negative outranking flow is of the form:

$$\varnothing^{-}(A_i) = \sum_{k=1}^{m} \pi(A_k,\ A_i) \tag{Eq. 23}$$

The net outranking flow is applied and is in the form of:

$$\varnothing(A_i) = \varnothing^{+}(A_i) - \varnothing^{-}(A_i),\ \forall\, i \in \{1, \ldots, m\} \tag{Eq. 24}$$

The positive outranking flow expresses how an alternative A_i outranks all the others. Higher $\varnothing^{+}(A_i)$ gives a better alternative. On the other hand, the negative outranking flow expresses how an alternative A_i is outranked by all the others. The lower $\varnothing^{-}(A_i)$ gives a better alternative. The higher $\varnothing(A_i)$ specifies the final better alternative.

4. Case study

In the previous section, a comparative approach, a F-AHP-based three F-MCDM methods has been presented to evaluate a set of green conceptual design alternatives in terms of the evaluation criteria in an NPD environment. In this section, a case study is presented for potential readers or practitioners to clearly explain how the comparative approach works on a real-life case. For this purpose, the case study is constructed inspired by a study previously done in a hot runner system manufacturer in Canada (Ayag, 2014). This case study has four different concepts, namely *Concept A, B, C* and *D,* respectively, together with the four-evaluation criteria given in Table 3, three of which were determined by utilizing the previous study. The last one, *green criterion* was newly-added by taking the principles of *Design for Environment (DfE)* into consideration in order to obtain environmental-friendly products, which are so vital and expected by most mold-manufacturers in today's business world.

4.1 Determining weights of the criteria through F-AHP

First, by following the steps in Section 3.1 (see also Figure 1), to weight the four-evaluation criteria; *cost, risk, quality* and *green*, the details of which are given in Table 3, the TFNs ($\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$) are used to express the preference in the pairwise comparisons using Table 1 and Figure 2, and the fuzzy pair-wise comparison matrix ($\tilde{A}$) for the relative importance of the criteria is constructed given in Table 4.

Second, the lower and upper limits of the fuzzy numbers in the fuzzy matrix ($\tilde{A}$), with respect to α, the confidence level are defined by applying Eq. (2) as follows:

$$\tilde{1}_\alpha = [1, 3-2\alpha], \tilde{3}_\alpha = [1+2\alpha, 5-2\alpha], \tilde{3}_\alpha^{-1} = \left[\frac{1}{5-2\alpha}, \frac{1}{1+2\alpha}\right], \tilde{5}_\alpha = [3+2\alpha, 7-2\alpha],$$

$$\tilde{5}_\alpha^{-1} = \left[\frac{1}{7-2\alpha}, \frac{1}{3+2\alpha}\right], \tilde{7}_\alpha = [5+2\alpha, 9-2\alpha], \tilde{7}_\alpha^{-1} = \left[\frac{1}{9-2\alpha}, \frac{1}{5+2\alpha}\right],$$

$$\tilde{9}_\alpha = [7+2\alpha, 11-2\alpha], \tilde{9}_\alpha^{-1} = \left[\frac{1}{11-2\alpha}, \frac{1}{7+2\alpha}\right]$$

Then, the values of $\alpha = 0.5$ and $\mu = 0.5$ were determined using the interval of [0–1] by the DM, who works as a design engineer at the company. They are substituted, where μ indicates the coefficient of optimism, above expression into the fuzzy comparison matrix, and the $\alpha - cuts$ fuzzy comparison matrix is obtained by Eq. (3) as presented in Table 5.

Later, the eigenvalue of the matrix A is calculated by solving the characteristic equation of A, $\det(A - \lambda I) = 0$ and found out all λ values for A ($\lambda_1, \lambda_2, \lambda_3$). Next, the largest eigenvalue

Table 3. List of criteria for green concept selection problem

Code	Criteria	Definition
C	Cost	Development cost, unit manufacturing cost
R	Risk	Envisioning risk, design risk, execution risk, on-time delivery
Q	Quality	Product quality, cycle time, quick color change, precision, flexibility, conductivity, strength, resistance, repeatability and reproducibility
G	Green	Environmentally friendly materials and production, amount of recycling content, environmentally friendly use of product and sustainable packaging, disposability at the end of the product life

Table 4. Fuzzy comparison matrix of the criteria using TFNs

Criteria	Cost	Risk	Quality	Green
Cost	1	$\tilde{3}$	$\tilde{9}$	$\tilde{9}$
Risk	$\widetilde{3^{-1}}$	1	$\tilde{3}$	$\tilde{7}$
Quality	$\widetilde{9^{-1}}$	$\widetilde{3^{-1}}$	1	$\tilde{1}$
Green	$\widetilde{9^{-1}}$	$\widetilde{7^{-1}}$	$\widetilde{1^{-1}}$	1

Table 5. $\alpha - cuts$ fuzzy comparison matrix for the criteria ($\alpha = 0.5, \mu = 0.5$)

Criteria	Cost	Risk	Quality	Green
Cost	1	[2, 4]	[8, 10]	[8, 10]
Risk	[1/4, 1/2]	1	[2, 4]	[6, 8]
Quality	[1/10, 1/8]	[1/4, 1/2]	1	[1, 2]
Green	[1/10, 1/8]	[1/8, 1/6]	[1/2, 1]	1

of pairwise matrix, λ_{max}, is calculated by using Eq. (1), where the matrix size, n is 4, and the RI(4) is 1.12. Finally, the CI and the CR of the matrix A are calculated by Eq. (4) and Eq. (5) and given in Table 6. As seen in the table, the CR value, 0.052 is less than to 0.10; and it means that all the pairwise comparisons of the DM are consistent. As also seen in the far-right column of the table, the e-vector of the criteria weights as crisp values are respectively as follows: W= (0.607, 0.263, 0.077, 0.053).

4.2 Ranking green concept alternatives using three F-MCDM methods

In the previous section, the relative weights of the evaluation criteria are determined; and next, the three F-MCDM methods for ranking green concept alternatives are implemented, respectively (see Figure 1);

F-TOPSIS for ranking: First, the four-green concept alternatives, *Concept A, B, C,* and *D* were compared in terms of each criterion; *cost, risk, quality* and *green* using Table 2 and Figure 2 in order to obtain the fuzzy decision matrix ($\tilde{X}$), shown in Table 7. Then, this matrix is converted to the normalized fuzzy decision matrix ($\tilde{R}$) by Eq. (6) (Table 8).

Later, the fuzzy weighted normalized decision matrix ($\tilde{V}$) is calculated by multiplying the fuzzy normalized decision matrix ($\tilde{X}$) by the column vector; W= (0.607, 0.263, 0.077, 0.053), shown in Table 9.

Table 6.
Eigenvector for comparison matrix of the criteria (CR = 0.052)

Criteria	Cost	Risk	Quality	Green	*e*-Vector
Cost	1.000	3.000	9.000	9.000	0.607
Risk	0.375	1.000	3.000	7.000	0.263
Quality	0.113	0.375	1.000	1.500	0.077
Green	0.113	0.146	0.750	1.000	0.053
				λ_{max}	4.174
				CI	0.058
				RI	1.12
				CR	0.052

Table 7.
Fuzzy decision matrix, $\tilde{X}$ for green alternatives in terms of each criterion

Criteria Alternatives	Cost	Risk	Quality	Green
Concept A	G	MP	MP	MG
Concept B	F	F	P	VG
Concept C	MP	VG	MG	G
Concept D	P	MP	F	MP

Table 8.
Fuzzy normalized matrix, $\tilde{R}$ for F-TOPSIS

Criteria Alternatives	Cost	Risk	Quality	Green
Concept A	(0.57, 0.65, 0.73)	(0.15, 0.26, 0.37)	(0.17, 0.30, 0.43)	(0.30, 0.40, 0.49)
Concept B	(0.33, 0.41, 0.49)	(0.29, 0.37, 0.44)	(0.09, 0.17, 0.26)	(0.49, 0.55, 0.61)
Concept C	(0.16, 0.28, 0.41)	(0.59, 0.66, 0.73)	(0.43, 0.56, 0.69)	(0.43, 0.49, 0.55)
Concept D	(0.08, 0.16, 0.24)	(0.15, 0.26, 0.37)	(0.35, 0.43, 0.52)	(0.12, 0.21, 0.30)

Next, the positive and negative-ideal solution values for each criterion are calculated by Eq. (7) and Eq. (8), and marked them as seen in Table 9. These values in the set form are as follows:

$$\tilde{A}^{*} = \{(0.35, 0.40, 0.44), (0.15, 0.17, 0.19), (0.03, 0.04, 0.05), (0.03, 0.03, 0.03)\}$$

$$\tilde{A}^{-} = \{(0.05 - 0.10, 0.15), (0.04, 0.07, 0.10), (0.01, 0.01, 0.02), (0.01, 0.01, 0.02)\}$$

Then, the separation measures d_{i^*} and d_{i-} by Eq. (9) and Eq. (10), and the relative closeness CI_i to the ideal solution by Eq. (11) are calculated and shown in Table 10. As seen in the table, the green concept alternative, *Concept A* with the highest CI_i value is found as the best alternative among the others.

Finally, the ranking is found as {Concept *A*-*Concept C* – *Concept B* – *Concept D*}

F-GRA for ranking: The weight column vector (W) and the fuzzy decision matrix ($\tilde{X}$) in Table 7 are used, and later the normalized fuzzy decision matrix ($\tilde{R}$) in Table 11 by Eq. (12) and Eq. (13).

$$u_1^{+} = \max_i\{9.0,\ 6.0,\ 5.0, 3.0\} = 9.0, \widetilde{r_{11}} = \left(\frac{7.0}{9.0}, \frac{8.0}{9.0}, \frac{9.0}{9.0}\right) = (0.78,\ 0.89, 1.00)$$

Next, the reference series for green concept alternatives are determined by Eq. (14) as follows:

$$\widetilde{R_0} = [(0.78, 0.89, 1.00), (0.20, 0.35, 0.50), (0.25, 0.44, 0.63), (0.50, 0.65, 0.80)]$$

Criteria Alternatives	Cost	Risk	Quality	Green
Concept A	(0.35*, 0.40*, 0.44*)	(0.04, 0.07, 0.10)	(0.01, 0.02, 0.03)	(0.02, 0.02, 0.03)
Concept B	(0.20, 0.25, 0.30)	(0.08, 0.10, 0.12)	(0.01–, 0.01–, 0.02–)	(0.03*, 0.03*, 0.03*)
Concept C	(0.10, 0.17, 0.25)	(0.15*, 0.17*, 0.19*)	(0.03*, 0.04*, 0.05*)	(0.02, 0.03, 0.03)
Concept D	(0.05–, 0.10–, 0.15–)	(0.04–, 0.07–, 0.10–)	(0.03, 0.03, 0.04)	(0.01–, 0.01–, 0.02–)

Note(s): *Indicates the positive-ideal solution and – indicates the negative-ideal solution for related criterion

Table 9. Fuzzy weighted normalized matrix, $\tilde{V}$

Alternatives	d_{i^*}	d_{i-}	CI_i	Ranking
Concept A	0.134	0.316	0.702	1
Concept B	0.255	0.196	0.434	3
Concept C	0.226	0.228	0.501	2
Concept D	0.431	0.020	0.044	4

Table 10. Final weights for the green concept alternatives through F-TOPSIS

Criteria Alternatives	Cost	Risk	Quality	Green
Concept A	(0.78, 0.89, 1.00)	(0.20, 0.35, 0.50)	(0.25, 0.44, 0.63)	(0.50, 0.65, 0.80)
Concept B	(0.44, 0.56, 0.67)	(0.40, 0.50, 0.60)	(0.13, 0.25, 0.38)	(0.80, 0.90, 1.00)
Concept C	(0.22, 0.39, 0.56)	(0.80, 0.90, 1.00)	(0.63, 0.81, 1.00)	(0.70, 0.80, 0.90)
Concept D	(0.11, 0.22, 0.33)	(0.20, 0.35, 0.50)	(0.50, 0.63, 0.75)	(0.20, 0.35, 0.50)

Table 11. Fuzzy normalized matrix, matrix, $\tilde{R}$ for F-GRA

The distance matrix (δ_{ij}) from the reference value to each comparison value is also calculated by Eq. (15) and shown in Table 12. An example on how a distance is calculated is also formalized for δ_{11} below:

$$\delta_{11} = \sqrt{\frac{1}{3}\left[(0.78-0.78)^2 + (0.89-0.89)^2 + (1.00-1.00)^2\right]} = 0.00$$

By using distance matrix (δ_{ij}), the values of δ_{min} and δ_{max} are found as *0.00* and *0.67*. Later, the matrix for the grey relational coefficient (ξ_{ij}) is also calculated by Eq. (16) and shown in Table 13.

Finally, by using criteria weights (W) and the matrix (ξ_{ij}), the grey relational grades (γ_i) are calculated by Eq. (17) for all the alternatives and are given in Table 14. More explanation of this computation is given below:

$$\gamma_1 = (1.00 * 0.607) + (0.38 * 0.263) + (0.47 * 0.077) + (0.57 * 0.053) = 0.773$$

As seen in the table, the ranking is found as {Concept *A-Concept C – Concept B – Concept D*}.

F-PROMETHEE II for ranking: First, the vector of criteria weights (W) and fuzzy decision matrix ($\tilde{X}$) using the TFNs from Table 7 are given to the alternatives with respect to all the criteria; *cost, risk, quality* and *green* as shown in Table 15. Moreover, the values of *s* in the table indicate a maximum as each criterion is maximum with the value of *s* being equal to *5*. For example, if the alternatives *Concept A, Concept B, Concept C* and *Concept D* are evaluated in

Table 12. Distance between reference value and each comparison value

Criteria Alternatives	Cost	Risk	Quality	Green
Concept A	0.000	0.552	0.375	0.253
Concept B	0.333	0.400	0.565	0.000
Concept C	0.502	0.000	0.000	0.100
Concept D	0.667	0.552	0.194	0.552

Table 13. Matrix of grey relational coefficient

Criteria Alternatives	Cost	Risk	Quality	Green
Concept A	1.00	0.38	0.47	0.57
Concept B	0.50	0.46	0.37	1.00
Concept C	0.40	1.00	1.00	0.77
Concept D	0.33	0.38	0.63	0.38

Table 14. Final weights for the green concept alternatives through F-GRA

Criteria Alternatives	Grade (γ_i)	Ranking
Concept A	0.773	1
Concept B	0.506	3
Concept C	0.624	2
Concept D	0.371	4

terms of the criterion *Cost*, using the TFNs, the fuzzy values {(7.0, 8.0, 9.0), (4.0, 5.0, 6.0), (2.0, 3.5, 5.0), (1.0, 2.0, 3.0)} are respectively obtained.

Later, the fuzzy decision matrix is converted into the crisp decision matrix by Eq. (18) as shown in Table 16. With respect to the crisp decision matrix in Table 16, the aggregated preference matrix for *P1 (Concept A, Concept B)* is shown in Table 17.

The Gaussian criterion function is chosen for all the criteria where the parameter *s* for each criterion is the value of 5. To show the calculation steps of how the values in Table 17 are obtained, the following example can be given as follows: If the alternative *Concept A* is compared with the alternative *Concept B*, the related the values $x_1,\ y_1$ for *P1 (Concept A, Concept B)* are calculated using the data in Table 16 by Eq. (20) and Eq. (21) given below:

$$x_1 = 8.00 - 5.00 = 3.00, y_1 = 1 - e^{\left(-\left(x_1^2\right)/\left(2*s^2\right)\right)} = 1 - e^{\left(\frac{-3.000^2}{2*5^2}\right)} = 0.1647, z = \sum_{i=1}^{4} w_1 * y_1$$
$$= 0.10338$$

In addition, the z value is found after determining all the values of $x_i,\ y_i$ for $P_i\,(i = 1, 2, 3, 4)$ as the number of the concept alternatives. The results of all the elements are given in Table 18.

Criteria Value	Cost Max.	Risk Max.	Quality Max.	Green Max.
s	5	5	5	5
Weight	0.607	0.263	0.077	0.053
Concept A	(7.0, 8.0, 9.0)	(2.0, 3.5, 5.0)	(2.0, 3.5, 5.0)	(5.0, 6.5, 8.0)
Concept B	(4.0, 5.0, 6.0)	(4.0, 5.0, 6.0)	(1.0, 2.0, 3.0)	(8.0, 9.0, 10.0)
Concept C	(2.0, 3.5, 5.0)	(8.0, 9.0, 10.0)	(5.0, 6.5, 8.0)	(7.0, 8.0, 9.0)
Concept D	(1.0, 2.0, 3.0)	(2.0, 3.5, 5.0)	(4.0, 5.0, 6.0)	(2.0, 3.5, 5.0)

Table 15. Fuzzy decision matrix for the green concept selection for F-PROMETHEE II

Criteria Value	Cost Max.	Risk Max.	Quality Max.	Green Max.
s	5	5	5	5
Weight	0.607	0.263	0.077	0.053
Concept A	8.000	3.500	3.500	6.500
Concept B	5.000	5.000	2.000	9.000
Concept C	3.500	9.000	6.500	8.000
Concept D	2.000	3.500	5.000	3.500

Table 16. Decision-making matrix after indexing

Pairwise comparison	w_i	x_i	y_i	z
P1 (Concept A, Concept B)	0.607	3.000	0.1647	0.10338
P2 (Concept A, Concept B)	0.263	−1.500	0.0000	
P3 (Concept A, Concept B)	0.077	1.500	0.0440	
P4 (Concept A, Concept B)	0.053	−2.500	0.0000	

Table 17. Calculation steps of each element of aggregated preference index matrix for P1 (Concept A, Concept B)

Later, by using the aggregated preference index matrix, the positive, negative and net outranking flows for each alternative are calculated by Eq. (22–24) and presented in Table 19. As seen in the table, the best alternative is *Concept A* and the ranking is found as {Concept *A*-*Concept C*–*Concept B*–*Concept D*}.

5. Comparative analysis of three F-MCDM methods in concept selection

In this section, a comparative analysis of the three F-MCDM methods, F-PROMETHEE II, F-TOPSIS and F-GRA, on green concept selection using the case study is carried out. Based on the case study in Section 4, Table 20 shows the numerical results of the three MCDM methods corresponding to the rankings of the green concept alternatives. As seen in the table, all the methods produce the same rankings {Concept *A*-*Concept C*–*Concept B*–*Concept D*} regardless of various technical background and evaluation approaches.

Let us discuss some of the foundational and structural background of the three F-MCDM methods in terms of normalization methods, distance metrics, aggregation functions, defuzzification methods, uncertainty and other issues, such as time complexity computational time, simplicity, number of mathematical calculations and stability.

(1) *Normalization:* It is a function to eliminate the element units so all the elements become dimensionless ranging from 0 to 1. Various normalization methods can be used by any MCDM. For example, the GRA uses linear normalization function, as the TOPSIS uses vector one. The main difference between two normalization methods is that the results of linear normalization does not depend on the original units of the data, as vector normalization cannot be independent from the evaluation unit.

Table 18.
Aggregated preference index matrix

Alternatives	Concept A	Concept B	Concept C	Concept D
Concept A	0	0.10338	0.20215	0.31154
Concept B	0.01780	0	0.02776	0.13562
Concept C	0.13440	0.09767	0	0.16713
Concept D	0.00339	0.01268	0.00000	0

Table 19.
Outranking flow indices and rank through F-PROMETHEE II

Alternatives	Concept A	Concept B	Concept C	Concept D
$\varnothing^+$	0.61707	0.18118	0.39919	0.01607
$\varnothing^-$	0.15559	0.21373	0.22990	0.61429
$\varnothing$	0.46148	−0.03255	0.16929	−0.59822
Ranking	1	3	2	4

Table 20.
Comparison of the numerical results of the three F-MCDM methods

Alternatives	F-TOPSIS (CI_i)	F-GRA (γ_i)	F-PROMETHEE II $\varnothing(A_i)$
Concept A	0.702 (1)	0.773 (1)	0.46148 (1)
Concept B	0.434 (3)	0.506 (3)	−0.03255 (3)
Concept C	0.501 (2)	0.624 (2)	0.16929 (2)
Concept D	0.044 (4)	0.371 (4)	−0.59822 (4)

Although, in literature, several normalization methods have been introduced, here both of them, linear and vector normalization methods were used for F-GRA and F-TOPSIS to determine whether any of these methods affect the ranking of the green alternatives. The results are presented in Table 21.

As seen in the table, the ranking changes in both the F-GRA and the F-TOPSIS with linear and vector normalization methods. In this case, it can be said that under the conditions for this case study, selecting the normalization method is critical of ranking at these methods.

(2) *Distance metrics:* It is a numerical description of how far apart two points are from each other. This metrics is used by the MCDM methods to determine how far a solution is from optimality. The TOPSIS uses the distance of a solution from positive and negative ideal solutions, as the GRA uses only the distance from an ideal solution. The TOPSIS and GRA methods use the Euclidean distance metric, the results are shown in Table 20 by Eq. (15). Moreover, the TOPSIS has been used with other distance metrics, especially with city-block (Manhattan) distance metrics (Banaeian *et al.*, 2018). On the other hand, in this study, the effect of different distance metrics with both methods are investigated; and the results are given in Table 22. As seen in the table, although the CI values in the F-TOPSIS are not similar, and the same results are obtained in the F-GRA under different distance metrics Euclidean and City-block (Manhattan), the rankings do not change in either of the methods.

(3) *Aggregation functions:* There are different aggregation functions used by MCDM methods to represent the reference points (Banaeian *et al.*, 2018). These functions for F-AHP, F-PROMETHEE II, F-TOPSIS and F-GRA are seen in Eq. (3, 11, 17, 21). The TOPSIS does not consider the relative importance of distances from the best to worst solutions, as a main drawback of the method.

(4) *Defuzzification methods:* MCDM methods use different defuzzification methods to mainly convert a fuzzy number to a crisp value. In this study, for the F-PROMETHEE II method, two different methods, the weighted defuzzification method ($(l, m, u) = (l + 2m + u)/4$) and centroid defuzzification method ($(l, m, u) = (l + m + u)/3$) by Eq. (18) are used to see whether a defuzzification method plays an important role on the final ranking. The results are given in Table 23.

Table 21. Results from F-TOPSIS and F-GRA under different normalization methods

Alternatives	Vector normalization F-TOPSIS rank	Vector normalization F-GRA rank	Linear normalization F-TOPSIS rank	Linear normalization F-GRA rank
Concept A	0.702 (1)	0.834 (1)	0.675 (2)	0.773 (1)
Concept B	0.434 (3)	0.783 (2)	0.688 (1)	0.506 (3)
Concept C	0.501 (2)	0.500 (3)	0.452 (3)	0.624 (2)
Concept D	0.044 (4)	0.359 (4)	0.072 (4)	0.371 (4)

Table 22. Results from F-TOPSIS and F-GRA under different distance metrics

Alternatives	Euclidean metric F-TOPSIS rank	Euclidean metric F-GRA rank	City-block (Manhattan) metric F-TOPSIS rank	City-block (Manhattan) metric F-GRA rank
Concept A	0.702 (1)	0.773 (1)	0.702 (1)	0.773 (1)
Concept B	0.434 (3)	0.506 (3)	0.433 (3)	0.505 (3)
Concept C	0.501 (2)	0.624 (2)	0.499 (2)	0.624 (2)
Concept D	0.044 (4)	0.371 (4)	0.044 (4)	0.371 (4)

As seen in the table, although the $\varnothing(A_i)$ values in the F-PROMETHEE II are partly dissimilar, and different defuzzification methods are used in the F-PROMETHEE II, the same ranking results are obtained. In short, applying each of the defuzzification methods does not change the ranking alternatives.

(5) *Uncertainty:* In case any uncertainty exists in the judgments of a DM related to qualitative variables, the parameters of the TFN (a, b, c) need to be selected in a way to better represent the linguistic terms. That is why, the fuzzy logic theory is utilized to overcome this difficulty by minimizing the effects of imprecise data. In looking at the methods in this study, only the F-GRA method defines situations with no available information as black and those with perfect information as white. Although neither of these kinds of situations might ever occur in reality, the F-GRA method addresses a situation with partly available information (Banaeian *et al.*, 2015). As a result of this, an integrated approach by combining fuzzy logic and the GRA methods can be used to handle both incomplete information and problem ambiguities.

Other issues are also discussed next. The F-TOPSIS does not impose any restrictions on the number of alternatives or criteria in the concept evaluation process, as the F-AHP imposes a limitation of them. Because, if the number of criteria and alternatives increases more than *nine* specified by Saaty (1981), a human evaluator cannot comprise human judgments and consistency (Lima *et al.*, 2014). Lima *et al.* (2014) also make suggestions that F-TOPSIS is a better choice when having a number of alternatives and criteria. Compared to the other methods, F-GRA and F-PROMETHEE II, F-GRA shows the best performance and no limit to their numbers because its computational steps are relatively simple. All the methods allow the aggregation of judgments with multiple DMs. Although the four methods support group decision-making, because of the impact on time complexity, F-GRA is preferable as these methods use different amounts of data required by each. On the other hand, the methods F-PROMETHEE II, F-TOPSIS and F-GRA require the same amount of data for ranking the green concept alternatives, as only the F-AHP needs less data because it is used to weight evaluation criteria. In addition, even if the same number of judgments are needed for three methods, the computational complexity may change according to Banaeian *et al.*, 2015. As seen in Table 20, the F-GRA method produces the same results in less time complexity, and the final ranking can be reached in smaller numbers of computational steps (Banaeian *et al.*, 2015).

Moreover, Wang *et al.* (2013) compared the following MCDM methods: AHP, TOPSIS, GRA and PROMETHEE II in terms of *computational time, simplicity, mathematical calculations involved* and *stability*. They also concluded that all the methods are *moderate* and *medium* in terms of *mathematical calculations involved* and *stability*. Furthermore, in terms of *simplicity*, except for the AHP, which is *very critical*, the others are *moderately critical*. Moreover, the AHP with *very high*, and PROMETHEE II with *high computational time*, the remaining two methods are *moderate*. Finally, it is revealed that in all aspects, based on the studies of Wang *et al.* (2013) and Banaeian *et al.*, 2015, the GRA clearly outperforms the other methods. This proves its universal applicability and flexibility as an effective MCDM tool in solving complex decision-making problems.

Table 23. Results from F-PROMETHEE II under different defuzzification methods

Alternatives	Weighted defuzzification approach	Centroid defuzzification approach
Concept A	0.46148 (1)	0.47021 (1)
Concept B	−0.03255 (3)	−0.03255 (3)
Concept C	0.16929 (2)	0.16929 (2)
Concept D	−0.59822 (4)	−0.60695 (4)

6. Conclusions

The designing and manufacturing environmental-friendly products in a product design process has been a vital issue for many companies which take account of reflecting environmental issues in their product design and meeting standards of recent green guidelines. These companies have utilized these guidelines by following special procedures at the design phase. Along the design process consisting of various steps, the environmental issues have been considered an important factor in the end-of-life of products since it can reduce the impact on nature. In the stage of developing a new product with the aim of environment-friendly design, the green thinking should be incorporated as early as possible in the process. On the other hand, green concept evaluation has been a critical milestone in a product design environment in transition leading to design and management of more environmentally sustainable concepts. Most modeling efforts on the issue of green concept evaluation are based on the integration of fuzzy logic and conventional MCDM methods. The objective of the research was to propose a F-AHP based F-MCDM approach to green concept selection problem through F-PROMETHEE II, F-TOPSIS and F-GRA methods. As the F-AHP is used to weight evaluation criteria, the other methods are respectively used for ranking the concept alternatives and determine the best concept alternative.

Furthermore, the case study was inspired by the previous work of the author, which was realized in a hot runner systems manufacturer, used in injection molding systems in Canada. In an NPD process, the back-and front-ends of development efforts mainly determine the following criteria: *cost, risk, quality* and *green* as used in this paper. The case study showed that the three fuzzy MCDM methods reach the same ranking outcomes. F-GRA has a better time complexity compared to the other two methods and used a smaller number of computational steps. Moreover, a comparative analysis of the three F-MCDM methods, F-PROMETHEE II, F-TOPSIS and F-GRA, are used in ranking for green concept alternatives using the numerical results of the case study. For the case study, as seen in Table 20, the three F-MCDM methods produced the numerical results on the rankings of the green concept alternatives as follows: {Concept *A-Concept C–Concept B–Concept D*}. Moreover, the incorporation of fuzzy set theory into these methods was discussed on a real-life case study, and a comparative analysis was done using its numerical results in which the three fuzzy-based methods revealed the same outcomes (or rankings), while F-GRA requires fewer computational steps.

The motivation and contribution of this paper lies on a comparative analysis through a case study in which the well-known MCDM methods F-AHP, F-TOPSIS, F-GRA and F-PROMETHEE II are used together for the green concept evaluation problem. The numerical results of the case study are used to do a comparative analysis to compare the performances of the three F-MCDM methods for the related problem in terms of the normalization methods, distance metrics, aggregation functions, defuzzification methods, time complexity and other issues, as F-AHP is only used for weighting evaluation criteria.

On the other hand, the F-MCDM methods have the following limitations: For instance, the result (or ranking) of any method depends on the judgments of a DM. The possibility of bias of the DM to any particular alternative cannot be easily managed as especially in the F-AHP because inconsistency value might lead to wrong results.

Inclusion of environmental-related criteria into the concept selection problem has been gaining increasing importance in the last decade. Therefore, to facilitate necessary calculations in applying each method, especially with its fuzzy extension, a knowledge-based (KB) or an expert system (ES) can be developed to help the DMs make the required calculations of each method and interpret its results with a detailed analysis. In addition, for future studies, these proposed methods in this work can be extended to Pythagorean fuzzy uncertain environments (i. e. Pythagorean fuzzy interactive Hamacher power aggregation operators, Pythagorean fuzzy interaction power Bonferroni mean aggregation operators) and other fuzzy approaches.

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