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Green supplier selection using multi-criterion decision making under fuzzy environment: A case study in automotive industry

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ABSTRACT

In the past few decades, it has been widely observed that environmental awareness is continuously increasing among people, stakeholders, and governments. However, rigorous environmental rules and policies pushed organizations to accept affirmative changes like green supply chain management practices in their processes of the supply chain. Selection of green supplier is a tedious task and comprises a lot of challenges starting from evaluation to their final selection, which is experienced by supplier management professionals. The development and implementation of practical decision-making tools that seek to address these challenges are rapidly evolving. In the present work, the evaluation of a set of suppliers is primarily based on both conventional and environmental criteria. This work proposes a multi-criteria decision making (MCDM) based framework that is used to evaluate green supplier selection by using an integrated fuzzy Analytical Hierarchy Process (AHP) with the other three techniques namely MABAC ("Multi-Attributive Border Approximation Area Comparison"), WASPAS ("Weighted Aggregated Sum-Product Assessment") and TOPSIS ("Technique for order preference by similarity to ideal Solution"). Initially, six green supplier selection environmental criteria (Environmental management system, green image, staff environment training, eco-design, pollution control, and resource consumption) and three conventional criteria (price, quality and service level) have been identified through literature review and expert's opinions to employ MCDM approach. A real-world case study of the automotive industry in India is deliberated to exhibit the proposed framework applicability. From AHP findings, 'Environment management system', 'Pollution control', 'Quality', and 'Green image' have been ranked as the topmost four green supplier selection criteria. Besides, the consistency test was performed to check the uniformity of the expert's input whereas the 'robustness' of the approach was tested by performing sensitivity analysis. The results illustrate that the applied fuzzy hybrid methods reach common green supplier rankings. Moreover, out of the four green supplier's alternatives, supplier number 'one' got the highest rank. This shows that the applied models are robust in nature. Further, this study relinquishes a single platform for the selection of green supplier under fuzzy environment. The applied methodology and its analysis will provide insight to decision-makers of supplier selection. It may aid decision-makers and the procurement department not only to differentiate the significant green supplier selection criteria but also to assess the most efficient green supplier in the supply chain in the global market.

1. Introduction

Selection of potential supplier has been acknowledged as one of the critical issues that an organization faces while maintaining a strategically competitive position. Supplier selection (SS) has a direct effect on both profitability and cash flow. Traditionally, SS was primarily considered on the basis of economic aspect but from the last two decades, organizations are becoming much more concerned over environmental protection issues. Due to increasing awareness on environmental issues and environmental regulatory mandates, both private and public sectors are facing tremendous pressure to consider environmental aspects in their supply chain practices (Gharaei, Karimi, & Hoseini Shekarabi, 2019b; Hao, Helo, & Shamsuzzoha, 2018; Rabbani, Foroozesh, Mousavi, & Farrokhi-Asl, 2019). The combination of environmental concerns with supply chain management (SCM) practices is termed as "green supply-chain-management" (G-SCM) (Sarkis, 2012). G-SCM practices in the SCM network results in higher competitiveness and economic performance (Dubey, Gunasekaran, Sushil, & Singh, 2015).

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According to Lee and Ou-Yang (2009) organizations cannot simply neglect the environmental issues to survive in the global market. In order to gain competitive advantage internationally, organizations are adopting the environmental aspects in their operation and supply chain practices (Gharaei, Karimi, & Shekarabi, 2019c). However, while managing environmental drift the organizations not only focus on greening the intra- organizational supply chain operations but they also need to equally concentrate on the inter-organizational aspects (Fahimnia, Sarkis, Choudhary, & Eshragh, 2015; Kusi-Sarpong, Bai, Sarkis, & Wang, 2015). As stated by Hussey and Eagan (2007), small organizations are unaware of how environmental enhancements can provide much more improvement in their business efficiency, reduce overall costs and help them to surge organizations profits.

SCM comprises of different stages from raw material purchase to the end-user product delivery (Gharaei, Hoseini Shekarabi, & Karimi, 2019a.). These stages require proper selection of supplier among many considering the need and expectations of the organization. Therefore, organizations need to go beyond their boundaries to look at the performance of their suppliers in order to meet high quality and environmental standards (Bai & Sarkis, 2010). The business environment is characterized as a highly volatile, competitive and dynamic market (Hoseini Shekarabi, Gharaei, & Karimi, 2018). For these challenges organizations regularly implement numerous programs and regulatory checks in their SCM practices to ensure better performance from their suppliers (Awasthi, Chauhan, & Goyal, 2010; Kuo, Hong, & Huang, 2010).

Hence, it can be believed that the selection of a potential supplier is a complex decision making procedure with the goal of reducing the preliminary set of suppliers to the final choices. A high degree of uncertainty is associated with these decision-making processes. Therefore, various Multi-criteria decision making (MCDM) techniques have been developed in the last few years to address these challenges. MCDM techniques used in the research consider both qualitative and quantitative factors for the assessment of a set of suppliers. Conventional supplier selection was based predominantly on criteria such as price, delivery time, quality and level of service (Banaeian, Mobli, Nielsen, & Omid, 2015; Choi, 2013; Weber, Current, & Benton, 1991). The majority of literature is available where supplier selection was based on conventional criteria. However, there is limited literature dedicated to green supplier evaluation (Handfield, Walton, Sroufe, & Melnyk, 2002; Humphreys, Wong, & Chan, 2003; Lee, Kang, Hsu, & Hung, 2009; Noci, 1997).

In view of the above discussion by exhaustively reviewing the literature, the following objectives are identified for the presented case study:

- Understand and identify the evaluation criteria for Green supplier selection (GSS) in the supply chain context;
- Determine the relative weights of the GSS evaluation criteria;
- Select the most potential green supplier from a set of alternatives in the supply chain and;
- Propose the managerial implications of the proposed work.

In order to achieve these objectives, this research is focused on evaluating the set of suppliers on the basis of both conventional and environmental criteria. The ranking and selection of the best potential supplier have been done using three prevalent MCDM methods namely MABAC ("Multi-Attributive Border Approximation Area Comparison"), WASPAS ("Weighted Aggregated Sum-Product Assessment") and TOPSIS ("Technique for order preference by similarity to ideal Solution") integrated with fuzzy set theory. However, the criteria weights are calculated by applying the extended form of Chang (1996) fuzzy AHP method.

The rest part of this paper is presented as follows. Section 2 demonstrates a detailed literature review of various evaluating criteria and provides a description of different models applied by various researchers in diverse fields of supplier selection. Section 3 primarily covers the different models applied to the case study attempted in this work. A numerical illustration is presented in Section 4, which offers a comprehensive technical explanation of the selected methods. Here, we get a closer look on the importance of Fuzzy Set Theory (FST) in the process of decision making. Additionally, consistency and sensitivity tests are employed to check the uniformity of experts input and robustness of the model. Various normalization processes are also applied to check the validity of the obtained results. Further, the managerial implications of the proposed work are discussed in Section 5. Further, presentation and discussion of the results along with directions for forthcoming work are well-depicted in Section 6.

2. Literature review

It was observed by Govindan, Khodaverdi, and Jafarian (2013) that GSS requires a combination of conventional supplier selection approaches and practices with the environmental criteria. SCM consists of several stages from raw-material procurement to final product delivery and in every stage, there is a need for a potential supplier. The most significant decision-making problem confronted by the department of purchase in supply chain operations is the proper evaluation and appropriate selection of vital suppliers which meets primary business objectives and needs. SS must satisfy multiple business criteria's and provides a competitive edge to either lessen costs, improve the quality or diminish adverse environmental effects (Wang Chen, Chou, Luu, & Yu, 2016).

2.1. Criteria selection

According to Weber et al. (1991), from 1966 through 1990, the majority of literature primarily considered capacity, cost, quality and delivery as the most essential criteria in SS. Whereas (Banaeian et al., 2015; Büyüközkan & Çifçi, 2012; Chen, Tseng, Lin, & Lin, 2010), considered both environmental and traditional criteria for selection of green supplier (GSS). Table 1 offers a list of shortlisted criteria that are determined by literature review and interviewing experts. Besides, Table 2 provides a brief description of various GSS evaluation criteria considered by numerous researchers in different fields.

Traditional approaches were limited to economic aspects, but customer awareness, strict environmental policies, eco-friendly technology and globalization of business forced organizations to add environmental aspects in their supply chain operations (Amindoust, Ahmed, Saghafinia, & Bahreininejad, 2012; Kazemi, Abdul-Rashid, Ghazilla, Shekarian, & Zanoni, 2018; Rabbani, Hosseini-Mokhallesun, Ordibazar, & Farrokhi-Asl, 2018).

In the given case study of green supplier selection, the criteria α_1 and α_7 are treated as cost criteria whereas others are considered as benefit criteria during the analysis process. The flow chart of the GSS process is presented in Fig. 2.

2.2. Model selection

FST has the ability to handle impreciseness in expert's inputs, therefore FST integrated with MCDM methods, is commonly applied to solve complex decision-making problems. Govindan, Rajendran, Sarkis, and Murugesan (2015), pointed out that in supplier selection a large number of modeling effort is predominantly based on the integration of traditional MCDM techniques with fuzzy concepts.

By reviewing various literature on MCDM problems it can be visualised that to solve decision-making problems under consideration, every technique has certain limitations and advantages. Their main restriction is that the generated solutions are generally tradeoff among the multiple objectives and are not the optimal ones due to the nature of

Table 1
Literature review summary of evaluation criteria.

Criteria	Zhu, Sarkis, and Lai (2007)	Lee et al. (2009)	Awasthi et al. (2010)	Shen et al. (2013)	Tseng, Wang, Chiu, Geng, and Lin (2013)	Bali, Kose, and Gumus (2013)	Govindan et al. (2013)	Chen, Wu, and Wu (2015)	Wang (2015)	Tsai et al. (2016)	Wang Chen et al. (2016)	Banaeian et al. (2015)	Sharma, Chandna, and Bhardwaj (2017)	Dos Santos, Godoy, and Campos (2019)	Yucesan, Mete, Serin, Celik, and Gul (2019)
Eco- design	√	√	√	√	√	√	√			√	√		√	√	
Green Image		√	√	√		√	√	√		√	√			√	
Environmental-management system	√		√	√	√	√	√	√		√	√	√		√	
Resource consumption	√	√		√			√	√			√			√	
Pollution control			√	√	√	√	√		√	√	√		√	√	
Staff environment- training.							√								
Price/Cost	√							√	√			√			√
Quality	√	√						√	√			√			√
Service level					√	√						√		√	√

the problem. Whereas, the major benefit is their ability to take into consideration the incommensurable, multi-dimensional, conflicting and uncertain effects of decisions explicitly. (Awasthi & Omrani, 2019).

There are large numbers of studies reporting the use of various models for decision-making problems in different research areas. This has been broadly divided into four categories as:

1. **Independent models**: Under this category model are qualitative in nature. These models select a limited and countable number of predetermined alternatives through multiple attributes or criteria. Some of the important models in this category are: Mathematical Analytical model – (Lin, Lin, Yu, & Tzeng, 2010), VIKOR- (Chen & Wang, 2009), TOPSIS- (Saen, 2010), AHP- (Levary, 2008), ELECTRE- (Sevkli, 2010), ANP- Sayyadi & Awasthi, 2018a, 2018b) etc.
2. **Mathematical programming model**: In this category models optimize the tradeoff and interaction among different factors of interest by considering constraints and different issues like logistic costs, single or multiple sourcing and discount (Sanayei, Mousavi, & Yazdankhah, 2010). Some of the important models in this class are linear programming- (Lin, Chen, & Ting, 2011), Non-linear Programming- (Hsu, Chiang, & Shu, 2010), Goal Programming- (Kull & Talluri, 2008), etc.
3. **AI-models**: In this category, models are based on computer-aided systems that in one way or another can be trained by expert or historic data, however, the complexity of the system is not suitable for enterprises to solve the issue efficiently without high capability in advanced computer programs (De Boer, Labro, & Morlacchi, 2001). Some of the important models in this class are: Neural-network – (Lee & Ou-Yang, 2009), Grey system theory- (Li, Yamaguchi, & Nagai, 2007; Wu, 2009), Support vector machine - (Guo, Yuan, & Tian, 2009), Genetic algorithm- (Yeh & Chuang, 2011).
4. **Hybrid models:** Under this category to gain the advantage of different models, authors usually integrate more than one method and apply them in their decision-making issues. Some of the important models in this class are (AHP + TOPSIS) – (Jain, Sangaiah, Sakhuja, Thoduka, & Aggarwal, 2018), (Entropy + Fuzzy-TOPSIS) – Mavi, Goh, & Mavi, 2016), (DEMETAL + Fuzzy-MABAC)- (Pamučar & Ćirović, 2015) etc.

Qualitative models are highly reliant on the opinion of decision-makers and numerical scaling methodology. However, quantitative models are dependent on the mathematical descriptive models that customs the numerical measurable indicators and are majorly based on data. Whereas hybrid models combine the quantitative and qualitative techniques leveraging their individual advantages (Sayyadi & Awasthi, 2018a, 2018b).

A brief literature review summary is presented in Table 3, where a list of researchers who applied decision-making models in a different industry for the common purpose to solve the SS problem is presented. It helps to formulate a new and better way to solve decision-making problems among different models.

By reviewing literature, it is observed that AHP and ANP are more commonly used methods for weight calculation; few have applied the combination of these models to rank the potential suppliers. Limited number of literature used optimization techniques like particle swarm optimization-Xu and Yan (2011) and few applied stochastic programming and dempster-shafter theory of evidence-Wu (2009).

A brief amount of studies provides comparative analysis among more than two decision-making techniques – Banaeian et al. (2015), compared fuzzy-(TOPSIS, VIKOR, GREY) method and explains the time complexity among three methods. Anojkumar, Ilangkumaran, and Sasirekha (2014) compared four hybrid techniques viz; Fuzzy-AHP with VIKOR, Fuzzy-AHP with TOPSIS, Fuzzy-AHP with PROMTHEE and Fuzzy-AHP with ELECTRE and proposed model for material selection. In this presented paper, integrated fuzzy methods such as Fuzzy -AHP

Table 2
Description of shortlisting criteria for evaluation and selection of green suppliers (Awasthi et al., 2010; Banaeian et al., 2015; Shen et al., 2013).

Criteria	Name of criteria	Description
α_1	Resource consumption (RL)	Resource consumption in terms of raw material, water and energy during the measurement period
α_2	Staff environment training (SET)	Staff training based on environmental targets.
α_3	Service level (SL)	On-time delivery, after-sales service and supply capacity
α_4	Eco-design (ED)	Product design for lessening the consumption of energy/material, products design for reuse, recycle, material recovery, product design to reduce or avoid the use of hazardous
α_5	Green Image (GI)	The ratio of green customers to total customers.
α_6	Environmental management system (EMS)	Environmental certifications such as ISO 14000, environmental policies, environmental objectives, checking and control of environmental activities
α_7	Price/cost (P/C)	Product/service price, capital and financial power
α_8	Pollution control (PC)	Pollution Control measures and actives to reduce pollutant air emission, wastewater, harmful materials, and Solid Waste
α_9	Quality (Q)	Quality of material, labor expertise, and operational excellence

with MABAC, Fuzzy -AHP with WASPAS, and Fuzzy- AHP with TOPSIS are used. The suggested approach will greatly help in comparative analysis and validation of results.

3. Methodology

3.1. Fuzzy set theory

Preferences, as well as judgments of humans, are often uncertain, ambiguous and subjective in nature and its exact numerical value cannot be estimated. If fuzziness or uncertainty of human decision making is not taken into consideration, the outcomes may be misleading (Shen, Olfat, Govindan, Khodaverdi, & Diabat, 2013).

Zadeh (1965) first introduced the concept of FST, within the process of decision making in order to map linguistic variables to numerical variables. Bellman and Zadeh (1970) proposed a fuzzy-MCDM methodology with manipulated fuzzy sets to sort out the deficiency of accurateness in allocating weights and rating alternatives against evaluating criteria. The logical tools on which the individuals rely on, considered being generally the outcome of bivalent logic, i.e. (true/false, yes/no). While the problems that pose in the human's real-life situation and the problem-solving human's approaches and thoughts are of no means bivalent. (Tong & Bonissone, 1980).

Conventionally as bivalent logic is based on classic sets, similarly the fuzzy logic is based on fuzzy sets. A fuzzy set is a set of objects in which there is no predefined or clear-cut boundary between the objects that are or are not members of the set. A fuzzy set is characterized by a membership function, which assigns to each element a grade of membership within the interval [0, 1], where '0' indicates the minimum membership function and '1′ as the maximum membership whereas the rest value between 1 and 0 indicates 'partial' degree of membership (Bevilacqua, Ciarapica, & Giacchetta, 2006).

The concept of FST has been notably carried out via decision-makers (DM's) to resolve complicated decision-making problems that consist of several alternatives and criteria in a productive, consistent and systematic way (Carlsson & Fullér, 1996; Wang & Chang, 2007). Due to vague information associated with the parameter in selecting suppliers, FST was considered as one of the major tools to model vague preferences into a mathematically precise way (Sanayei et al., 2010). It handles imprecise information and uncertainty with the aim to find the overall best rating supplier.

A multi-objective linear model is developed by Amid, Ghodsypour, and O'Brien (2006) to succeed in dealing with vague information. Chen and He (1997) combines the MCDM TOPSIS method with FST and introduced a model to solve the MCDM problem.

3.1.1. Definitions and operations associated with triangular fuzzy numbers (TFN's)

Definition 1. A triangular fuzzy number [TFN's] ($\widetilde{\widetilde{n}}$) denoted by triplet ($l_a$, m_b, u_c), is a fuzzy number, where [l_a-lower, m_b-middle, u_c-upper]. The graphical presentation is displayed in Fig. 3 in terms of membership function ($\mathscr{U}_{\widetilde{\widetilde{n}}}$) and is interpreted as:

$$(\mathscr{U}_{\widetilde{\widetilde{n}}}) = \begin{cases} \frac{\mathscr{X}-l_a}{m_b-l_a}; & \text{for } l_a \le \mathscr{X} \le m_b \\ \frac{\mathscr{X}-u_c}{u_c-m_b}; & \text{for } m_b \le \mathscr{X} \le u_c \\ 0; & \text{otherwise} \end{cases} \quad \text{(i)}$$

Definition 2. Let $\widetilde{\widetilde{\mathscr{X}_1}} = (l_{a_1}, m_{b_1}, u_{c_1})$ and $\widetilde{\widetilde{\mathscr{X}_2}} = (l_{a_2}, m_{b_2}, u_{c_2})$ are the two fuzzy-triangular no.'s, their mathematical operations associated with these no.'s are as follows:

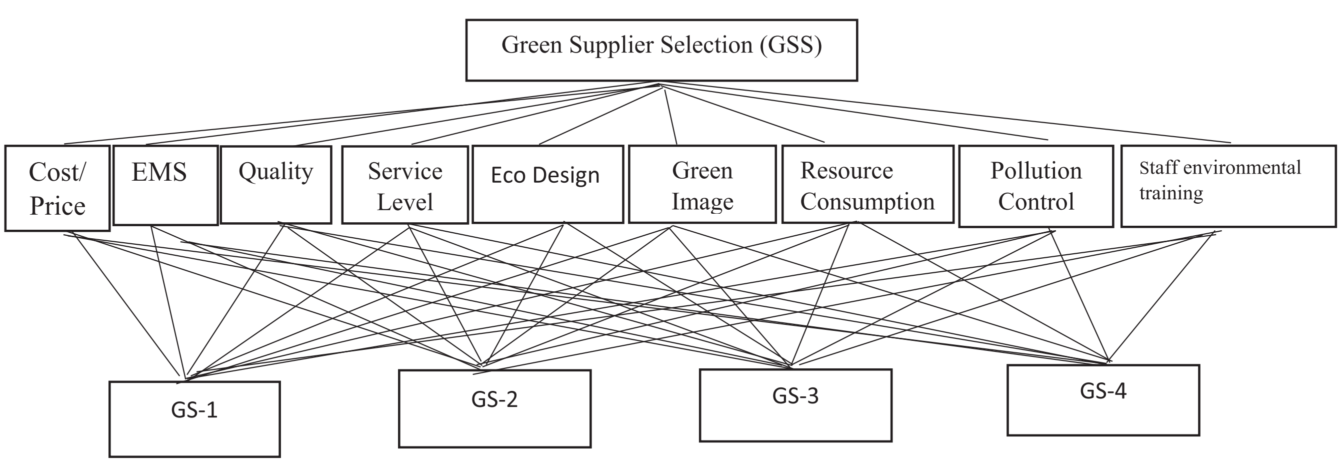

Fig. 1. AHP hierarchy for the Green supplier selection problem.

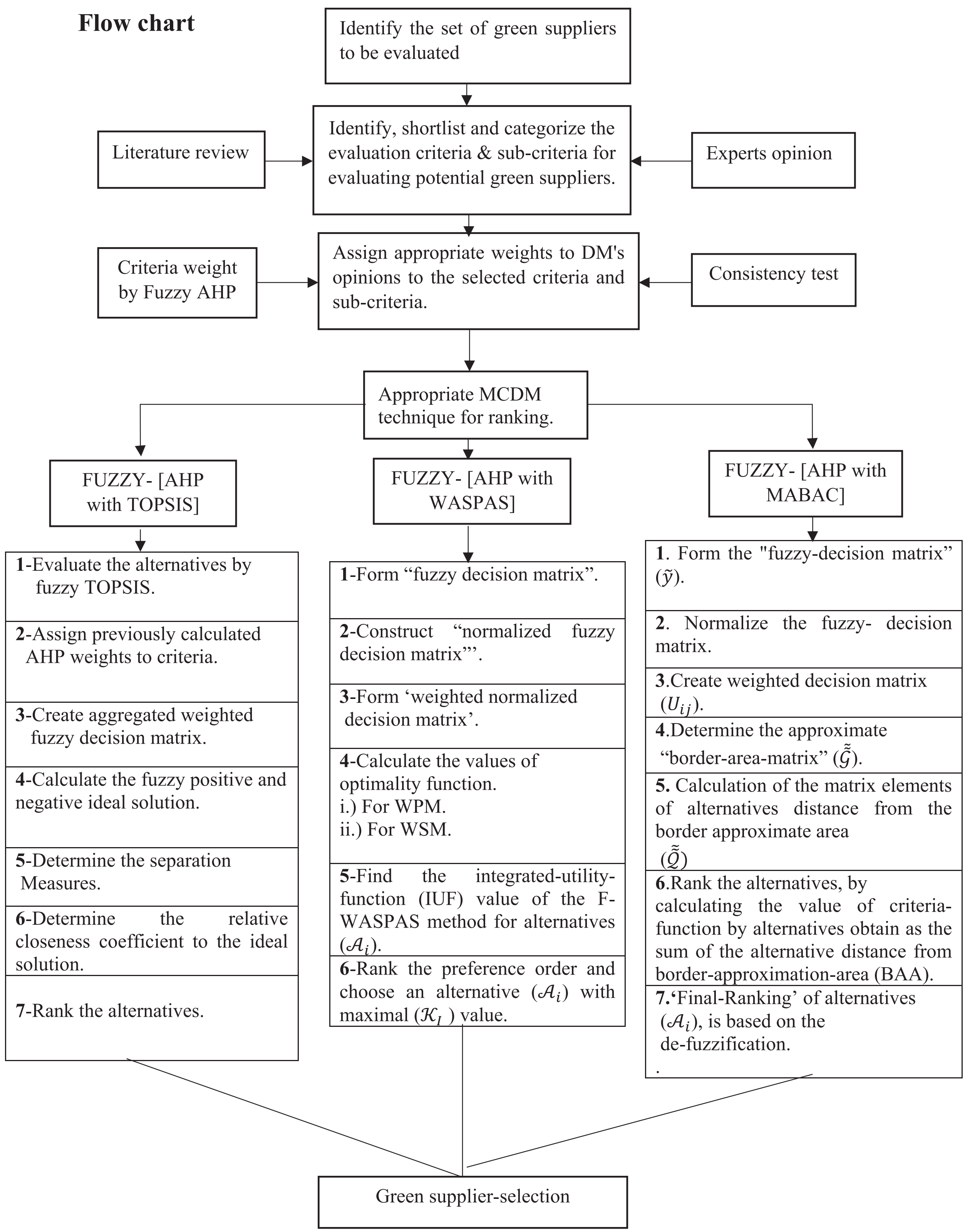

Fig. 2. Flow chart of GSS process.

Table 3
Literature review of various MCDM methods for supplier selection in different industries.

Author	Year	Technique	Industry
Farzad and Aidy	2008	AHP	Manufacturing
Kirytopoulos, Leopoulos, and Voulgaridou	2008	ANP	Pharmaceutical
Önüt, Kara, and Işik	2009	Fuzzy (ANP +TOPSIS)	Telecom
Kuo, Hong, and Huang	2010	Neural network	Semiconductor
Lin et al.	2010	ANP	Electronics
CT Lin et al	2011	ANP+ TOPSIS+ Linear programming	illustrative example
Karimi Azari	2011	Fuzzy-TOPSIS	Construction
Liao and Kao	2011	Fuzzy TOPSIS+ MCGP	illustrative example
Büyüközkanand and Çifçi	2012	Fuzzy (DEMATEL+ANP +TOPSIS)	Automobile
Anojkumar, Ilangkumaran, and Sasirekha	2014	FAHP-TOPSIS, FAHP-VIKOR, FAHP-ELECTRE, FAHP-PROMTHEE	Sugar
Azadi, Jafarian, Saen, and Mirhedayatian	2015	Fuzzy DEA	Petrochemical
Aksoy, Sucky, and Öztürk	2014	AN-FIS	Illustrative example
Hashemi, Karimi, and Tavana	2015	ANP + GREY Relational	Automobile
Paul	2015	FIS	Illustrative example
Dotoli, Epicoco, Falagario, and Sciancalepore	2015	DEA	Health-care
Galankashi, Helmi, and Hashemzahi	2016	Fuzzy AHP	Automobile
Trapp and Sarkis	2016	Integer Programming	Illustrative example
Gupta and Barua	2017	BWM + Fuzzy TOPSIS	S &ME
Nallusamy, Sri Lakshmana Kumar, Balakannan, and Chakraborty	2016	Fuzzy AHP +ANN	Manufacturing
Jain et al.	2018	Fuzzy AHP +TOPSIS	Automobile
Banaeian et al.	2015	F-TOPSIS, F-VIKOR, F-GREY	Agri-food
Liu	2018	ANP+DEMATEL + Game Theory	Illustrative example
Fu	2019	AHP+ARAS + Goal-Programming	Airline
Percin	2019	Fuzzy SWARA + fuzzy AD	Manufacturing

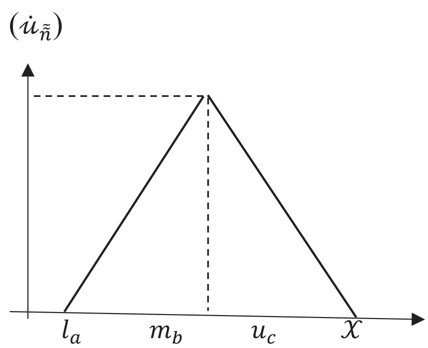

Fig. 3. Illustration of Fuzzy-Triangular number $\widetilde{\mathcal{X}} = (l_a, m_b, u_c)$.

(1) 'Addition' of two TFN's:

$$(\widetilde{\mathcal{X}_1} \oplus \widetilde{\mathcal{X}_2}) = (l_{a_1}, m_{b_1}, u_{c_1}) \oplus (l_{a_2}, m_{b_2}, u_{c_2}) = [(l_{a1} \oplus l_{a2}), (m_{b1} \oplus m_{b2}), (u_{c1} \oplus u_{c2})] \quad \text{(ii)}$$

(2) 'Subtraction' of two TFN's:

$$(\widetilde{\mathcal{X}_1} \ominus \widetilde{\mathcal{X}_2}) = (l_{a_1}, m_{b_1}, u_{c_1}) \ominus (l_{a_2}, m_{b_2}, u_{c_2}) = [(l_{a1} \ominus l_{a2}), (m_{b1} \ominus m_{b2}), (u_{c1} \ominus u_{c2})] \quad \text{(iii)}$$

(3) 'Multiplication' of two TFN's:

$$(\widetilde{\mathcal{X}_1} \oplus \widetilde{\mathcal{X}_2}) = (l_{a_1}, m_{b_1}, u_{c_1}) \oplus (l_{a_2}, m_{b_2}, u_{c_2}) = [(l_{a_1} \oplus l_{a_2}), (m_{b_1} \oplus m_{b_2}), (u_{c_1} \oplus u_{c_2})] \quad \text{(iv)}$$

(4) 'Division' of two TFN's:

$$(\widetilde{\mathcal{X}_1} / \widetilde{\mathcal{X}_2}) = (l_{a_1}, m_{b_1}, u_{c_1}) / (l_{a_2}, m_{b_2}, u_{c_2}) = [(l_{a1}/u_{c2}), (m_{b1}/m_{b2}), (u_{c1}/l_{a2})] \quad \text{(v)}$$

Definition 3. Distance between two fuzzy no.'s:

Let $\widetilde{\mathcal{X}_1} = (l_{a_1}, m_{b_1}, u_{c_1})$ and $\widetilde{\mathcal{X}_2} = (l_{a_2}, m_{b_2}, u_{c_2})$ be the two fuzzy-triangular no.'s, the distance between these are defined by the 'Vertex Method' (Chen, 2000).

Table 4
Linguistic variables for the rating.

Linguistic variables	TFN's
Very Poor (VP)	(0,0,1)
Poor (P)	(0,1,3)
Medium poor (MP)	(1,3,5)
Fair (F)	(3,5,7)
Medium good (MG)	(5,7,9)
Good (G)	(7,9,10)
Very good (VG)	(9,10,10)

Source: Wang and Elhag (2006).

$$d(\widetilde{\mathcal{X}_1}, \widetilde{\mathcal{X}_2}) = \sqrt{\frac{1}{3}[(l_{a1} \ominus l_{a2})^2 + (m_{b1} \ominus m_{b2})^2 + (u_{c1} \ominus u_{c2})^2]} \quad \text{(vi)}$$

Definition 4. *De-fuzzify the fuzzified values*:

Let $\widetilde{\mathcal{X}} = (l_a, m_b, u_c)$ represents fuzzy no's. The fuzzy no's can de-fuzzify by expression (vii), (viii) as proposed by Seiford (1996).

$$\text{De} - \text{fuzzify } (\widetilde{\mathcal{X}_i}) = \frac{1}{3}[(u_c \ominus l_a) + (m_b \ominus l_a)] \oplus l_a; \quad \text{(vii)}$$

$$\text{De} - \text{fuzzify } (\widetilde{\mathcal{X}_i}) = \frac{1}{2}[\lambda.\ u_c \oplus m_b \oplus (1 \ominus \lambda).\ l_a]; \quad \text{(viii)}$$

In AHP, an aggregated pairwise comparison matrix is constructed among the considered criteria for their weight calculation. Supplier ratings are obtained in linguistic terms from decision-makers based on various criteria (refer to Table 5). The linguistic variables for this study are chosen and converted into TFN's as per the Table 4.

Further, the integrated fuzzy decision matrix, $(\tilde{y})$ is derived from table 5 using the table 4. Each element value of matrix, $(\tilde{y})$ is formed by synthesizing fuzzy rating values by using equation (ix).

$$\tilde{y}_{ij} = \frac{1}{k}[\tilde{y}_{ij}^{\,1} + \tilde{y}_{ij}^{\,2} + \cdots + \tilde{y}_{ij}^{\,n}]; \quad \text{(ix)}$$

where, k = no. of experts; n = no. of alternates (suppliers), m = no. of criteria and j = (1.,2.,……m), i = (1.,.,., n).

The expression in equation (x), *represents the integrated fuzzy decision matrix*:

Table 5
Linguistic ratings of the suppliers by decision-makers w.r.t various criteria.

	DM1				DM2				DM3			
	GSS1	GSS 2	GSS 3	GSS4	GSS1	GSS2	GSS3	GSS4	GSS1	GSS2	GSS3	GSS4
α_1	F	MG	F	MG	F	G	MG	G	G	G	MG	MG
α_2	G	MG	G	F	MG	MG	MG	F	F	MG	G	MG
α_3	F	MP	G	G	MG	F	F	G	MG	F	MG	MG
α_4	MG	MG	G	MG	G	MG	G	F	MG	G	F	F
α_5	VG	G	F	F	VG	G	G	MG	G	MG	MG	G
α_6	G	MG	G	MP	F	F	G	F	G	MG	F	G
α_7	MP	F	MG	G	F	F	MG	MP	MP	G	G	F
α_8	MG	MG	F	F	G	G	F	MG	G	MG	G	VG
α_9	MG	F	MG	F	MG	MG	G	G	G	F	MG	F

Table 6
[TOPSIS] Integrated Matrix.

	GSS1	GSS2	GSS4	GSS4
α_1	(4.33,6.33,8.00)	(6.33,8.33,9.66)	(4.33,6.33,8.33)	(5.66,7.67,9.33)
α_2	(5.00,7.00,8.66)	(5.00,7.00,9.00)	(6.33,8.33,9.67)	(3.67,5.67,7.67)
α_3	(4.33,6.33,8.33)	(2.33,4.33,6.33)	(5.00,7.00,8.67)	(6.33,8.33,9.67)
α_4	(5.66,7.66,9.33)	(5.66,7.66,9.33)	(5.67,7.67,9.00)	(3.67,5.67,7.67)
α_5	(8.33,9.66,10.0)	(6.33,8.33,9.67)	(5.00,7.00,8.67)	(5.00,7.00,8.67)
α_6	(5.66,7.66,9.00)	(4.33,6.33,8.33)	(5.67,7.67,9.00)	(3.67,5.67,7.33)
α_7	(1.66,3.66,5.66)	(4.33,6.33,8.00)	(5.67,7.67,9.33)	(3.67,5.67,7.33)
α_8	(6.33,8.33,9.66)	(5.66,7.66,9.33)	(4.33,6.33,8.00)	(5.67,7.33,8.67)
α_9	(5.66,7.66,9.33)	(3.66,5.66,7.67)	(5.67,7.66,9.33)	(4.33,6.33,8.00)

$$\tilde{y} = \begin{bmatrix} \tilde{y}_{11} & \cdots & \tilde{y}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{y}_{m1} & \cdots & \tilde{y}_{mn} \end{bmatrix} \quad (x)$$

After following this procedure, the integrated fuzzy decision matrix, ($\tilde{y}$) *is obtained and the same is presented in* Table 6. *This matrix will be used in supplier ranking in TOPSIS procedure.*

3.1.2. Introducing fuzzy AHP method

Chang (1996) proposed the popular extended form of widely accepted AHP method. In this paper, the extended form of the AHP method is applied, to determine the weights of the evaluation criteria. It combines widely applied FST with the AHP method. The traditional basic AHP method is not capable to handle the vagueness of human judgments. Whereas fuzzy AHP an improved form of AHP is able to handle this issue. AHP for the GSS problem is presented in Fig. 1.

Let the triangular fuzzy number (TFN) is represented by

$$\widetilde{\mathscr{X}}_i^j = (l_{aj}, m_{bj}, u_{cj}) \ \ where \ \ j = (1, 2, \cdots, m)$$

The complete process can be described in 4 steps.

Step 1: Calculate the value of "fuzzy synthetic extent" Z_i, w.r.t the i^{th} criteria given by expression (1) (Chang, 1996).

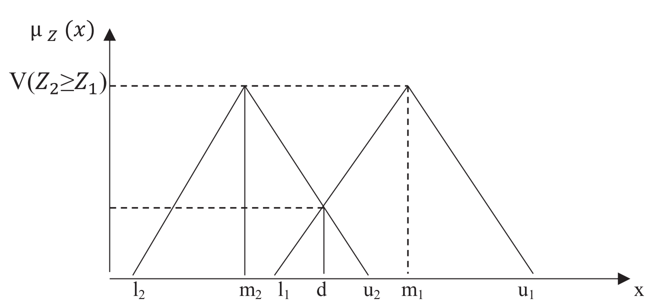

Fig. 4. The Interaction between Z_1 and Z_2. Source: Kutlu and Ekmekçioğlu (2012).

$$Z_i = \sum_{j=1}^{n} \widetilde{\mathscr{X}}_i^j \left(\sum_{i=1}^{n} \sum_{i=1}^{m} \widetilde{\mathscr{X}}_i^j \right)^{-1} \quad (1)$$

Step 2: Find the degree of possibility of $Z_b \geq Z_a$, based on the given conditions in Eq. (2),

$$V(Z_b \geq Z_a) = \begin{cases} 1, & if \ \ m_{b1} \geq m_{b2}; \\ 0, & if \ \ l_{a1} \geq u_{c2}; \\ \frac{(l_{a2} - u_{c1})}{(m_{b1} - u_{c1}) - (m_{a2} - l_{a2})}, & \text{otherwise} \end{cases} \quad (2)$$

Step 3: For convex fuzzy number, the degree of possibility should be more than 'k' convex fuzzy number $Z_i(\imath = 1, 2, \cdots, k)$ and is given by expression (3):

$$\mathscr{V}(Z_i \geq Z_1, Z_2, \cdots, Z_k) = \min \mathscr{V}(Z_b \geq Z_a) = \omega(Z_i); \quad (3)$$

$$d''(A_i) = \min \mathscr{V}(Z_i \geq Z_k), \ where \ \ k \neq i; \ and \ \ (k = 1, 2, \cdots, n)$$

The weight vector can be presented by expression (4) below asFig. 4:

$$(\mathscr{W}''=(d''(A_1), (d''(A_2), \cdots, (d''(A_n)\Big)^T \quad (4)$$

Step 4: By performing the normalization process, we obtain the normalized weight vectors and it is defined by expression (5):

$$W = (d(A_1), d(A_1), \cdots\cdots, d(A_1))^T \quad (5)$$

where W denote the non-fuzzy number.

3.1.3. Introducing fuzzy TOPSIS method

Hwang and Yoon (1981) introduced the MCDM TOPSIS method, the concept behind TOPSIS is predominantly focused on "relative closeness to ideal solution", i.e. the elected alternatives should have the shortest geometrical distance from the positive ideal solution ('PIS') and the farthest geometrical distance from the negative ideal solution ('NIS').

The procedure of TOPSIS is explained in the following steps:

Step 1: The fuzzy normalized decision matrix ($\tilde{R}$ normalized) can be represented as-

$$\tilde{R}\text{normalized} = [\tilde{r}\text{ij}]\text{m*n} \quad (6)$$

Normalized fuzzy decision matrix ($\tilde{R}$ normalized) is obtained as explained in expression (6)

The normalization process is performed in a fuzzy decision matrix ($\tilde{y}$) by using Eqs. (7) and (8) (Chen, 2000).

$$\tilde{r}_{ij} = \left(\frac{l_{aij}}{u_{cj}^*}, \frac{m_{bij}}{u_{cj}^*}, \frac{u_{cij}}{u_{cj}^*} \right), \text{j} \in \text{B}; \quad (7)$$

$$\tilde{r}_{ij} = \left(\frac{l_{aj}^-}{u_{cij}}, \frac{l_{aj}^-}{m_{bij}}, \frac{l_{aj}^-}{l_{aij}} \right), \text{j} \in \text{C}; \quad (8)$$

where $u_{cj}^* = \max_i u_{cij}$, j ∈ B ; $l_{aj}^- = \min_i l_{aij}$, j ∈ C;

C denotes sets of Cost criteria;
and B denotes sets of Benefit criteria.

Step 2: Weighted Decision Matrix (U_{ij}) is obtained by computing the product of a fuzzy normalized decision matrix ($\widetilde{R}$normalized) with the calculated weights of the criteria ($\widetilde{W}_{ij}$).

$$U = [U_{ij}]_{mn}; \tag{9}$$

where j = (1,2,3…,n); i = (1,2,3…,m) and $\widetilde{\mathscr{W}_i}$ denotes the weight of the jth criterion or attribute.

Step 3: Both fuzzy positive (PIS, B^+) and fuzzy negative ideal solution (NIS, B^-) are calculated as – (Büyüközkan & Çifçi, 2012; Chen, 2000).

$$B^+ = (U_1^+, U_2^+, \cdots, U_n^+);$$

$$B^- = (U_1^-, U_2^-, \cdots, U_n^-);$$

where $U_j^+ = \{(1, 1, 1); U_j^- = \{(0, 0, 0)\}; j = (1, 2, \cdots, n);$

Step 4: Each alternative distance from (PIS, B^+) and (NIS, B^-) is calculated as:

$$d_i^+ = \sum_{j=1}^{n} d_u(U_{ij}, U_j^+), \ i = 1, 2, 3\cdots\cdots m; \tag{10}$$

$$d_i^- = \sum_{j=1}^{n} d_u(U_{ij}, U_j^-), \ i = 1, 2, 3\cdots\cdots m; \tag{11}$$

Step 5: Considering these calculated distances values in step 4, the value of closeness coefficient (Ci) is calculated for each alternative as-

$$C_i = \frac{(d_i^+)}{(d_i^+) + (d_i^-)}; \tag{12}$$

Step 6: Finally, by comparing the Ci values for each alternative the best alternative is determined with the highest closeness coefficient (Ci) value i.e. the alternative ($\mathscr{A}_i$) closer to the **F-PIS (B^+)** and farther from **F-NIS (B^-)** w.r.t others as the best alternative with highest (Ci) value.

3.1.4. Introducing fuzzy WASPAS method:

Zavadskas, Turskis, Antucheviciene, and Zakarevicius (2012) introduced the WASPAS ("Weighted Aggregated Sum-Product Assessment method") method. Later, WASPAS-IFIV, as WASPAS modification introduced by Zavadskas, Antucheviciene, Hajiagha, and Hashemi (2014). The integrated model of FST with WASPAS was introduced by Turskis, Zavadskas, Antucheviciene, and Kosareva (2015), to solve the construction site selection problem.

WASPAS is based on two aggregated models-

Weighted-sum model (WSM): The fundamental concept behind this technique is based on the determination of the overall score of alternatives ($\mathscr{A}_i$) as a weighted-sum of attribute values.

Weighted-product model (WPM): This concept is developed to circumvent the alternatives ($\mathscr{A}_i$) with poor-attribute values. Each alternative ($\mathscr{A}_i$) score is determined as the product of scale rating of each attribute to a power equal to the importance of weight $\left(\widetilde{\mathscr{W}_i}\right)$ of the attribute (Easton, 1973; Lashgari, Antuchevičienė, Delavari, & Kheirkhah, 2014; MacCrimmon, 1968).

Steps for Fuzzy WASPAS as follows

Step 1: Form the fuzzy decision matrix ($\widetilde{y}$).

Step 2: Formulate "Normalized fuzzy decision matrix" ($\widetilde{R}_{normalized}$), it is defined as:

$$\widetilde{R}_{normalized} = [\widetilde{r}_{ij}]_{m.n}$$

where $C_\alpha \rightarrow$ denotes sets of Cost criteria.;
and $B_\alpha \rightarrow$ denotes sets of Benefit Criteria.

In order to form the normalized fuzzy decision matrix ($\widetilde{R}$ normalized). The normalization for fuzzy decision matrix ($\widetilde{y}$) is done using Eqs. (2) and (3).

Step 3: (i) For WSM, determine the Weighted Decision Matrix ($\widehat{X}q$)-

$$\widetilde{X}_q = \begin{bmatrix} \widehat{X}11 & \cdots & \widehat{X}1n \\ \vdots & \ddots & \vdots \\ \widehat{X}1m & \cdots & \widehat{X}mn \end{bmatrix}; \widehat{X}_{ij} = (\widetilde{r}_{ij}) \times (\widetilde{\mathscr{W}_i}); j = (1, 2, \cdots .n); \ and \ \ i = (1, 2, \cdots .m); \tag{13}$$

(ii) For WPM, determine "Weighted normalized fuzzy decision matrix"($\widehat{X}p$)-

$$\widehat{X}p = \begin{bmatrix} \widehat{\widetilde{X}}11 & \cdots & \widehat{\widetilde{X}}1n \\ \vdots & \ddots & \vdots \\ \widehat{\widetilde{X}}1m & \cdots & \widehat{\widetilde{X}}mn \end{bmatrix}; \widehat{\widetilde{X}}_{ij} = \widetilde{r}_{ij}^{\widetilde{\mathscr{W}_i}} \tag{14}$$

Step 4: Calculate the values of optimality function:

(i) For each alternative, according to the WSM;

$$\widetilde{\mathscr{Q}_i} = \sum_{j=1}^{n} \widehat{X}ij; \ i = 1, 2, \cdots .m; \tag{15}$$

(ii) For each alternative, according to the WPM;

$$\widetilde{\mathscr{P}_i} = \prod_{j=1}^{n} \widehat{\widetilde{X}}ij; \ i = 1, 2, \cdots .m; \tag{16}$$

The fuzzy numbers $\widetilde{\widetilde{Q}}_i$ and $\widetilde{\mathscr{P}_i}$ are the result of fuzzy- performance measurement for each alternative.

For de-fuzzification, the "center of area" method is easier and the most practical to apply.

$$\mathscr{Q}_{i\,[defuzzification]} = \frac{1}{3}(\mathscr{Q}_{ia} + \mathscr{Q}_{ib} + \mathscr{Q}_{ic}); \tag{17}$$

$$\mathscr{P}_{i\,[defuzzification]} = \frac{1}{3}(\mathscr{P}_{ia} + \mathscr{P}_{ib} + \mathscr{P}_{ic}); \tag{18}$$

Step 5: The value of an integrated utility function (IUF) for an alternative ($\mathscr{A}_i$) can be determined as:

$$\mathscr{K}_I = \lambda \sum_{J=1}^{n} \mathscr{Q}_I + (1 - \lambda) \sum_{J=1}^{n} \mathscr{P}_I; \ \lambda = 0, ..,1; \ 0 \le \mathscr{K}_I \le 1, \tag{19}$$

In Eq. (19), λ value is determined based on the hypothesis that "total of all alternatives WSM scores" must be equal to the "total of WPM scores":

$$\lambda = \frac{\sum_{i=1}^{n} \mathscr{P}_i}{\sum_{i=1}^{m} \mathscr{Q}_i + \sum_{i=1}^{m} \mathscr{P}_i}; \tag{20}$$

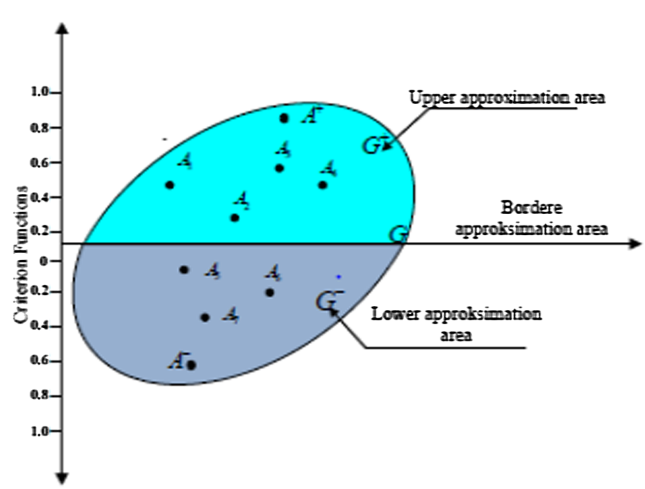

Fig. 5. Exhibition of the border [$\widetilde{\mathscr{G}}$], lower [$\widetilde{\mathscr{G}}^-$], and upper [$\widetilde{\mathscr{G}}^+$] approximation areas. Source: (Bozanic, Tešić, & Milićević, 2018).

Step 6: Rank the preference order and choose an alternative ($\mathscr{A}_i$) with the highest obtained "$\mathscr{K}_I$" value.

3.1.5. Introducing fuzzy MABAC method

Pamučar and Ćirović (2015), developed the popular MABAC method. This decision-making method is focused on defining the "distance of the criteria function of each observed alternative from the border approximate area". Fig. 5, exhibits the border [$\widetilde{\mathscr{G}}$], lower [$\widetilde{\mathscr{G}}^{-}$], and upper [$\widetilde{\mathscr{G}}^{+}$] approximation areas. However, modification of the MABAC method has been done from time to time by several researchers. Xue, You, Lai, and Liu (2016) proposed an interval-valued intuitionistic fuzzy MABAC approach. Peng and Yang (2016), developed "Pythagorean Fuzzy-Choquet Integral (CI)" based MABAC Method. The modified MABAC approach with interval type-2 fuzzy numbers was developed by Roy, Ranjan, and Kar (2016) and Yu, Wang, and Wang (2017). MABAC method was further extended by (Roy, Chatterjee, Bandyopadhyay, & Kar, 2018) using rough numbers. The mathematical formulation and implementation of fuzzified MABAC technique are presented in simple seven steps.

Step 1: Form the fuzzy-decision matrix ($\tilde{y}$), and alternatives ($\mathscr{A}_i$) are represented by Vectors.

Step 2: Obtain the normalized decision matrix (21) by normalization process using Eqs. (22) and (23).

$$\tilde{r}ij = \begin{pmatrix} \tilde{r}11 & \cdots & \tilde{r}1n \\ \vdots & \ddots & \vdots \\ \tilde{r}1m & \cdots & \tilde{r}mn \end{pmatrix}; \widetilde{R}normalized = [\tilde{r}ij]m*n; \tag{21}$$

$$\tilde{r}ij = \frac{y_{ij} - y_i^{-}}{y_i^{+} - y_i^{-}}, j \in B; \tag{22}$$

$$\tilde{r}ij = \frac{y_{ij} - y_i^{+}}{y_i^{+} - y_i^{-}}, j \in C; \tag{23}$$

Here, B and C denote sets of benefit and cost criteria respectively; y_{ij}, y_i^{-}andy_i^{+} denotes the elements of fuzzy-decision matrix ($\tilde{y}$).

$y_i^{+} = \max\,(y_{1r}, y_{2r}, \cdots, y_{mr})$, shows the max-values of the 'right distribution of fuzzy-numbers' of the observed criterion by alternatives ($\mathscr{A}_i$).

$y_i^{-} = \min\,(y_{1l}, y_{2l}, \cdots..,y_{ml})$, shows the min-value of 'left distribution of the fuzzy-numbers' of observed criteria by alternatives ($\mathscr{A}_i$).

Step 3: Obtain the Weighted Decision Matrix (U_{ij}), which is the product of the normalized decision matrix ($\widetilde{R}$ normalized) and the weights of the criteria ($\widetilde{W}_{ij}$). The resultant product is added with the weight$\widetilde{\mathscr{W}}_i$

$$U = \begin{pmatrix} U_{11} & \cdots & U_{1n} \\ \vdots & \ddots & \vdots \\ U_{m1} & \cdots & U_{mn} \end{pmatrix}; U = [U_{ij}]_{m.n}, i = (1, 2, \cdots m); \tag{24}$$

where $\left[Uij = \tilde{r}ij.\ \widetilde{\mathscr{W}}_i + \widetilde{\mathscr{W}}_i \right]$, and $\widetilde{\mathscr{W}}_i$ denotes the weighted coefficient of (j[th]) attribute or criterion.

Step 4: Using Eq. (25), determine the approximate border area matrix ($\widetilde{\mathscr{G}}$).

$$\tilde{\tilde{g}}_i = \lfloor \prod_{j=1}^{m} U_{ij} \rfloor^{1/m}; \tag{25}$$

In Eq. (25) 'm' symbolizes the total number of alternatives ($\mathscr{A}_i$) and 'Uij' as the weighted decision matrix elements calculated at step 3. After determining the expression (25), develop the border approximate area matrix of dimension (n × 1); where 'n' denotes the total number of criteria by which selection is made from the alternatives offered. i.e. ($\widetilde{\mathscr{G}}$).

α1,α2……,αn

$$\widetilde{\mathscr{G}} = [\tilde{\tilde{g}}_1, \tilde{\tilde{g}}_2, \cdots..\tilde{\tilde{g}}_n \tag{26}$$

Step 5: Determination of distances of the matrix elements of alternative from border-approximate-area $\left(\widetilde{\mathscr{Q}}\right)$.

$$(\widetilde{\mathscr{Q}}) = \begin{pmatrix} \widetilde{\mathscr{q}}_{11} & \cdots & \widetilde{\mathscr{q}}_{1n} \\ \vdots & \ddots & \vdots \\ \widetilde{\mathscr{q}}_{m1} & \cdots & \widetilde{\mathscr{q}}_{mn} \end{pmatrix}; \tag{27}$$

Alternatives distance from BAA matrix $\left(\widetilde{\mathscr{q}}_{ij}\right)$can be calculated by evaluating the difference between the elements of the weighted decision matrix (U) (Eq. (24)) and the values of "border-approximate areas" ($\widetilde{\mathscr{G}}$) (Eq. (26)) and is given by expression as -

$$\widetilde{\mathscr{Q}} = U - \widetilde{\mathscr{G}} \tag{28}$$

Alternatives ($\mathscr{A}_i$) value can lie in one of the two portions of the BAA matrix $\left(\widetilde{\mathscr{G}}\right)$. The area at the upper portion of the border approximate area (Upper approximate area ($\widetilde{\mathscr{G}}^{+}$) represents the area where the ideal alternatives ($\mathscr{A}_i^{+}$)is found. Similarly, lower portion of border-approximate-area (Lower-approximate-area ($\widetilde{\mathscr{G}}^{-}$) represents the area where anti ideal- alternatives ($\mathscr{A}_i^{-}$) is found as shown in Fig. 5.

Belonging of alternative ($\mathscr{A}_i$) to the approximation area ([$\widetilde{\mathscr{G}}^{+}$], [$\widetilde{\mathscr{G}}$] and [$\widetilde{\mathscr{G}}^{-}$]) is calculated using equation (29)

$$(\mathscr{A}_i) \in \begin{cases} \widetilde{\mathscr{G}}^{+})if\ \widetilde{\mathscr{q}}_{ij} > 0 \\ \widetilde{\mathscr{G}}\ \ )if\ \widetilde{\mathscr{q}}_{ij} = 0 \\ \widetilde{\mathscr{G}}^{-})if\ \widetilde{\mathscr{q}}_{ij} < 0 \end{cases} \tag{29}$$

The best-chosen alternative ($\mathscr{A}_i$), from the set must be associated with as many as possible criteria of the upper approximation-area $\left(\widetilde{\mathscr{G}}^{+}\right)$.where as $\widetilde{\mathscr{q}}_{ij} \in \widetilde{\mathscr{G}}^{+}$ indicates the closeness of alternative from the ideal-alternative.

Similarly, $\widetilde{\mathscr{q}}_{ij} \in \widetilde{\mathscr{G}}^{-}$ indicates the alternative closeness from the anti-ideal alternative.

Step 6: Alternatives ($\mathscr{A}_i$) ranking can be done by calculating criteria function values for the alternatives ($\mathscr{A}_i$) as the sum of the alternative distance from border-approximation-area (BAA). Adding up all the matrix $\left(\widetilde{\mathscr{Q}}\right)$ elements per rows, the overall value of the criteria function of alternatives can be calculated as-

$$\widetilde{\mathscr{S}}_i = \sum_{j=1}^{n} \widetilde{\mathscr{q}}_{ij}; i = 1, 2\cdots, m; j = 1, 2, \cdots.., n; \tag{30}$$

where m → number of alternatives and n → number of criteria.

Step 7: After calculating $\widetilde{\mathscr{S}}_i$ value at step (6), the final ranking of alternatives ($\mathscr{A}_i$) can be done by de-fuzzifying values of ($\widetilde{\mathscr{S}}_i$) process, by using equation (vii),(viii).

4. Numerical illustration

Steps to obtain the final supplier ranking has been illustrated in this section.

Table 7
The Integrated comparison matrix of criteria (for all DM's), by taking the geometric mean.

	α1	α2	α3	α4	α5	α6	α7	α8	α9	Weight	Rank
α1	(1.00,1.00,1.00)	(0.48,0.63,1.00)	(0.69,1.00,1.44)	(0.55,0.79,1.26)	(0.30,0.44,0.79)	(0.37,0.44,0.55)	(0.34,0.40,0.48)	(0.40,0.61,0.91)	(0.63,0.87,1.14)	0.05561	9
α2	(1.00,1.58,2.08)	(1.00,1.00,1.00)	(1.00,1.59,2.08)	(0.41,0.63,1.00)	(0.46,0.63,0.87)	(0.48,0.79,1.44)	(0.69,1.00,1.44)	(0.41,0.63,1.00)	(0.63,0.69,0.79)	0.08686	7
α3	(0.69,1.00,1.44)	(0.48,0.63,1.00)	(1.00,1.00,1.00)	(0.69,1.26,2.08)	(0.41,0.63,1.00)	(0.30,0.44,0.79)	(0.69,1.00,1.44)	(0.37,0.44,0.55)	(0.61,0.91,1.59)	0.0769	8
α4	(0.79,1.26,1.82)	(1.00,1.59,2.47)	(0.48,0.79,1.44)	(1.00,1.00,1.00)	(0.63,1.10,1.65)	(0.69,0.79,1.00)	(0.44,0.69,1.14)	(0.51,0.72,1.10)	(0.61,0.91,1.59)	0.09593	6
α5	(1.26,2.29,3.30)	(1.14,1.59,2.15)	(1.00,1.59,2.47)	(0.61,0.91,1.59)	(1.00,1.00,1.00)	(0.87,1.44,2.29)	(0.40,0.61,0.91)	(0.44,0.69,1.14)	(0.48,0.79,1.44)	0.11702	4
α6	(1.82,2.29,2.71)	(0.69,1.26,2.08)	(1.26,2.29,3.30)	(1.00,1.26,1.44)	(0.44,0.69,1.14)	(1.00,1.00,1.00)	(1.26,2.29,3.30)	(0.87,1.44,2.29)	(0.87,1.44,2.29)	0.16912	1
α7	(2.08,2.52,2.92)	(0.69,1.00,1.44)	(0.69,1.00,1.44)	(0.87,1.44,2.29)	91.19,1.65,2.52)	(0.30,0.44,0.79)	(1.00,1.00,1.00)	(0.69,0.79,1.00)	(0.44,0.55,0.79)	0.10729	5
α8	(1.10,1.65,2.52)	(1.00,1.59,2.47)	(1.82,2.29,2.71)	(0.91,1.39,1.96)	(0.87,1.44,2.29)	(0.44,0.69,1.14)	(1.00,1.26,1.44)	(1.00,1.00,1.00)	(0.58,1.00,1.44)	0.15457	2
α9	(0.87,1.14,1.59)	(1.26,1.44,1.59)	(0.63,1.10,1.65)	(0.63,1.10,1.65)	(0.69,1.26,2.08)	(0.44,0.69,1.14)	(1.26,1.82,2.29)	(0.69,1.00,1.71)	(1.00,1.00,1.00)	0.13669	3

Table 8
Fuzzy synthetic extent value.

	ℓ_a	m_b	u_c	$\frac{1}{\sum_{i=1}^{n} u_{ci}}$	$\frac{1}{\sum_{i=1}^{n} m_{bi}}$	$\frac{1}{\sum_{i=1}^{n} l_{ai}}$
α1	4.764	6.173	8.58	0.0378	0.069	0.1368
α2	6.079	8.552	11.71	0.0482	0.096	0.1867
α3	5.243	7.302	10.9	0.0416	0.082	0.1737
α4	6.151	8.858	13.21	0.0488	0.100	0.2106
α5	7.198	10.91	16.29	0.0571	0.123	0.2598
α6	9.214	13.97	19.56	0.0730	0.157	0.3119
α7	7.874	10.39	14.21	0.0624	0.117	0.2265
α8	8.721	12.31	16.98	0.0691	0.138	0.2707
α9	7.477	10.56	14.7	0.0593	0.119	0.2344
Sum	62.72	89.02	126.1			

4.1. *Fuzzy AHP for weight calculation:*

Step 1: Following the procedure explained in Section 3.1.2, the integrated pairwise comparison matrix of criteria (for all DM's) is obtained and presented in Table 7.

The pairwise comparison matrix is further used to find the "fuzzy synthetic extent value" for every criterion. As mentioned earlier, the fuzzy synthetic extent is expressed as:

$$Z_i = \sum_{j=1}^{n} \widetilde{\mathscr{X}_i}^{j} \left(\sum_{i=1}^{n} \sum_{j=1}^{m} \widetilde{\mathscr{X}_i}^{j} \right)^{-1}$$

The computation of $\sum_{j=1}^{n} \widetilde{\mathscr{X}_i}^{j}$ is done in the following way:
$\alpha_1 =$
$(1 + 0.48 + 0.69 + 0.55 + 0.30 + 0.37 + 0.34 + 0.40 + 0.63;$
$1 + 0.63 + 1 + 0.79 + 0.44 + 0.44 + 0.40 + 0.61 + 0.87;$
$1 + 1 + 1.44 + 1.26 + 0.79 + 0.55 + 0.48 + 0.91 + 1.14).$
$= (4.764; 6.173; 8.58)$, etc.

Next, the expression $\left(\sum_{i=1}^{n} \sum_{i=1}^{m} \widetilde{\mathscr{X}_i}^{j}\right)$ value is calculated as-
$=(4.764;6.173;8.58)+(6.079;8.552;11.71)+(5.243;7.302;10.9)$
$+(6.11;8.858;13.21)+(7.198;10.91;16.29)+(9.214;13.97;19.6)$
$+(7.874;10.39;14.21)+(8.721;12.31;16.98)+(7.477;10.6;14.7)$
$=(62.72;\ 89.02;\ 126.1)$. $Z_i = \sum_{j=1}^{n} \widetilde{\mathscr{X}_i}^{j} \left(\sum_{i=1}^{n} \sum_{j=1}^{m} \widetilde{\mathscr{X}_i}^{j}\right)^{-1}$

Thus, $Z_1 = (4.764;\ 6.173;\ 8.58) \times (\frac{1}{126.1}; \frac{1}{89.02}; \frac{1}{62.72})$;
$= (0.0378;\ 0.069;\ 0.1368)$ etc.,

Table 8 represents the fuzzy synthetic extent value obtained by solving step-(1).

The value of degree of possibility, V in step (2) is calculated as:

$$V(Z_b \geq Z_a) = \begin{cases} 1, if m_{b1} \geq m_{b2}; \\ 0, if l_{a1} \geq u_{c2}; \\ \frac{(l_{a2} - u_{c1})}{(m_{b1} - u_{c1}) - (m_{a2} - l_{a2})}; otherwise \end{cases}$$

$$V(Z_1 > Z_2) = \left(\frac{(0.0482 - 0.1368)}{(0.069 - 0.1368) - (0.096 - 0.0482)} \right) = 0.768$$

Table 9
The normalized weight value of each criterion.

	Degree of possibility	Normalized weight
α1	0.32884614	0.05561468
α2	0.51359142	0.08685893
α3	0.45472477	0.07690335
α4	0.56725072	0.09593383
α5	0.69190514	0.11701547
α6	0.98999999	0.16912068
α7	0.63440792	0.10729154
α8	0.91396632	0.15457066
α9	0.80824511	0.13669096

Table 10
[TOPSIS] Normalized Matrix.

	GS-1	GS-2	GS-3	GS-4
α_1	(0.54,0.68,1.00)	(0.44,0.52,0.68)	(0.52,0.68,1.00)	(0.46,0.56,0.76)
α_2	(0.51,0.72,0.89)	(0.51,0.72,0.93)	(0.65,0.86,1.00)	(0.37,0.54,0.79)
α_3	(0.44,0.65,0.86)	(0.24,0.44,0.65)	(0.51,0.72,0.89)	(0.65,0.86,1.00)
α_4	(0.60,0.82,1.00)	(0.60,0.82,1.00)	(0.60,0.82,0.96)	(0.39,0.60,0.82)
α_5	(0.83,0.97,1.00)	(0.63,0.83,0.97)	(0.50,0.70,0.86)	(0.50,0.70,0.86)
α_6	(0.62,0.85,1.00)	(0.48,0.70,0.96)	(0.62,0.85,1.00)	(0.40,0.62,0.81)
α_7	(0.29,0.45,1.00)	(0.20,0.26,0.35)	(0.17,0.21,0.29)	(0.22,0.29,0.45)
α_8	(0.44,0.52,0.68)	(0.46,0.56,0.76)	(0.54,0.68,1.00)	(0.50,0.59,0.76)
α_9	(0.61,0.82,1.00)	(0.39,0.60,0.82)	(0.60,0.82,1.00)	(0.46,0.67,0.85)

$V(Z_1 > Z_3) = 0.883$; $V(Z_1 > Z_4) = 0.745$; $V(Z_1 > Z_5) = 0.600$;$V(Z_1 > Z_6) = 0.421$; $V(Z_1 > Z_7) = 0.611$;$V(Z_1 > Z_8) = 0.329$;$V(Z_1 > Z_9) = 0.611$ etc.

The weights priority is calculated as;

$d'' =$ (C1) min (0.768; 0.88; 0.75; 0.600; 0.42; 0.611; 0.329; 0.611) = 0.329;

$d'' =$ (C2) min (1; 0.976; 0.830; 0.651; 0.857; 0.514; 0.850) = 0.514; etc.

Similarly, the value of the remaining criteria are obtained

After computing the values in step (4), the weight and their normalized value of each criterion is presented in Table 9.

$W'' =$ (0.329; 0.514; 0.455; 0.568; 0.691; 1.00; 0.634; 0.913; 0.808);

$W =$ (0.0556;0.087;0.078;0.0959;0.117;0.1691;0.1072;0.1545;0.1366)

4.2. Fuzzy TOPSIS solution

Fuzzy-TOPSIS and fuzzy-WASPAS method hold a similar normalization process. The normalized fuzzy decision matrix ($\widetilde{R}$ normalized) is constructed using Eqs. (6) and (7).

For GSS, the normalized value for $\tilde{r}_{11}$ and $\tilde{r}_{21}$ is calculated as:

$\tilde{r}_{11} = \left(\frac{4.33}{8.00}, \frac{4.33}{6.33}, \frac{4.33}{4.33}\right)$; where $l_{aj}^{-} = \min_i l_{aij} = (4.33)$, **for cost criteria.**

$\tilde{r}_{11} =$ (0.54,0.68,1.00);

$\tilde{r}_{21} = \left(\frac{5.00}{9.67}, \frac{7.00}{9.67}, \frac{8.66}{9.67}\right)$; where $u_{cj}{}^{*} = \max_i u_{cij} = (9.667)$, **for benefit criteria.**

$\tilde{r}_{21} =$ (0.51,0.72,0.89);

Similar, steps are followed to calculate values of other elements; the complete normalized decision matrix is given in Table 10.

After calculating the value of each element in the normalized matrix, the subsequent step is to construct the weighted normalized matrix ($Uij = \tilde{r}ij \cdot \widetilde{\mathscr{W}_i}$ using Eq. (9). Table 8 represents the weighted normalized matrix.

By considering Eqs. (10) and (11) distance measure of altenatives from Positive (d_i^{+}) and negative ideal solution (d_i^{-}) is calculated as;

$$d_1^{+} = \sqrt{\frac{1}{3}[((1-0.031)^2 + (1-0.038)^2 + (1-0.056)^2)]} + \sqrt{\frac{1}{3}[((1-0.044)^2 + (1-0.062)^2 + (1-0.077)^2)]} + \sqrt{\frac{1}{3}[((1-0.082)^2 + (1-0.112)^2 + (1-0.136)^2)]} = 8.263$$

where $U_j^{+} = \{(1,1,1)\}$; $U_j^{-} = \{(0,0,0)\}$;

Similarly, other values are calculated, and the obtained results are shown in Table 12.

Finally, w.r.t each green supplier, the value of the closeness coefficient (Ci), is calculated using Eq. (12).

$$\text{CiforGS} - 1 = \left(\frac{8.263}{8.263 + 0.744}\right) = 0.08258$$

Based on obtained Ci value for each alternative as shown in Table 12, it can be concluded by integrated fuzzy AHP and fuzzy TOPSIS results that, GSS1 with highest coefficient index value hold rank 1, followed by GSS3, followed byGSS2 which holds rank 3 followed by GSS4 at last.

4.3. Fuzzy WASPAS solution

The fuzzy aggregated decision matrix for both fuzzy WASPAS and fuzzy TOPSIS methods are identical. The matrix is presented in Table 6. Subsequently, the weighted normalized decision matrix for both WSM and WPM is constructed. From Eq. (13) the obtained weighted normalized decision matrix for fuzzy-TOPSIS is the same as for WSM ($\widehat{X}q$) presented in Table 11.

For WPM, each element value in a "weighted normalized fuzzy decision matrix" ($\widehat{X}p$) is calculated as-

$(\widehat{X}p_{11}) = [(0.54)^{0.056}; (0.68)^{0.056}; (1.00)^{0.056})]$;

Similarly, the calculation steps for others elements will remain same. Table 13 represents the weighted normalized matrix for WPM ($\widehat{X}p$).

The optimality function value is calculated for both WSM and WPM using Eqs. (15) and (16).

For WSM, the value of optimality function for each alternative can be calculated as;

$\widetilde{\widetilde{Q}}_1 =$ (0.30 + 0.049 + 0.0345 + 0.0582 + 0.0975……0.0.0829;
0.0380 + 0.629 + 0.0504 + 0.0788…………..0.0.1122;
0.0556 + 0.0778 + 0.0663 + ………………………0.1366)

$\widetilde{\widetilde{Q}}_1 =$ (0.555, 0.7285, 0.9312);

Similarly, other values for WSM optimality function are calculated;

For WPM, the optimality function value is calculated as;

$\widetilde{\widetilde{\mathscr{P}}}_1 = (0.96 \times 0.94 \times 0.94 \times 0.953 \times 0.978 \times 0.924\ldots\ldots\ldots 0.93;$
$0.98 \times 0.97 \times 0.96 \times 0.98 \times 0.99 \times \ldots\ldots\ldots\ldots\ldots\ldots 0.97;$
$1 \times 0.99 \times 0.98 \times 1 \times 1 \times \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1)$

$\widetilde{\widetilde{\mathscr{P}}}_1 =$ (0.5359; 0.7089; 0.9236);

De-fuzzify the obtained result by using equation (17) and (18).

$$\mathscr{Q}_{1[defuzzification]} = \frac{1}{3}(0.55 + 0.728 + 0.93) = (0.7384);$$

$$\mathscr{P}_{1[defuzzification]} = \frac{1}{3}(0.535 + 0.70 + 0.923) = (0.7228);$$

By using Eq. (19), the value of integrated utility function (IUF) in fuzzy WASPAS method for an alternative ($\mathscr{A}_i$) is calculated as :

$\lambda = 0.4912$; $\mathscr{K}_1 = (0.4912*0.73) + (1–0.4912)*(0.7228) = 0.7305$.

Similarly, the value of ki can be calculated for other alternatives, Table 14 shows obtained ki values. The maximum $\mathscr{K}_I$ value defines the highest rank of alternative., by Table 14 GS-1 Ki score is highest followed by GS-3, so the ranking order by hybrid fuzzy AHP and Fuzzy-WASPAS method is as follows GS-1 > GS-3 > GS-2 > GS-4.

4.4. Fuzzy MABAC solution:

By using Eqs. (22) and (23), values in the fuzzy normalized matrix for cost criteria can be obtained as:

$$\tilde{r}_{11} = \left(\frac{8.00 - 9.677}{4.33 - 9.677}; \frac{6.33 - 8.00}{4.33 - 9.677}; \frac{4.33 - 9.667}{4.33 - 9.677}\right);$$

Thus, $\tilde{r}_{11} =$ (0.3125, 0.6250, 1.00).

Table 15 represents the normalized matrix whose values are obtained using similar steps explained previously.

For weighted normalized matrix (U_{ij}), value is calculated using Eq. (24), and is presented in Table 16.

By using Eq. (25), the border approximation area matrix of dimension (n × 1) is formed. Table 17, presents the geometric mean value, and its calculation is as follows-

Table 11
[TOPSIS] Weighted Normalized Matrix.

	GS-1	GS-2	GS-3	GS-4
α_1	(0.031,0.038,0.056)	(0.024,0.028,0.038)	(0.028,0.038,0.05)	(0.025,0.031,0.042)
α_2	(0.044,0.062,0.077)	(0.044,0.062,0.080)	(0.056,0.074,0.086)	(0.032,0.050,0.068)
α_3	(0.034,0.050,0.066)	(0.018,0.034,0.050)	(0.039,0.055,0.068)	(0.050,0.066,0.076)
α_4	(0.058,0.078,0.095)	(0.058,0.078,0.095)	(0.058,0.078,0.092)	(0.037,0.058,0.078)
α_5	(0.097,0.113,0.117)	(0.074,0.097,0.131)	(0.058,0.081,0.101)	(0.058,0.081,0.101)
α_6	(0.106,0.144,0.169)	(0.081,0.118,0.156)	(0.106,0.144,0.169)	(0.068,0.106,0.137)
α_7	(0.031,0.048,0.107)	(0.022,0.028,0.041)	(0.019,0.023,0.031)	(0.024,0.031,0.048)
α_8	(0.069,0.080,0.105)	(0.071,0.087,0.118)	(0.083,0.105,0.154)	(0.077,0.091,0.118)
α_9	(0.082,0.112,0.136)	(0.053,0.082,0.112)	(0.082,0.112,0.136)	(0.063,0.092,0.117)

Table 12
[TOPSIS] Final Analysis Result.

Alternative	d_i^+	d_i^-	Ci	Rank
GS-1	8.263	0.744	0.08258	1
GS-2	8.376	0.634	0.07036	3
GS-3	8.286	0.716	0.07957	2
GS-4	8.388	0.621	0.06884	4

$\tilde{\tilde{g}}_1$=([0.0730 × 0.0556 × 0.0695 × 0.0591]$^{\frac{1}{4}}$;

[0.090 × 0.069 × 0.090 × 0.076]$^{\frac{1}{4}}$;

[0.11 × 0.0903 × 0.112 × 0.097]$^{\frac{1}{4}}$).

Alternative distance from BAA matrix can be obtained by using Eq. (28) as

$\widetilde{\widetilde{\mathscr{Q}}}_1$ = (0.0730–0.1021; 0.0904–0.0812; 0.111–0.063);

$\widetilde{\widetilde{\mathscr{Q}}}_1$ = (−0.0291; 0.0092; 0.0473);

Similarly, other values are calculated and Table 18 represents the distance of each alternative from BAA matrix.

By Eq. (30), the overall value of criteria-function of alternatives $\widetilde{\widetilde{\mathscr{S}_i}}$,is obtained as

$\widetilde{\widetilde{\mathscr{S}_i}}$ = (−0.029 + (−0.053) + (−0.040) ………..+ (−0.069);
0.009 + 0.0006+……………………..+0.021;
0.047 + 0.053+……………………+0.109)

$\widetilde{\widetilde{\mathscr{S}_i}}$ = (−0.4982; 0.114046; 0.7107).

Table 19 presents Si value for all the four alternatives. By defuzzifying the $\widetilde{\widetilde{\mathscr{S}_i}}$ value we rank the alternative based on defuzzified Si score w.r.t each supplier. From the Table 19, it is observed that the ranks of suppliers are similar from both integrated Fuzzy AHP with fuzzy TOPSIS and fuzzy AHP with WASPAS method. Green Supplier-1 with the highest $\widetilde{\widetilde{\mathscr{S}_i}}$ value of 0.1088 holds 1 position, followed by supplier 3 and 2 with value (0.072245, −0.05921) and finally supplier 4 with the lowest $\widetilde{\widetilde{\mathscr{S}_i}}$ value (−0.0859) is ranked 4.

Table 14
[WASPAS] Final Result.

Alternatives	Qi	Pi	Ki	Rank
GS-1	0.738369	0.72281	0.730450	1
GS-2	0.625412	0.59982	0.612391	3
GS-3	0.715323	0.67765	0.696153	2
GS-4	0.613373	0.59874	0.605926	4

4.5. Consistency test

This test is performed in order to get ensure that the given expert's inputs are consistent or not (Jain et al., 2018). Consistent inputs can be defined in the matrix as the expert inputs that are neither illogical nor random. In the fuzzy-AHP method, it is recommendable to test the consistency ratio after performing the comparison (Kutlu & Ekmekçioğlu, 2012). For this, the "Graded mean integrated" method is used for the de-fuzzification process.

Let the given fuzzy-number be $\widetilde{\widetilde{\mathscr{X}}}$ =(l_a, m_b, u_c), it is converted into a crisp number by the expression (31) (Kutlu & Ekmekçioğlu, 2012).

$$P\left(\widetilde{\widetilde{\mathscr{X}}}\right) = \mathscr{X} = \frac{(l_a + 4.\ m_b + u_c)}{6} \tag{31}$$

By applying Eq. (31), each value gets deffuzified in the matrix, and consistency-ratio (C-R) value is computed and compared with the original CR value of 0.10, i.e. check the obtained value of CR is smaller than the original value of '0.10' or not. If the CR value is greater than 0.10, then the expert will be requested to re-do the portion of the questionnaire.

Values of consistency index is found out by Eq. (32):

$$(CI) = \frac{\boldsymbol{\lambda_{max}} - \mathbf{N}}{\boldsymbol{N} - 1} \tag{32}$$

CR value is calculated by dividing the consistency index value by random consistency-index value. In the presented case study, the CI value is tested for each pairwise comparison matrix and the observed CR value for each pairwise matrix is less than 0.10. Thus, Table 20 demonstrates that the obtained results are consistent in nature.

Table 13
[WASPAS] Weighted Normalized Matrix for WPM.

	GSS1	GSS2	GSS3	GSS4
α_1	(0.966,0.967,1.00)	(0.956,0.964,0.979)	(0.964,0.979,1.00)	(0.959,0.968,0.985)
α_2	(0.944,0.972,0.99)	(0.944,0.972,0.993)	(0.963,0.987,1.00)	(0.919,0.954,0.980)
α_3	(0.941,0.968,0.98)	(0.896,0.940,0.968)	(0.95,0.975,0.991)	(0.968,0.988,1.000)
α_4	(0.953,0.981,1.00)	(0.953,0.981,1.000)	(0.95,0.981,0.996)	(0.914,0.953,0.982)
α_5	(0.978,0.996,1.00)	(0.947,0.978,0.996)	(0.92,0.959,0.983)	(0.921,0.959,0.983)
α_6	(0.924,0.973,1.00)	(0.883,0.942,0.987)	(0.924,0.976,1.00)	(0.859,0.924,0.965)
α_7	(0.877,0.918,1.00)	(0.845,0.866,0.902)	(0.83,0.849,0.877)	(0.853,0.877,0.918)
α_8	(0.883,0.903,0.93)	(0.888,0.915,0.959)	(0.909,0.944,1.00)	(0.898,0.921,0.959)
α_9	(0.934,0.973,1.00)	(0.880,0.934,0.973)	(0.934,0.973,1.00)	(0.900,0.948,0.979)

Table 15
[MABAC] Normalized Matrix.

	GS-1	GS-2	GS-3	GS-4
α_1	(0.312,0.625,1.00)	(0.00,0.25,0.625)	(0.250,0.625,1.00)	(0.068,0.375,0.75)
α_2	(0.2220.556,0.833)	(0.22,0.556,0.889)	(0.444,0.778,1.00)	(0.00,0.333,0.667)
α_3	(0.27,0.545,0.818)	(0.00,0.273,0.546)	(0.364,0.636,0.86)	(0.545,0.818,1.00)
α_4	(0.352,0.705,1.00)	(0.352,0.705,1.00)	(0.358,0.706,0.94)	(0.00,0.352,0.706)
α_5	(0.667,0.932,1.00)	(0.267,0.667,0.93)	(0.000,0.40,0.733)	(0.000,0.40,0.733)
α_6	(0.375,0.751,1.00)	(0.125,0.50,0.875)	(0.375,0.751,1.00)	(0.00,0.375,0.685)
α_7	(0.478,0.739,1.00)	(0.173,0.3917,0.65)	(0.000,0.21,0.477)	(0.261,0.478,0.79)
α_8	(0.000,0.25,0.625)	(0.068,0.375,0.75)	(0.325,0.625,1.00)	(0.185,0.435,0.75)
α_9	(0.352,0.705,1.00)	(0.00,0.352,0.706)	(0.352,0.705,1.00)	(0.117,0.478,0.761)

Table 16
[MABAC] Weighted Normalized Matrix.

	GS-1	GS-2	GS-3	GS-4
α_1	(0.072, 0.090, 0.111)	(0.055, 0.069, 0.090)	(0.069, 0.090, 0.112)	(0.059, 0.076, 0.097)
α_2	(0.191, 0.135, 0.159)	(0.106, 0.135, 0.166)	(0.125, 0.154, 0.173)	(0.086, 0.115, 0.147)
α_3	(0.097, 0.115, 0.139)	(0.076, 0.093, 0.115)	(0.104, 0.125, 0.143)	(0.111, 0.132, 0.158)
α_4	(0.129, 0.169, 0.198)	(0.129, 0.169, 0.191)	(0.129, 0.163, 0.182)	(0.095, 0.129, 0.163)
α_5	(0.195, 0.226, 0.234)	(0.148, 0.195, 0.226)	(0.117, 0.168, 0.228)	(0.170 ,0.168, 0.202)
α_6	(0.235, 0.295, 0.338)	(0.190, 0.253, 0.317)	(0.235, 0.295, 0.338)	(0.169, 0.235, 0.285)
α_7	(0.158, 0.186, 0.214)	(0.125, 0.149, 0.177)	(0.107, 0.130, 0.158)	(0.135, 0.158, 0.186)
α_8	(0.154, 0.193, 0.251)	(0.164, 0.212, 0.270)	(0.202, 0.251, 0.301)	(0.183, 0.222, 0.270)
α_9	(0.184, 0.235, 0.273)	(0.136, 0.184, 0.231)	(0.184, 0.231, 0.273)	(0.152, 0.206, 0.242)

Table 17
[MABAC] Border Approximation Area Matrix.

Criteria	BAA
α_1	(0.063, 0.081, 0.102)
α_2	(0.105, 0.134, 0.153)
α_3	(0.098, 0.119, 0.138)
α_4	(0.120, 0.154, 0.182)
α_5	(0.141, 0.185, 0.216)
α_6	(0.204, 0.268, 0.318)
α_7	(0.130, 0.154, 0.183)
α_8	(0.175, 0.218, 0.274)
α_9	(0.163, 0.211, 0.254)

Table 19
[MABAC] Final Result.

Alternative	Si			Defuzzification of Si	Rank
GS-1	−0.49827	0.114046	0.710756	0.10884552	1
GS-2	−0.69687	−0.06744	0.586667	−0.0592136	3
GS-3	−0.55645	0.079933	0.693884	0.07245597	2
GS-4	−0.71222	−0.08897	0.543327	−0.0859526	4

Table 20
Consistency computation in AHP.

Items	Values
Maximum Eigen value (λ_{max})	9.3059
Consistency Index (CI)	0.0382
Random Index (RI) at n = 9	0.0880
Consistency ratio (CR)	0.4348

4.6. Sensitivity analysis

The purpose of performing sensitivity analysis (SA) in the decision-making problems is to test the consequences of the weights of criteria. Based on different scenarios obtained in analysis, it can result in changed alternative precedence. By varying the importance of criteria, if the obtained order of ranking changes, it can be referred that the obtained results are sensitive else robust in nature. SA may also offer insight to the decision-makers at the conditions where uncertainties exist in the definition of the importance of different factors. l. Interchanging of the weights of one criterion with other is done in order to know that does the exchange of weight results in a change in the precedence of alternatives (Senthil, Murugananthan, & Ramesh, 2018). In order to do so, 36 experiments were performed and the closeness coefficient (CC_j) value was obtained. Further, the radar graph is also plotted (Fig. 6b) where α.x-y denotes the weights, interchanged between criteria x and criteria y whereas else criteria weights remain unchanged.

In this case study, it can be concluded from the radar plot (6-b) and line plot (6-a) that the GS-1 alternative score has the highest score in all 36 experiments. Followed by GS-3, whereas GS-2 and GS-4 are

Table 18
[MABAC] Distance of Alternative from BAA Matrix.

	GS-1	GS-2	GS-3	GS-4
α_1	(−0.029, 0.009, 0.047)	(−0.046, − 0.011, 0.026)	(-0.032, 0.009, 0.047)	(−0.043, −0.004, 0.031)
α_2	(−0.053, 0.006, 0.053)	(−0.053, 0.006, 0.0581)	(−0.034, 0.019, 0.068)	(−0.073, −0.080, 0.039)
α_3	(−0.040, −0.007, 0.041)	(−0.061, −0.021, 0.020)	(−0.033, 0.006, 0.044)	(−0.019, 0.020, 0.055)
α_4	(−0.053, 0.009, 0.071)	(−0.053, 0.009, 0.0712)	(−0.053, 0.009, 0.065)	(−0.087, −0.024, 0.043)
α_5	(−0.021, 0.040, 0.092)	(−0.067, 0.009, 0.0850)	(−0.09, −0.021, 0.064)	(−0.099, −0.021, 0.061)
α_6	(−0.086, 0.027, 0.133)	(−0.128, −0.014, 0.112)	(−0.086, 0.020, 0.130)	(−0.149, −0.031, 0.081)
α_7	(−0.024, 0.031, 0.084)	(−0.057, −0.005, 0.046)	(−0.075, −0.024, 0.028)	(−0.047, 0.003, 0.056)
α_8	(−0.119, −0.02, 0.075)	(−0.110, −0.006, 0.095)	(−0.071, 0.032, 0.133)	(−0.090, 0.003, 0.095)
α_9	(−0.069, 0.021, 0.109)	(−0.117, −0.027, 0.069)	(−0.069, 0.021, 0.109)	(−0.101, −0.011, 0.077)

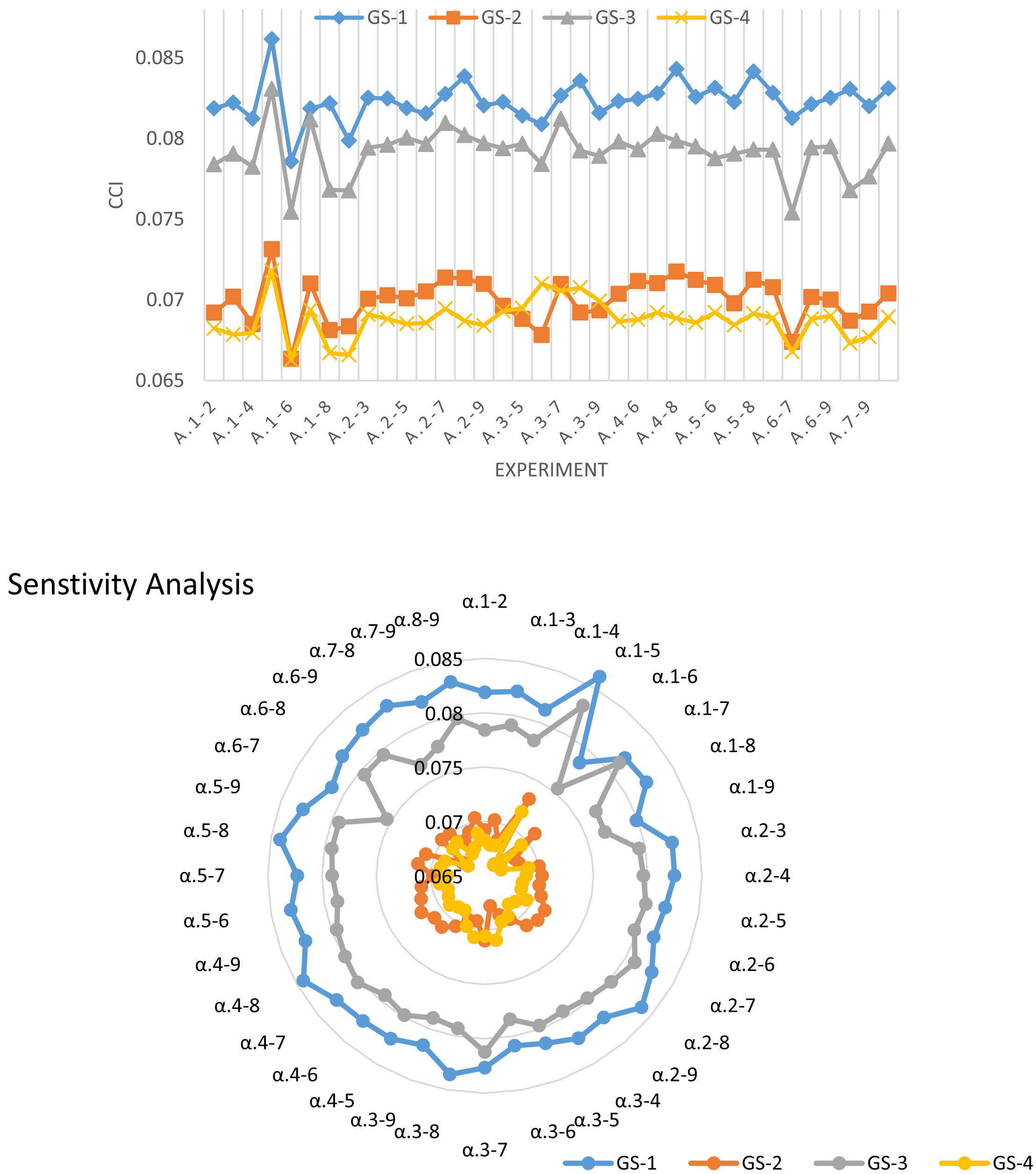

Fig. 6. (a) Line plot for sensitivity analysis. (b) Radar plot for sensitivity analysis.

Table 21
[TOPSIS] Obtained green supplier ranking results under different normalization methods.

Green Supplier	linear normalization Ci	Vector normalization Ci
GS-1	0.08258(1)	0.08064(1)
GS-2	0.07036(3)	0.06953(3)
GS-3	0.07956(2)	0.07664(2)
GS-4	0.06884(4)	0.06142(4)

relatively quite close with each other even though GSS 2 score is slightly higher than GS-4 score Since by varying the importance of the criterion, the alternative precedence remains unchanged, therefore it can be concluded that obtained results are robust in nature.

4.7. Normalization

Normalization is a process used to eliminate the criteria units so that they become dimension less and encompasses values between 0 and 1. Sałabun (2013) has applied several normalization processes for the TOPSIS method. Two types of normalization procedures that are commonly defined are linear normalization and vector normalization. The key difference between these two normalization procedures is that the results scaled by the vector normalization process are dependent on the evaluation criteria whereas, in the case of linear normalization, it is independent of the original units of the data (Banaeian et al., 2015). In this case study, the applied MCDM methods follows the linear normalization process.

From table 21, it can be observed that by performing a vector

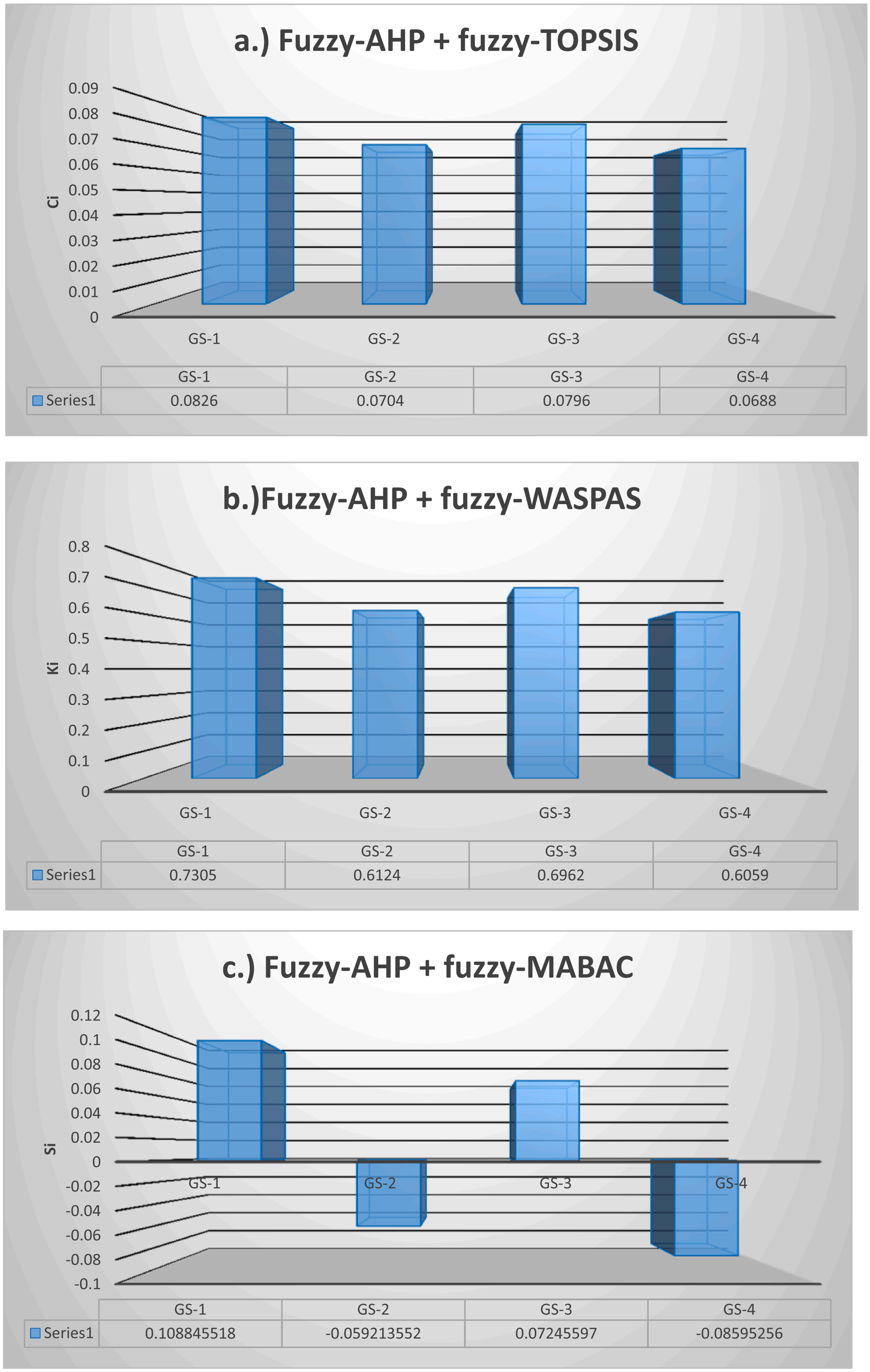

Fig. 7. Final ranking obtained by three separate hybrid fuzzy methods. (a) fuzzy-(AHP, TOPSIS); (b) Fuzzy-(AHP, WASPAS); and (c) Fuzzy- (AHP, MABAC).

normalization process in fuzzy-TOPSIS, the obtained ranking results remain unchanged. Therefore, the obtained ranking results will be independent of the adopted normalization function.

5. Managerial implications

In the proposed case study, an effective method for GSS with prominence on G-SCM issues has been established. Managers of allied businesses can utilize the proposed framework to evaluate their suppliers. Thus, the obtained results can be utilized as a guideline for the supply chain of the organization such that it does not allow to enter an insignificant supplier in the supply chain. This will help in noteworthy resource and cost-saving and lessening of the environmental impacts.

All the listed criteria will help organizations to handle numerous

Table 22
Numerical results of three hybrid MCDM technique.

	RANK F-[AHP,TOPSIS] Ci	RANK F-[AHP,WASPAS] Ki	RANK F-[AHP,MABAC] Si
GS-1	0.08258(1)	0.7304(1)	0.1088(1)
GS-2	0.07036(3)	0.6123(3)	−0.0591(3)
GS-3	0.07956(2)	0.6961(2)	0.0724(2)
GS-4	0.06884(4)	0.6059(4)	−0.0859(4)

challenges and to improve their efforts to develop eco-friendly products. Additionally, the significant advantage of this proposed work is the development of GSS evaluation criteria by means of industry expert's response and literature. The applied sensitivity analysis will allow managers to test the observation stability.

6. Results and conclusion

The fusion of environmental criteria in the process of green supplier selection processes is attaining more importance day by day. The availability and development of new supplier selection models and analytical tools can aid DM's and managers by addressing numerous challenges faced in procurement processes by supply chain management professionals.

The presented research work introduces a fuzzy-based ranking model for green supplier selection in the Indian automotive industry. The trustworthiness of the proposed integrated framework is presented by considering a case study of the Indian automotive industry. Different evaluation criteria were shortlisted from literature and consulting industry experts. Finally, 'nine' criteria were shortlisted considering both conventional and environment criteria by aggregating the expert's inputs, aggregated pair-wise comparison matrix was constructed, from which weights are obtained by applying Chang's extended form of fuzzy AHP method. Evaluation criteria that have obtained maximum weight priority in the analysis are 'environmental management system' 'pollution control', 'quality' and 'green image', which later have been employed as an input for the other three methods in order to select the potential alternative Further set of suppliers were analyzed by integrating three popular decisions. making method, fuzzy-TOPSIS, fuzzy-MABAC, and fuzzy-WASPAS with fuzzy-AHP. Results obtained supports the similar green supplier ranking as presented in Fig. 7(a), (b) and (c).

The consistency test was also performed for the purpose to check the consistency of the expert's inputs. Additionally, a sensitivity analysis was performed to check the robustness of the applied system which is presented in Fig. 6(a), (b). Results depict that the first alternative (GS-1) acquired the highest score followed by a third (GS-3). However, there is a small hazy line between GS-2 and 3, but the final score of GS-2 is greater than GS-3. Hence, the ranking of GS in descending order is obtained as GS-1 > GS-3 > GS-2 > GS-4. Table 22, represents overall results obtained from different hybrid MCDM techniques.

In the presented case study, the applied methods follow the same normalization process. By differing, their normalization in fuzzy AHP and fuzzy-TOPSIS does not alter the obtained rank. This study delivers a single platform or framework for GSS under fuzzy environment and provides the stage for further exploration in this most significant and developing knowledge area. Generally, DM's used to express their assessments in the linguistic term rather than pure numbers. So, the degree of subjectivity is reserved in the presented integrated models. But in the applied models' authors introduced the way to mitigate the subjectivity in the problems of decision making.

For further research, this methodology can also accommodate the dynamic and uncertain environment by including novel factors affecting the change. This research could be applied to specific supply chain cases of industries such as electronics, textiles, food and oil &gas in order to test the general validity of the results. Future research could also use different decision-making tools like VIKOR, PROMETHEE, and GRA. A limitation in the proposed model is that subsystems associated with the criterions are not considered to minimize complexity. While several efforts have been made for the green supplier selection, bearing in mind environmental subject remains a challenge. Additionally, how to allocate orders to the potential green suppliers in the model will be a matter for future research.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cie.2019.07.038.

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