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SOFT COMPUTING IN DECISION MAKING AND IN MODELING IN ECONOMICS

Sustainable supplier selection using HF-DEA-FOCUM-MABAC technique: a case study in the Auto-making industry

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Abstract

The assessment of sustainable supplier is very significant for supply chain management (SCM). The procedure of sustainable supplier selection (SSS) is a complex process for decision experts (DEs) due to the association of diverse qualitative and quantitative attributes. As the uncertainty is usually ensued in the SSS and hesitant fuzzy set (HFS), an extension of fuzzy set (FS) has been demonstrated as one of the effective ways to treat the uncertain information in realistic problems. The objective of this paper is to propose an integrated hesitant fuzzy–data envelopment analysis (DEA)–full consistency method (FOCUM)–multi attribute border approximation area comparison (MABAC) method called HF-DEA-FUCOM-MABAC framework to assess the multi-attribute decision-making (MADM) problems on HFSs settings. In this line, first, the efficient alternatives are chosen using the DEA method. Second, The FUCOM is used to compute the subjective weight of attributes. Third, The HF-MABAC method is presented to prioritize the alternatives in an MADM problem. In the following, a case study of SSS problem for an Auto-making company is taken to show the practicality and utility of the presented approach. Next, we present a sensitivity investigation with different attribute weights set to observe the steadiness of the presented approach. Finally, we draw attention toward a comparison between presented approach with the extant HF-FOCUM-TOPSIS model to show its advantage and potency as well.

Keywords Hesitant fuzzy sets · DEA · FOCUM · MABAC · Sustainable supplier selection (SSS)

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1 Introduction

Over the past recent years, public awareness regarding environmental problems has globally increased. Most of the developing and developed countries have focused on environmental sustainability, leading to the proliferation of environmental standards and guidelines (Wang et al., 2017). Because of this, industries cannot omit their ecological assessment if they intend to expand reasonable benefits in the global marketplace. The "sustainable supply chain management (SSCM)" has been received great attention from industries and enterprises (Fallahpour et al. 2017; Mohammed, 2019). In SSCM, "sustainable supplier selection (SSS)" has a great impression on the integration of supply chain association. Sustainable supplier considers all three aspects of sustainability such as economic, social and environmental, and improves the performance of the supply chain. Therefore, the decision of selecting a proper supplier is one of the main concerns in SSCM to increase the global competitive benefits of the companies (Ghoushchi et al., 2018; Luthra et al., 2017). Recently, the notion of sustainability has established much significance from the researchers and academicians due to the fast depletion of natural resources and public concerns in a corporate setting (Govindan et al., 2013). Presently, most of the firms and businesses need to have an appropriate and precise evaluation of their suppliers to meet their requirements and achieve the goal of sustainability in SCM. Consequently, numerous qualitative and quantitative indicators require to be used in the process of assessment (Govindan et al., 2013). Due to the involvement of several attributes, the process of SSS can be thought of as a "multi-attribute decision-making (MADM)" problem. In this line, various MADM models have been introduced for evaluating the desirable supplier in earlier studies and tried to help the organizations to improve their sustainable perspectives (Feng et al., 2018; Jia and Liu, 2019). In the procedure of supplier selection, precise and accurate information are not sufficient to express natural realistic concerns due to the difficulty of the SSS problem with the uncertainty of the human mind (Chen and Han, 2018; Ghadimi et al., 2018).

Uncertainty is frequently occurred in SSS because of the occurrence of multiple restrictions, lack of information, vague human thinking and inconsistency of the problem. The doctrine of "fuzzy sets (FSs)" has successfully been employed in different supplier selection problems and evidenced its ability to treat with inaccurate and uncertain information (Rani et al., 2020a, b). As an extension of FSs, the doctrine of "hesitant fuzzy sets (HFSs)" (Torra, 2010) has been shown as an advanced tool to tackle the inaccurate and uncertain information in the realistic problems (Faizi et al., 2018; Mishra et al., 2019a, b; Xu and Cheng, 2019). The "data envelopment analysis (DEA)" tool is a "linear programming (LP)"-based model for estimating the relative significance of "organizational units (OUs)" or "decision-making units (DMUs)," namely in government organizations, airlines, hospitals and manufacturing firms, where the occurrence of several inputs and outputs makes comparisons challenging. The "full consistency method (FUCOM)" utilizes the doctrines of pairwise comparisons of attributes and validates the outcomes with the "deviation from the full consistency (DFC)." The advantages of the implementation of FUCOM are: (i) minimum number of pairwise comparisons of attributes (only s-1 comparison); (ii) validating the outcome with the DFC of the comparison; (iii) considering the transitivity in the pairwise comparison of attributes; and (iv) eliminating the concern of redundancy of pairwise comparison of attributes, which shows the subjective models for estimating the attribute weight. The "multi attribute border approximation area comparison (MABAC)" uses the distance from the alternative to the "border approximation area (BAA)," which shows that it is reasonable to enhance the MADM solutions. It has several characteristics as (i) computation outcomes by MABAC model are stable; (ii) calculation procedures are simple; (iii) it considers the latent degrees of gains and losses into account; (iv) it has availability to associate with other models. Hence, the MABAC approach is a significant tool to assess reasonable decision-making problems. Due to above-mentioned advantages, we develop an integrated HF-DEA-FUCOM-MABAC framework to treat the MADM problem. As for our knowledge, there is no paper in the literature, which integrates the DEA, FOCUM and MABAC methods on HFSs setting. In this methodology, the efficient alternatives are determined by DEA, HF-weighted aggregation operators are utilized for the purpose of aggregation and the subjective criteria weights are estimated by the FUCOM. Next, the MABAC method is used to rank the sustainable suppliers for an Auto making company. The major contributions of the study is given as.

- An integrated HF-DEA-FOCUM-MABAC framework is developed for assessing MADM problems.
- DEA tool is utilized to identify efficient alternatives from set of considered alternatives.
- The FOCUM is used to compute the subjective weight of attributes.
- To exhibit the effectiveness of the introduced approach, a practical case study of SSS for an Auto-making industry is discussed under HFSs setting.
- Comparative discussion and "sensitivity investigation (SI)" are discussed to validate the results obtained by the presented approach.

We summarize the remaining paper as follows: In Sect. 2, we give a concise literature of different aspects related to the study. In Sect. 3, we present basic notions of HFSs. In Sect. 4, we develop an integrated HF-DEA-FUCOM-MABAC approach where HFSs have been used to express the attribute values. A case study of SSS for Auto-making industry has been deployed in Sect. 5. Section 6 shows the sensitivity investigation and comparative discussion. Finally, Sect. 7 concludes the entire study and gives further future directions.

2 Literature review

In this section, we discuss the literature of the HFSs, DEA tool, FUCOM, MABAC method and SSS:

2.1 Hesitant fuzzy sets

The main aim of an MADM procedure is to choose the best alternative(s) depending on certain attributes. Several flexible factors, namely a loss of information, hardness in information expulsion, incertitude of the MADM setting and others, will come in attention particularly in diverse practical concern of the socioeconomic situations. Consequently, for "decision-experts (DEs)," it comes true a difficult task to provide crisp values to the attributes. In this line, exemplification of the prioritization with "fuzzy sets (FSs)" or "fuzzy numbers (FNs)" or extended FNs is more suitable indeed. In recent times, it has been observed that the several models about MADM have been put forward in FSs setting. Afterward, the notion of the HFSs, initiated by Torra (2010) is discussed as a generalization of FSs (Zadeh, 1965) which provides the "belongingness grades (BDs)" considering a set of possible BDs instead of a single one. Xu and Zhang (2013) extended the "technique for order preference by similarity to ideal solution (TOPSIS)" model on HFSs to treat the "renewable energy sources" selection. It has been observed the widespread of the HFSs and some varieties in its extension particularly in the fields of group decision-making (Liao et al., 2018; Mishra et al, 2019a, b; Mardani et al., 2020), preference relations (Zhu et al., 2014), clustering analysis (Zhang and Xu, 2015) and other applications (Ye, 2014; Liao et al., 2015; Zhao et al., 2015). Liao and Xu (2015) provided vital contribution for developing several hybrid-weighted AOs and formed an MADM procedure to tackle decision-making problems utilizing HFSs settings.

Recently, various researchers have applied HFSs for treating MADM problems in several disciplines namely arctic route planning (Wang et al., 2017), selection of fire rescue plans (Liao et al., 2018), exploration of the risk factors (Liu et al., 2019a, b), green supplier assessment problem (Mishra et al., 2019a), service quality selection (Mishra et al., 2019b), selection of venture capital investment projects (Liu et al., 2020), sustainable supplier selection (Rani et al., 2020a, b), assessing the main challenges of digital health interventions adoption in COVID-19 outbreak scenario (Mardani et al., 2020). Mishra et al. (2021a, b) gave the "additive ratio assessment (ARAS)" model based on discrimination measure to select the drugs for patients with mild symptoms of the COVID-19 on HFSs settings. To choose the most appropriate "sustainable third party reverse logistic provider (S3PRLP)," Mishra et al. (2021a, b) presented the "combined compromise solution (CoCoSo)" model with a discrimination measure on HFSs. Saraji et al. (2022) conducted a literature survey framework to analyze and assess the challenges to adapt the online education during the COVID-19 outbreak. They presented an integrated MADM model with the "stepwise weight assessment ratio analysis (SWARA)" and "multi-attribute multiple objective optimizations based on ratio analysis (MULTIMOORA)" models to prioritize the higher education institutions on HFSs.

2.2 DEA method

The DEA tool is an LP-based model for estimating the relative significance of OUs/DMUs such as in government organizations, airlines, hospitals, and manufacturing firms, where the occurrence of diverse inputs and outputs offers comparisons challenging. In view of appraisal of the performance of a collection of peer entities (often known as decision-making units (DMUs) or alternatives), we may refer DEA that is considered as one of the best suited quantitative and analytical tools and it plays a major role in the conversion of multiple inputs into multiple outputs. Apart from some existing conventional approaches, there is a great opportunity to use DEA to the approaches too which possess the complex (often unknown) behavior of the DMUs (alternatives) included relations formed in between the multiple inputs and outputs. It has been observed in the last few years the wide applications of DEA in a great deal in several contexts for various deeds. To measure the efficiency and selection of definite distribution channels, a collective principal component assessment-DEA procedure was imputed by Andrejic and Kilibarda (2015). Fallahpour et al. (2016) used a combined fuzzy MADM procedure with the help of a genetic programming approach and DEA to do the proper evaluation of green suppliers. In the PFSs environment, the DEA approach was undertaken by Fan et al. (2019) and they successfully utilized this technique to rank the GSS problem by setting both the criterion of subjective and quantitative. To draw the attention toward the GSS problem in the framework of interval-valued PFSs, an all-inclusive

DEA approach was sketched by Wu et al. (2019). In the interest of the logistics industry's efficiency assessment in the Wuhan area of Central China, Li et al. (2019) proposed DEA model. To select the logistics centers in Spanish autonomous communities, an integrated model was proposed by Yazdani et al. (2020) and that model comprises DEA, FUCOM and CoCoSo techniques in the vicinity of rough set theory. Zhou et al. (2021) modified the conventional DEA models for two-stage models by considering the uncertain data. They constructed the dual deterministic linear models from the stochastic CCR models under the assumption that all components of inputs, outputs and intermediate products and related only with some basic stochastic factors, which follow continuous and symmetric distributions with nonnegative compact supports. Zhu et al. (2021) established a relation between the DEA tool and "machine learning (ML)" approaches and proposed a common procedure merges DEA and ML (ML-DEA) tools to estimate and forecast the DEA efficiency of DMUs. They discussed four ML-DEA tools such as "DEA with back-propagation neural network (BPNN-DEA)," "DEA with genetic algorithm integrated with back-propagation neural network (GANN-DEA)," "DEA with support vector machines (SVM-DEA)" and "DEA with improved support vector machines (ISVM-DEA)." Also, they measured, predicted and compared the performance of Chinese industries listed in 2016 with the DEA efficiency scores obtained by the DEA- "Charnes, Cooper and Rhodes (CCR)" tool. Here, the considered industries or DMUs are compared based on seven assessment attributes using the DEA to obtain the efficient and inefficient DMUs for SSS of Auto-making industry.

2.3 FUCOM method

One of the latest procedures which is the identical way as the "analytic hierarchy process (AHP)" method (Saaty, 1980) and "best–worst method (BWM)" (Rezaei, 2015), based on the doctrines of pairwise comparisons of attributes and the validation of the outcomes with DFC, is the "full consistency method (FUCOM)" (Pamucar et al., 2018a, b, c, d). The advantages of the FUCOM are: (i) minimum number of pairwise comparisons of attributes (only s-1 comparison); (ii) validates the results by DFC; (iii) considering the transitivity in the pairwise comparison of attributes; and (iv) excluding the redundancy concerns of pairwise comparisons of attributes. Badi and Abdulshahed (2019) applied the FUCOM for evaluating the airline traffic in the Libyan airlines with AHP tool. Pamucar et al., (2018b) utilized the FUCOM- "multi-attributive ideal-real comparative analysis (MAIRCA)" model to solve the period of installation of security tools assessment. Noureddine and Ristic (2019) gave the FUCOM-MABAC tool for assessing the routes in the transport of hazardous products by road traffic. Fazlollahtabar et al., (2019) presented the FUCOM for selecting the equipment for storage procedures in the logistics. Also, FUCOM in diverse disciplines, namely sustainable supplier selection (Matic et al., 2019) and supply chain management (Prentkovskis et al., 2018). Since FUCOM is the latest one, therefore, it has only presentations of conventional (crisp) FUCOM (Fazlollahtabar et al., 2019; Pamučar et al., 2018b; Bozanic et al., 2019; Nenadic, 2019; Durmic, 2019). Pamučar et al., (2019) proposed fuzzy FUCOM-D'Bonferroni mean approach for evaluating Istanbul's urban mobility system. For constructing logistics firms, Yazdani et al. (2020) discussed a DEA-FUCOM-CoCoSo tool on "rough sets (RSs)" to select the appropriate region in the autonomous societies of Spain. Here, we apply the FUCOM to obtain the subjective weight of criteria of SSS for Auto-making industry.

2.4 MABAC method

The MABAC approach was initiated by Pamucar and Cirovic (2015), and it coins the distances between the options and BAA. The main advantages as (i) computation outcomes obtained by MABAC are stable; (ii) calculation procedures are simple; and (iv) availability to merges the MABAC model with other tools. By comparing with the extant studies, the precious advantage of the MABAC model (Pamucar et al., 2018c) and taking into accounts the indeterminacy of experts on FSs were used to obtain more precise and efficient MADM outcomes. Xue et al. (2016) proposed the MABAC procedure under IVIFSs. Peng and Yang (2016) used the MABAC tool with Choquet integral on "Pythagorean fuzzy sets (PFSs)." Bozanic et al., (2016) utilized the MABAC model for assessing the implementation of force in a defensive task. Yu et al. (2017) discussed hotel's assessment on a tourism website with a likelihood-based MABAC approach under "interval type-2 fuzzy sets (IT2FSs)." Bojanic et al., (2018) gave AHP-MABAC tool in a defensive procedure of the guided antitank missile battery under FSs. Veskovic, et al. (2018) determined the railway administration structure by utilizing the delphi-SWARA-MABAC approach. Pamucar et al. (2018d) discussed the amendment of the BWM and MABAC models on interval-valued fuzzy-rough sets. Corresponding to the picture 2-tuple linguistic numbers, Zhang et al., (2019) used the MABAC method to solve with MADM. Wei et al., (2019) integrated the "criteria importance through intercriteria correlation (CRITIC)" and MABAC methods on "probabilistic linguistic sets (PLTSs)" to select suitable medical-product supplier. Mishra et al. (2020a, b) proposed the MABAC approach on IVIFSs. Wang et al., (2020) introduced a MABAC procedure to tackle MADM concerns "q-rung orthopair fuzzy sets (q-ROFSs)." Wei et al., (2020) combined the entropy weights and MABAC with uncertain PLTSs to choose the suitable green supplier. Mishra et al. (2020a, b) presented the MABAC tool based on discrimination measure under "intuitionistic fuzzy sets (IFSs)" to tackle the "smartphone selection (SPS)" problem. Liu and Cheng (2020) improved the MABAC method under the "probability multi-valued neutrosophic sets (PMVNSs)" and established a three-way MADM tool based on the "regret theory (RT)" to treat the decision-making problem. Zhao et al. (2021) gave the idea of "cumulative prospect theory (CPT)" with MABAC method on IFSs. The presented tool not only has resilient operability, but also inherits the feature of CPT that assumes the impact of Des' views to treat MADM problem, which consider the given DEs' behavior psychology. Due to above-mentioned advantages, we develop an integrated HF-DEA-FUCOM-MABAC framework to treat the MADM problem.

2.5 Sustainable supplier selection with decision-making models

The SSCM states to incorporating and recognizing a firm's social, environmental and economic objectives entirely in accordance with serious business processes in a way to improve the enduring economic evaluation of the firm (Alrasheedi et al., 2022). Assessing the suitability of the existing suppliers associated to the key sustainability perspectives helps firms advance toward sustainability development and concurrently considers the associated risks. For logistics executives, assessing and choosing a "sustainable supplier (SS)" for manufacturing facilities with minimum risks through SSCM is a key concern, particularly when taking several attributes for making strategic decisions. Numerous MADM procedures have been established and utilized for solving the SSS problem. In this section, we provide a summary of decision making approaches for handling SSS under different environments. For instance, Awasthi et al. (2018) suggested a combined AHP-"visekriterijumska optimizacija I kompromisno resenje (VIKOR)" tool on FSs to assess and choose the best sustainable global supplier among a set of sustainable supliers. Ghoushchi et al. (2018) utilized an integrated "goal programming-data employment analysis (GP-DEA)" based model for assessing the relative effectiveness of SSS when there exist ordinal as well as cardinal numbers. Foroozesh et al. (2018) studied a failure mode and effect assessment procedure for assessing an appropriate SS under FSs situations. Sen et al. (2018) employed three MADM methods with IFSs for assessing of SSS. Meksavang et al. (2019) presented the VIKOR tool under "picture fuzzy sets (PiFSs)" for assessing the SSS problem. Rashidi and Cullinane (2020) conducted a systematic assessment of results obtained by the DEA-TOPSIS model for SSS. Abdel-Baset et al. (2019) suggested a model by combining neutrosophic "analytic network process (ANP)"-VIKOR method to treat the SSS problem. Ahmed et al. (2019) suggested a hybrid MADM for the assessment of SSS and optimal order allocation problem. Liu et al. (2019a, b) studied an integrated MADM tool using the BWM and option queuing model on uncertain conditions for the evaluation of a suitable SS alternative.

In recent time, Zeng et al. (2020) designed an MADM model with a "single-valued neutrosophic fuzzy sets (SVNFSs)" and entropy-weighting method for assessing of SSS problem. Jain et al. (2020) evaluated the SSS problem by employing a new combined model using "fuzzy inference systems (FISs)" and fuzzy MADM techniques. You et al. (2020) presented a framework for assessing the best SS alternative. Rani et al. (2020a, b) presented an integrated HF-SWARA-COPRAS methodology for evaluating an ideal SS alternative. Peng et al. (2020) designed a picture fuzzy MCDM approach with entropy and VIKOR method to assess the desirable SS with uncertain information. Rani et al. (2020a, b) discussed a model with the "complex proportional assessment (COPRAS)" tool and the SWARA to assess and choose the desirable SSs on HFSs. To choose the most suitable S3PRLP, Mishra and Rani (2021) presented the CoCoSo the CRITIC tools under "single-valued neutrosophic sets (SVNSs)." Baidya et al. (2021) combined the CRITIC- and the MULTIMOORA tools under "bipolar complex fuzzy sets (BCFSs)" to solve the S3PRLP assessment problem. Mishra et al. (2022) presented a hybrid model using the CRITIC and the EDAS tools with "Fermatean fuzzy sets (FFSs)" to treat the S3PRLP selection problem with new score function. Thus, this study provides a comprehensive tool that takes into account not only the three sustainability aspects but also the industry perspective. Furthermore, the practicability of presented model is validated by implementing a case study of SSS for Auto-making industry.

3 Prerequisites

Here, we discuss basic idea of HFSs. Next, we recall the concept of HF-weighted aggregation operations on "hesitant fuzzy elements (HFEs)." At the end, we show the distance measure between HFSs.

Definition 1 (Torra, 2010): Suppose U denotes a universe set. Then a HFS ξ on U is described by.

$$\xi = \left\{ \left\langle x, \mu_{\xi}^{h}(x) \right\rangle : x \in U \right\},$$

where $\mu_{\xi}^{h}: U \rightarrow 2^{[0,1]}$ is a function and $\mu_{\xi}^{h}(x)$ signifies a finite set of possible BDs of an object $x \in U$. For $x \in U$, μ_{ξ}^{h} is known as a "hesitant fuzzy element (*HFE*)" (Xia and Xu, 2011). For simplicity, an HFS ξ is characterized by $\left\langle \mu_{\xi}^{h} \right\rangle$. The collection of all *HFEs* on U can be signified by HFE^{U}.

Definition 2 (Xia and Xu, 2011): Let $\mu_{\xi_1}^{h}$ and $\mu_{\xi_2}^{h} \in HFEs^{U}$, then the operations on HFEs can be defined by.

(i) $\mu_{\xi_1}^{h} \cup \mu_{\xi_2}^{h} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}, \alpha_2 \in \mu_{\xi_2}^{h}} max\{\alpha_1, \alpha_2\}$,

(ii) $\mu_{\xi_1}^{h} \cap \mu_{\xi_2}^{h} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}, \alpha_2 \in \mu_{\xi_2}^{h}} min\{\alpha_1, \alpha_2\}$,

(iii) $\left(\mu_{\xi_1}^{h}\right)^{c} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}} \{1 - \alpha_1\}$,

(iv) $\mu_{\xi_1}^{h} \oplus \mu_{\xi_2}^{h} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}, \alpha_2 \in \mu_{\xi_2}^{h}} \{\alpha_1 + \alpha_2 - \alpha_1\alpha_2\}$,

(v) $\mu_{\xi_1}^{h} \otimes \mu_{\xi_2}^{h} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}, \alpha_2 \in \mu_{\xi_2}^{h}} \{\alpha_1\alpha_2\}$,

(vi) $\lambda * \mu_{\xi_1}^{h} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}} \left\{1 - (1 - \alpha_1)^{\lambda}\right\}$, $\lambda > 0$,

(vii) $\lambda \circ \mu_{\xi_1}^{h} = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}} \left\{(\alpha_1)^{\lambda}\right\}$, $\lambda > 0$.

Definition 3 (Xia and Xu, 2011): Let $\mu_{\xi}^{h} \in HFE^{U}$. Then the score value of μ_{ξ}^{h} is given by.

$$S\left(\mu_{\xi}^{h}\right) = \frac{1}{\#\mu_{\xi}^{h}} \sum_{\alpha \in \mu_{\xi}^{h}} \alpha, \tag{1}$$

where $\#\mu_{\xi}^{h}$ denotes the number of objects in μ_{ξ}^{h}.

Based on the score values of HFEs, a comparison method of HFEs is described below:

Definition 4 Xia and Xu, 2011): Let $\mu_{\xi_1}^{h}$ and $\mu_{\xi_2}^{h} \in HFEs^{U}$, then.

(i) $S\left(\mu_{\xi_1}^{h}\right) > S\left(\mu_{\xi_2}^{h}\right) \Rightarrow \mu_{\xi_1}^{h} \succ \mu_{\xi_2}^{h}$,

(ii) $S\left(\mu_{\xi_1}^{h}\right) < S\left(\mu_{\xi_2}^{h}\right) \Rightarrow \mu_{\xi_1}^{h} \prec \mu_{\xi_2}^{h}$,

(iii) $S\left(\mu_{\xi_1}^{h}\right) = S\left(\mu_{\xi_2}^{h}\right) \Rightarrow \mu_{\xi_1}^{h} = \mu_{\xi_2}^{h}$.

Definition 5 (Xia et al., 2013): Suppose $\mu_{\xi_j}^{h}, j = 1, 2, 3, ..., n$, be a collection of *HFEs* on U. Then, the "hesitant fuzzy weighted averaging (HFWA)" and the "hesitant fuzzy weighted geometric (HFWG)" operators are defined by.

$$HFWA_{w}\left(\mu_{\xi_1}^{h}, \mu_{\xi_2}^{h}, ..., \mu_{\xi_n}^{h}\right) = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}, \alpha_2 \in \mu_{\xi_2}^{h}, ..., \alpha_n \in \mu_{\xi_n}^{h}} \left\{1 - \prod_{j=1}^{n} (1 - \alpha_j)^{w_j}\right\}, \tag{2}$$

$$HFWG_{w}\left(\mu_{\xi_1}^{h}, \mu_{\xi_2}^{h}, ..., \mu_{\xi_n}^{h}\right) = \bigcup_{\alpha_1 \in \mu_{\xi_1}^{h}, \alpha_2 \in \mu_{\xi_2}^{h}, ..., \alpha_n \in \mu_{\xi_n}^{h}} \left\{\prod_{j=1}^{n} (\alpha_j)^{w_j}\right\}, \tag{3}$$

where $w_j > 0$ with $\sum_{j=1}^{n} w_j = 1$ is the weight value of $\mu_{\xi_j}^{h}$.

Definition 6 (Xu and Xia, 2011): Let $\xi = \left\{\left\langle x, \mu_{\xi}^{h}(x) \right\rangle : x \in U\right\}$ and $\eta = \left\{\left\langle x, \mu_{\eta}^{h}(x) \right\rangle : x \in U\right\}$ be two HFSs on U. Then, the distance between ξ and η is given by.

$$D(\xi, \eta) = \frac{1}{m} \sum_{i=1}^{m} \left[\frac{1}{l_{x_i}} \sum_{j=1}^{l_{x_i}} \left|\mu_{\xi}^{h}(x_i) - \mu_{\eta}^{h}(x_i)\right|\right], \tag{4}$$

where $l_{x_i} = \max\left\{\mu_{\xi}^{h}, \mu_{\eta}^{h}\right\}$ and μ_{ξ}^{h} and μ_{η}^{h} are the j^{th} largest degree in $\mu_{\xi}^{h}(x_i)$ and $\mu_{\eta}^{h}(x_i)$, respectively.

4 The proposed HF-DEA-FOCUM-MABAC approach

In this section, we present an integrated HF-DEA-FUCOM-MABAC framework to treat the MADM problem. In this line, the DEA model is used to elect the efficient alternatives. It is a LP-based tool for determining the relative significance of DMUs such that the existence of various inputs and outputs makes assessments challenging. The FUCOM utilizes to compute the criteria weights, which is based on the pairwise comparisons of attributes and validates the outcomes with the DFC. The MABAC uses to rank the alternatives. It measures distance from the alternative to the BAA may be positive or negative, which means that it is reasonable to enhance the conventional MABAC with the use of HFSs. The procedural steps for HF-DEA-FOCUM-MABAC method are given as follows (see Fig. 1):

Step 1 Obtain the efficient alternatives using DEA tool.

We may refer here that it can be possible to make use of the idea of multiple inputs or outputs proportion in view of measuring the organizational efficiency having no data in prior, associated to the relative significance of inputs and outputs and this phenomenon was addressed in the Charnes, Cooper and Rhodes (CCR) procedure (Cooper et al., 2011) which is nothing but the extended version of the Farrell's model (Farrel, 1957). Basically, it involves the scale concept of constant returns and the chosen alternatives could be identified against the inefficient ones by the

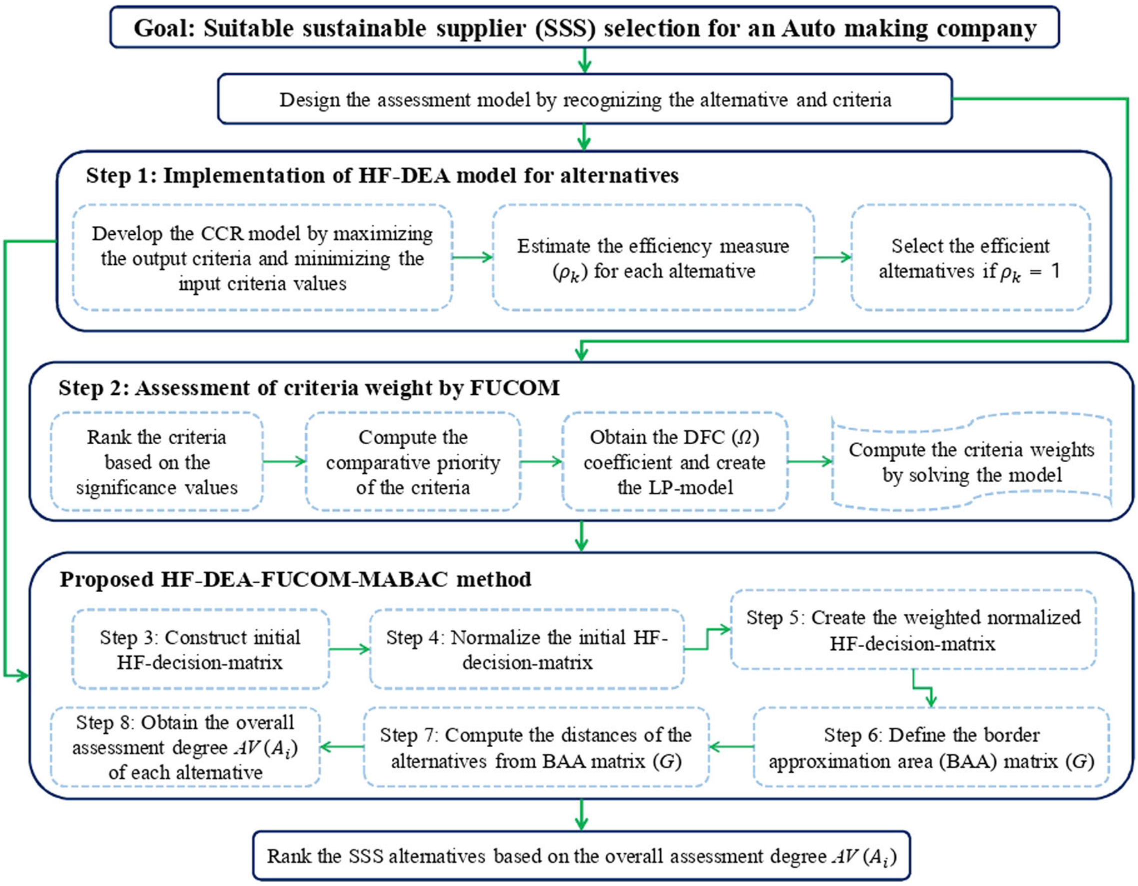

Fig. 1 Graphical representation of proposed HF-DEA-FUCOM-MABAC framework

CCR model. With the view of the fact of generating a big amount of outputs with the same inputs and vice versa, it is judged whether a specific alternative is at all efficient or not than the other existing ones. Merging the pure technological proficiency with the single-valued ability of scale, an aggregated efficiency score as a whole can be surveyed by utilizing the CCR procedure. The key issue of this model is the formation of an enveloping surface endowed by a convex cone in which, at the top of the envelope, efficient alternatives are placed and the bottom place is occupied by the inefficient alternatives under the cone. The CCR procedure is classified in two ways: input- and output-based models. It can be observed that when in the input-oriented procedure, the outputs are being regulated then the inputs get consolidated as much as possible. In contrast, during the control over the inputs, it is viewed to get expansions in the outputs for the output-based model.

Let m alternatives, namely- $\tilde{A}_1, \tilde{A}_2, \tilde{A}_3, ..., \tilde{A}_m$ to be assessed over various input and output attributes. Generally, non-beneficial and beneficial attributes are termed as inputs and outputs respectively. Consider n input attribute for each option signified by a_{qk} (q = 1,…,n) and t output attribute for each option signified by b_{pk} (p = 1,…..,t), where a_{qk} and b_{pk} signify the degrees of q^t input attribute and p^{th} output attribute for k^{th} alternative. Getting motivated by the inflexibility occurred during computation of the CCR model (Cooper et al., 2011) oriented fractional non-convex programming problem while aiming at to nurture the decision-making problems, Charnes et al. (1978) were able to develop the corresponding linear programming (LP) model characterized by either output criteria values maximization or input criteria values minimization. The CCR model's input minimization model has been considered in this study which is prescribed below:

$$g_k = \min\left(\sum_{q=1}^{n} v_q \hat{a}_{qk}\right)$$
$$\text{subject to} \sum_{k=1}^{r}\left(\sum_{q=1}^{n} v_q \hat{a}_{qk} - \sum_{p=1}^{t} u_p \hat{b}_{pk}\right) \geq 0, \sum_{p=1}^{t} u_p \hat{b}_{pk} = 1,$$
$$u_p \geq 0 \ (p = 1, 2, ..., t), \ \ v_q \geq 0 \ (q = 1, 2, ..., n) \tag{5}$$

where u_p and v_q (both positive) are to be assessed by explaining this LP-model. The normalized values

$\hat{a}_{qk}$ and $\hat{b}_{pk}$ are calculated by: $\hat{a}_{qk} = 1 - \frac{a_{qk}}{\max_q a_{qk}}$, $\hat{b}_{pk} = \frac{b_{pk}}{\max_p b_{pk}}$.

To estimate the efficiency measure of an alternative $\tilde{A}_k$, the following formula developed by Charnes et al. (1978) can be utilized as

$$\rho_k = \frac{1}{g_k},\ k = 1, 2, ..., m. \tag{6}$$

where ρ_k is the efficiency measure of the k^{th} alternative $\tilde{A}_k$.

In the CCR model, an alternative is treated as efficient if it reaches a score of 1; else, it is considered as inefficient. Suppose efficient alternatives are given as $A_1, A_2, A_3, ..., A_r$ $(r < m)$ (Yazdani et al., 2020; Zhu et al., 2021).

Step 2 Calculation of criteria weights by FUCOM.

In the MADM procedure, it is considered the resolution of criteria's relative weight to be as one of the tangible problems on the verge of subjectivity without loss of generality. Due to the essential impact of weight values to the assessment in diverse models, the FUCOM gets vital significance and shows a key character in the results of MADM solutions. Here, in this study, for computing the criteria weights, we deploy FOCUM. Under the conviction of a definite level of hierarchy alongside the joint fulfillment of the comparison consistency's conditions, it is possible to measure accurately the degree of the criteria weight coefficients by FUCOM. Here, we present the steps of FOCUM to obtain the criteria weight as.

Step 2.1 At the very beginning, we attempt the ranking of the assessment criteria C_1, C_2, C_3, …, C_s. The rank is done depending on the attribute's significance, i. e., highest significance to lowest significance of criteria. Thus, we refer that the obtained desired degrees of the weight coefficients make it enable to frame the ranking of the criteria that can be viewed as:

$$C_{j(1)} > C_{j(2)} > C_{j(3)} > ... > C_{j(\sigma)}, \tag{7}$$

where σ expresses the priority of observed attribute. We may replace " $>$ " in Eq. (7) by the sign of equality between these attributes while letting the implication associated with the existence of minimum two attributes having the identical importance.

Step 2.2 In this step, we discuss a comparative discussion of the prioritized attributes as well as the determination of the assessment of attributes comparative priority $\left(\Theta_{\sigma/(\sigma+1)};\ \sigma = 1, 2, 3, ..., s\right)$. Significantly, the prioritization is specified to the comparative priority $\Theta_{\sigma/(\sigma+1)}$ of considered attribute associated to the rank $C_{j(\sigma)}$ while compared with that of the $C_{j(\sigma+1)}$. In this line, we can suggest an expression which is responsible to vectors of the comparative priorities associated to the corresponding evaluation attribute:

$$\psi = \left(\Theta_{1/2}, \Theta_{2/3}, ..., \Theta_{\sigma/(\sigma+1)}\right), \tag{8}$$

where it is pursued the significance by the $\Theta_{\sigma/(\sigma+1)}$ that the criterion of the rank $C_{j(\sigma)}$ is assessed by the criterion of rank $C_{j(\sigma+1)}$.

Step 2.3 In this step, it requires to compute the outcomes of weight coefficients of considered attributes $(w_1, w_2, ..., w_s)^T$. We present two constraints that are obeyed by the final results of weight coefficients.

(i) The comparative order on considered attributes agrees with the ratio of the weight coefficients and mentioned condition must be fulfilled.

$$\frac{w_\sigma}{w_{\sigma+1}} = \Theta_{\sigma/(\sigma+1)} \tag{9}$$

(ii) Furthermore to Eq. (9), the mathematical transitivity condition, i. e., $\Theta_{\sigma/(\sigma+1)} \times \Theta_{(\sigma+1)/(\sigma+2)} = \Theta_{\sigma/(\sigma+2)}$ must be fulfilled by final degrees of the weight coefficients. Since $\Theta_{\sigma/(\sigma+1)} = \frac{w_\sigma}{w_{\sigma+1}}$ and $\Theta_{(\sigma+1)/(\sigma+2)} = \frac{w_{\sigma+1}}{w_{\sigma+2}}$, so $\frac{w_\sigma}{w_{\sigma+2}} = \frac{w_\sigma}{w_{\sigma+1}} \times \frac{w_{\sigma+1}}{w_{\sigma+2}}$ is achieved, thus, yet another constraint that the final degrees of weight coefficients of considered attributes require to meet is found, namely,

$$\frac{w_\sigma}{w_{\sigma+2}} = \Theta_{\sigma/(\sigma+1)} \times \Theta_{(\sigma+1)/(\sigma+2)}. \tag{10}$$

It is significant to discuss that the minimum DFC (Ω) is fulfilled only if we successfully get into the transitivity i. e., when we undertake both the conditions $\frac{w_\sigma}{w_{\sigma+1}} = \Theta_{\sigma/(\sigma+1)}$ and $\frac{w_\sigma}{w_{\sigma+2}} = \Theta_{\sigma/(\sigma+1)} \times \Theta_{(\sigma+1)/(\sigma+2)}$. To implement so, the values of the weight coefficients $(w_1, w_2, ..., w_s)^T$ should comply with the conditions $\left|\frac{w_\sigma}{w_{\sigma+1}} - \Theta_{\sigma/(\sigma+1)}\right| \le \Omega$ and $\left|\frac{w_\sigma}{w_{\sigma+2}} - \Theta_{\sigma/(\sigma+1)} \times \Theta_{(\sigma+1)/(\sigma+2)}\right| \le \Omega$, with the minimization of the value Ω.

Corresponding to the constraints and settings cited above, below we address the desired procedure for estimating the degrees of weight coefficients of considered attributes:

$$\begin{aligned} &\text{Min } \Omega \left|\frac{w_\sigma}{w_{\sigma+1}} - \Theta_{\sigma/(\sigma+1)}\right| \\ &\le \Omega,\ \left|\frac{w_\sigma}{w_{\sigma+2}} - \Theta_{\sigma/(\sigma+1)} \times \Theta_{(\sigma+1)/(\sigma+2)}\right| \le \Omega,\quad \forall \sigma \\ &w_j \ge 0,\ j = 1, 2, ..., s,\ \sum_{j=1}^{s} w_j = 1. \end{aligned} \tag{11}$$

By simplifying the model (11), the final weight values $(w_1, w_2, ..., w_s)^T$ of considered attributes are computed.

Step 3 Construct an initial hesitant fuzzy-decision matrix (HF-DM).

Consider the set of efficient options $\{A_1, A_2, A_3, \ldots, A_r\}$ and a set of evaluation attributes $\{C_1, C_2, \ldots\ldots, C_l\}$. The DE offers his/her evaluation values of option $A_i\,(i = 1, 2, \ldots.., r)$ over attributes $C_j\,(j = 1, 2, \ldots.., s)$ in terms of *HFE*s μ_{ij}^h. Suppose $D = \left[\mu_{ij}^h\right]_{r\times s}$ represents the initial HF-DM.

Step 4 Obtain the "normalized HF-DM (N-HF-DM)."

In case of realistic MADM, the attributes are often separated into two types such as benefit and cost attributes. To solve the MADM problem, we need to change whole problem either benefit-type or cost-type. Here, the N-HF-DM is obtained and denoted by $\tilde{D} = \left[\tilde{\mu}_{ij}^h\right]_{r\times s}$, where

$$\tilde{\mu}_{ij}^h = \begin{cases} \mu_{ij}^h & \text{if } C_j \text{ is of benefit type} \\ (\mu_{ij}^h)^c & \text{if } C_j \text{ is of cost type} \end{cases} \tag{12}$$

Step 5 Make the "weighted N-HF-DM (WN-HF-DM)."

The WN-HF-DM is obtained using the HFWA operator, given in Eq. (2) and denoted by $\tilde{M} = \left[\vartheta_{ij}^h\right]_{r\times s}$ where

$$\begin{aligned}\vartheta_{ij}^h &= HFWA_w\left(\tilde{\mu}_{i1}^h, \tilde{\mu}_{i2}^h, \ldots, \tilde{\mu}_{is}^h\right) \\ &= \bigcup_{\alpha_{i1}\in\tilde{\mu}_{i1}^h, \alpha_{i2}\in\tilde{\mu}_{i2}^h, \ldots\ldots\ldots, \alpha_{is}\in\tilde{\mu}_{is}^h} \left\{1 - (1-\alpha_{ij})^{w_j}\right\},\ i \\ &= 1, 2, \ldots, r,\ j = 1, 2, \ldots.., s.\end{aligned} \tag{13}$$

Step 6 Define the matrix G of BAA.

The BAA of each attribute is estimated using the HFWG operator, given in Eq. (3) and defined as

$$\begin{aligned}\zeta_j &= HFWG_r\left(\tilde{\mu}_{i1}^h, \tilde{\mu}_{i2}^h, \ldots, \tilde{\mu}_{is}^h\right) \\ &= \bigcup_{\alpha_{i1}\in\tilde{\mu}_{i1}^h, \alpha_{i2}\in\tilde{\mu}_{i2}^h, \ldots, \alpha_{is}\in\tilde{\mu}_{is}^h} \left\{\prod_{i=1}^{r} (\alpha_{ij})^{1/r}\right\},\ i = 1, 2, \ldots, r,\ j \\ &= 1, 2, \ldots, s.\end{aligned} \tag{14}$$

After computing the values ζ_j for the attribute C_j, a matrix G is designed, where $G = (\zeta_1, \zeta_2, \zeta_3, \ldots\ldots, \zeta_s)$ is a row matrix of order $1 \times s$.

Step 7 Calculate the distances of the alternatives from the BAA matrix G.

The distances of each option from the BAA matrix G are defined as the distance between the objects occurring in the WN-HF-DM $\tilde{M}$ and the elements of BAA matrix G and are termed as the HF distances defined by

$$\delta_{ij} = \bigcup_{\theta_{ij}\in\vartheta_{ij}^h} \bigcup_{\eta_j\in\zeta_j} \left|\theta_{ij} - \eta_j\right|,\ i = 1, 2, \ldots, r;\ j = 1, 2, \ldots, s. \tag{15}$$

Construct the matrix $Q = \left[\delta_{ij}\right]_{r\times s}$.

Step 8 The overall assessment degree of the alternative are defined by

$$\begin{aligned}AV(A_i) &= \text{Arithmetic mean of } \frac{1}{s}\sum_{j=1;\,\beta_j\in\delta_{ij}}^{s} \beta_j, i \\ &= 1, 2, 3, \ldots, r.\end{aligned} \tag{16}$$

Step 9 Alternatives are ranked according to their final assessment values.

5 Case study

Iranian's Auto-manufacturing organization is the most vital and developing organizations of the country. Auto-manufacturing organizations seek suppliers to assist them to supply their manufactured goods with the finest quality and most reduced cost. The most appropriate supplier improves product quality, diminishes total cost, provides superior customer service, etc. In 1985, the "Sazeh Gostare Saipa Co. (SGSC)" was established for managing the Iranian industrial plants to build various automobiles, namely Vanet and Nissan-Patrol. In 1994, latest stage of corporation was initiated to design engineering and supply of the auto parts in Iran. At present, this corporation has more than 500 auto-parts firms in its supply chain. SGSC desires to evaluate and choose an ideal supplier of hydraulic tank from sustainable perspective. To assess the best sustainable supplier, lists of 14 alternatives that produce hydraulic tank are presented in Table 1.

To evaluate the sustainability of suppliers, the present study employs few inputs and outputs (Table 2). These aspects are assumed as outputs owing to the more degrees of these aspects, the more interest of suppliers from sustainability perspectives. Customer PPM is a crucial attribute in assessing the SSSs, and more PPM is preferred and is taken as an output attribute. PPM is an attribute utilized nowadays by many customers to assess the quality assessment (Van Der Pol et al. 1996; Bebr et al. 2017). One PPM describes one defect in a million or 1/1,000,000. For instance, assume that a supplier has 27 broken pieces in a consignment of 1000 pieces; ie., 0.027 or 2.7% are defective. Then, customer PPM amount is 0.027 × 1, 000, 000 = 27, 000 PPM. Now, the rate of most automotive components is set at 27 PPM or 0.0027%. Table 1 shows the description of 14 suppliers. These suppliers are our goal suppliers, and our goal to assess and rank the suppliers with the use of introduced method. Dataset dates back to 2014–2015. Table 3 presents all factors and evaluation criteria for assessing the SSS.

To solve the SSS problem, we utilize the developed HF-DEA-FOCUM-MABAC model for evaluating the options with HFSs. The presented approach incorporates the following steps as.

Table 1 The data related to the case study and fourteen suppliers

Supplier	T_1	T_2	T_3	T_4	T_5	T_6	T_7
Iran Hydraulic industries ($\tilde{A}_1$)	15	9	66.38	4	53.46	30	139
Poua Gostar Khorasan company ($\tilde{A}_2$)	897	14	80	3	37.28	20	153
Javid Sanat Arak company ($\tilde{A}_3$)	288	18	62.97	4	48.04	18.76	141
Tehran Fam industrial production ($\tilde{A}_4$)	15	12	60.63	3	56.12	19.44	100
Polad Ozhan company ($\tilde{A}_5$)	15	18	77.35	3	38.44	18.22	112
Soheil Ghete Alborz company ($\tilde{A}_6$)	155	11	73.29	5	56.81	19.95	143
Rexsun Parsian company ($\tilde{A}_7$)	15	21	85.58	2	45.82	17.45	104
Niro Saz company ($\tilde{A}_8$)	156	18	55.02	4	46.39	21	153
Shahin Shahr Sepahan industries ($\tilde{A}_9$)	432	15	50.86	3	49.76	30	147
Hamed automotive industry ($\tilde{A}_{10}$)	220	20	52.33	3	17.73	22.18	130
Dirin Sanat company ($\tilde{A}_{11}$)	334	16	66.27	2	36.25	19.12	148
Hydraulic structures engineering services ($\tilde{A}_{12}$)	15	7	75.37	4	58.71	21	133
Famco industrial company ($\tilde{A}_{13}$)	15	15	82.56	3	48.55	18.75	128
Charkheshgar company (Tabriz) ($\tilde{A}_{14}$)	624	23	78.24	2	21.45	20.54	108

Table 2 The considered criteria for SSCM

Factor	Criteria	Dimension
Inputs	Distance (T_1)	Economic
	Cost of work security and labor health (T_2)	Social
	Hydraulic tank rate (T_3)	Economic
Outputs	No. of gained ISO certificates (T_4)	Environmental
	Process and product audit (T_5)	Economic and Social
	Customer PPM (T_6)	Economic
	No. of on-time shipments (T_7)	Economic

Table 3 Definitions of assessment supplier attributes for sustainability

Dimension	Criteria	References	Type
Economic	On-time delivery (C_1)	Kuo et al., 2010; Tseng et al., 2013; Yeh and Chuang, 2011; Zhu et al., 2010; Orji and Wei, 2014; Bai and Sarkis, 2010; Amindoust et al., 2012; Azadnia et al., 2012; Dai and Blackhurst, 2011; Govindan et al., 2013	Benefit
	Cost (C_2)	Bai and Sarkis, 2010; Keskin et al., 2010; Kuo et al., 2010; Yeh and Chuang, 2011; Zhu et al., 2010; Büyüközkan and Çifçi, 2011; Amindoust et al., 2012; Azadnia et al., 2012; Dai and Blackhurst, 2011; Orji and Wei, 2014; Govindan et al., 2013	Cost
	Flexibility (C_3)	Tseng et al., 2013; Zhu et al., 2010; Orji and Wei, 2014; Bai and Sarkis, 2010; Büyüközkan and Çifçi, 2011; Amindoust et al., 2012	Benefit
Social	Occupational health and safety (C_4)	Bai and Sarkis, 2010; Keskin et al., 2010; Amindoust et al., 2012; Azadnia et al., 2012; Dai and Blackhurst, 2011; Orji and Wei, 2014; Govindan et al., 2013	Benefit
Environmental	Environmental management system (C_5)	Humphreys et al., 2003; Bai and Sarkis, 2010; Lee et al., 2009; Bai and Sarkis, 2010; Awasthi et al., 2010; Kuo et al., 2010; Tseng et al., 2013; Yeh and Chuang, 2011; Hsu et al., 2013; Zhu et al., 2010; Amindoust et al., 2012; Azadnia et al., 2012; Orji and Wei, 2014	Benefit
	Pollution control initiatives (C_6)	Bai and Sarkis, 2010; Bai and Sarkis, 2010; Tseng et al., 2013; Yeh and Chuang, 2011; Awasthi et al., 2010; Zhu et al., 2010; Amindoust et al., 2012; Azadnia et al., 2012; Orji and Wei, 2014	Benefit

Step 1 The DEA-CCR method is used to recognize the efficient options among the 14 given companies according to Table 1. Utilizing the model (5), the outcomes are given in Table 4. From Eq. (6), we obtain the efficiency measure (ρ_k) and it is found that among all the 14 alternatives, only 3 companies, namely Poua Gostar Khorasan company $(\tilde{A}_2)$, Rexsun Parsian company $(\tilde{A}_7)$ and Charkheshgar company (Tabriz) $(\tilde{A}_{14})$ are assessed as the efficient companies. Hence, a decision-making process containing of these 3 alternatives and 6 assessment attributes, and is depicted in Table 4. To reduce the length of this article, the corresponding LP problem, given in model (5) for the alternative $A_{1,}$ is described as a illustrative example.

$$g_1 = \min(0.9833\, v_1 + 0.6087\, v_2 + 0.2244\, v_3)$$

Subject to

$$\begin{aligned}
&0.9833\, v_1 + 0.6087\, v_2 + 0.2244\, v_3 - 0.8\, u_1 \\
&\quad - 0.9106\, u_2 - u_3 - 0.9085\, u_4 \geq 0, \\
&0.3913\, v_2 + 0.0652\, v_3 - 0.6\, u_1 - 0.635\, u_2 \\
&\quad - 0.6667\, u_3 - u_4 \geq 0, \\
&0.6789\, v_1 + 0.2174\, v_2 + 0.2642\, v_3 - 0.8\, u_1 \\
&\quad - 0.8183\, u_2 - 0.6253\, u_3 - 0.9216\, u_4 \geq 0, \\
&0.9833\, v_1 + 0.4783\, v_2 + 0.2915\, v_3 - 0.6\, u_1 \\
&\quad - 0.9559\, u_2 - 0.648\, u_3 - 0.6536\, u_4 \geq 0, \\
&0.9833\, v_1 + 0.2174\, v_2 + 0.0962\, v_3 - 0.6\, u_1 \\
&\quad - 0.6547\, u_2 - 0.6073\, u_3 - 0.732\, u_4 \geq 0, \\
&0.8272\, v_1 + 0.5217\, v_2 + 0.1436\, v_3 - u_1 - 0.9676\, u_2 \\
&\quad - 0.665\, u_3 - 0.9346\, u_4 \geq 0, \\
&0.9833\, v_1 + 0.087 v_2 - 0.4\, u_1 - 0.7804\, u_2 - 0.5817\, u_3 \\
&\quad - 0.6797\, u_4 \geq 0, \\
&0.8261\, v_1 + 0.2174\, v_2 + 0.3571\, v_3 - 0.8\, u_1 \\
&\quad - 0.7902\, u_2 - 0.7\, u_3 - u_4 \geq 0, \\
&0.5184\, v_1 + 0.3478\, v_2 + 0.4057\, v_3 - 0.6\, u_1 \\
&\quad - 0.8476\, u_2 - u_3 - 0.9608\, u_4 \geq 0, \\
&0.7547\, v_1 + 0.1304\, v_2 + 0.3885\, v_3 - 0.6\, u_1 - 0.302\, u_2 \\
&\quad - 0.7393\, u_3 - 0.8497\, u_4 \geq 0, \\
&0.6276\, v_1 + 0.3043\, v_2 + 0.2256\, v_3 - 0.4\, u_1 - 0.6174\, u_2 \\
&\quad - 0.6373\, u_3 - 0.9673\, u_4 \geq 0, \\
&0.9833\, v_1 + 0.6957\, v_2 + 0.1193\, v_3 - 0.8\, u_1 - u_2 \\
&\quad - 0.7\, u_3 - 0.8693\, u_4 \geq 0, \\
&0.9833\, v_1 + 0.3478\, v_2 + 0.0353\, v_3 - 0.6\, u_1 - 0.8269\, u_2 \\
&\quad - 0.625\, u_3 - 0.8366\, u_4 \geq 0, \\
&0.3043\, v_1 + 0.0858\, v_3 - 0.4\, u_1 - 0.3654\, u_2 - 0.6847\, u_3 \\
&\quad - 0.7059\, u_4 \geq 0, \\
&0.8\, u_1 + 0.9106\, u_2 + u_3 + 0.9085\, u_4 = 1, \\
&v_1, v_2, v_3 \geq 0, \quad u_1, u_2, u_3, u_4 \geq 0.
\end{aligned}$$

Table 4 Results of the DEA-CCR model

Alternatives	g_k	ρ_k
$\tilde{A}_1$	2.06696	0.4838
$\tilde{A}_2$	1	1
$\tilde{A}_3$	1.4274	0.7005
$\tilde{A}_4$	1.9201	0.5208
$\tilde{A}_5$	1.4364	0.6961
$\tilde{A}_6$	1.2664	0.7896
$\tilde{A}_7$	1	1
$\tilde{A}_8$	1.7018	0.5876
$\tilde{A}_9$	1.4003	0.7141
$\tilde{A}_{10}$	1.9867	0.5033
$\tilde{A}_{11}$	2.0143	0.4964
$\tilde{A}_{12}$	1.7453	0.5729
$\tilde{A}_{13}$	1.20808	0.8277
$\tilde{A}_{14}$	1	1

Let us assume that the efficient alternatives are A_1, A_2, A_3 where $\tilde{A}_2 = A_1, \tilde{A}_7 = A_2, \tilde{A}_{14} = A_3$.

Step 2 Here, FOCUM is implemented to calculate the subjective weight of attributes as.

Step 2.1 The priority order of attributes as Eq. (7): $C_4 > C_2 > C_1 > C_6 > C_3 > C_5$.

Step 2.2 The comparison is prepared over the first-ranked C_4 attribute. The comparison is according to the scale $[1,\ 9]$. Thus, the priority order of attribute $(\varpi_{C_{j(k)}})$ for all attributes is prioritized in Step 2.1 and is depicted in Table 5.

Utilizing Eqs. (8)–(10) and corresponding to the priority order of the attributes, the comparative prioritization of the attributes is estimated as $\varphi_{C_4/C_2} = 2/1 = 2$, $\varphi_{C_2/C_1} = 3/2 = 1.5$, $\varphi_{C_1/C_6} = 4/3 = 1.33$, $\varphi_{C_6/C_5} = 5/4 = 1.25$ and $\varphi_{C_3/C_5} = 9/5 = 1.8$.

Table 5 Priority order of attributes

Attributes	C_4	C_2	C_1	C_6	C_3	C_5
$\varpi_{C_{j(k)}}$	1	2	3	4	5	9

Table 6 The initial HF-DM for SSS

	A_1	A_2	A_3
C_1	{0.1, 0.2, 0.4}	{0.5}	{0.3, 0.4}
C_2	{0.8}	{0.6, 0.7}	{0.5, 0.7, 0.9}
C_3	{0.5, 0.6}	{0.3, 0.4, 0.6}	{0.3}
C_4	{0.3}	{0.1, 0.2, 0.4}	{0.5}
C_5	{0.7, 0.8, 0.9}	{0.8}	{0.6, 0.7, 0.8}
C_6	{0.2, 0.3}	{0.1,0.3}	{0.1, 0.2}

Table 7 The N-HF-DM for SSS

	A_1	A_2	A_3
C_1	{0.1, 0.2, 0.4}	{0.5}	{0.3, 0.4}
C_2	{0.2}	{0.4, 0.3}	{0.5, 0.3, 0.1}
C_3	{0.5, 0.6}	{0.3, 0.4, 0.6}	{0.3}
C_4	{0.3}	{0.1, 0.2, 0.4}	{0.5}
C_5	{0.7, 0.8, 0.9}	{0.8}	{0.6, 0.7, 0.8}
C_6	{0.2, 0.3}	{0.1,0.3}	{0.1, 0.2}

Table 8 The WN-HF-DM for SSS

	A_1	A_2	A_3
C_1	{0.01454,0.01454, 0.03054,0.04837}	{0.09185}	{0.04837,0.06854}
C_2	{0.04557}	{0.10126,0.07183}	{0.13486,0.07183, 0.02178}
C_3	{0.05656,0.07408,}	{0.02952,0.04200, 0.07408}	{0.02952}
C_4	{0.13820}	{0.19186,0.04298, 0.08885}	{0.25102}
C_5	{0.10257,0.0550, 0.0728}	{0.0728}	{0.0728,0.04215, 0.05501}
C_6	{0.037445,0.02359}	{0.01121,0.03744}	{0.01121,0.02359}

Step 2.3 Utilizing the model (11) for calculating the weight values as follows:

$$\min \chi$$
$$s.t.\begin{cases} \left|\frac{w_4}{w_2}-2\right|\leq\chi,\ \left|\frac{w_2}{w_1}-1.5\right|\leq\chi,\ \left|\frac{w_1}{w_6}-1.33\right|\leq\chi,\ \left|\frac{w_6}{w_3}-1.25\right|\leq\chi,\\ \left|\frac{w_6}{w_5}-1.8\right|\leq\chi,\ \left|\frac{w_4}{w_1}-3\right|\leq\chi,\ \left|\frac{w_2}{w_6}-1.995\right|\leq\chi,\ \left|\frac{w_1}{w_3}-1.663\right|\leq\chi,\\ \left|\frac{w_6}{w_5}-2.25\right|\leq\chi,\ \sum_{j=1}^{6}w_j=1,\ w_j\geq0,\ j=1,2,\ldots,6. \end{cases}$$

By simplifying the model with LINGO 17.0 software, the attribute weight is computed as $(0.139, 0.209, 0.084, 0.417, 0.047, 0.107)^T$ and DFC of the outcomes is obtained as $\chi = 0.00$.

Step 3 In this step, the DE will evaluate the three alternatives A_1, A_2, A_3 in relation to six attributes $C_j\,(j = 1, 2, \ldots, 6)$. The initial HF-DM $D = \left[\mu_{ij}^h\right]_{3\times6}\left(=\left[\mu_{ij}^h\right]_{6\times3}\right)$ is presented in Table 6.

Step 4 Here, attribute C_2 is cost-type and rest of attributes are benefit-type. Therefore, from Eq. (12) and Table 6, the N-HF-DM is obtained and is presented in Table 7.

Step 5 Using Eq. (13), the WN-HF-DM $\tilde{M}$ is constructed and is given in Table 8.

Step 6 Utilizing formula (14), we obtain the matrix G of border approximation areas (BAA) given in Table 9.

Step 7 We determine the distances between the elements of WN-HF-DM $\tilde{M}$ and the elements of BAA matrix G. The outcomes are mentioned in Table 10.

Step 8 The final assessment value of the options is calculated as

$$\begin{aligned} AV(A_1) = \frac{1}{36} \times (&0.170989602 + 0.180812507 + 0.187225052 + 0.197047958 + 0.20496897\\ &+ 0.214791876 + 0.167932824 + 0.177755729 + 0.184168275 + 0.19399118 + 0.201912192\\ &+ 0.211735098 + 0.173603311 + 0.183426217 + 0.189838762 + 0.199661668 + 0.20758268\\ &+ 0.217405586 + 0.174232692 + 0.184055597 + 0.190468143 + 0.200291048 + 0.208212061\\ &+ 0.218034966 + 0.175073831 + 0.184896737 + 0.191309282 + 0.201132188 + 0.2090532\\ &+ 0.218876106 + 0.177155148 + 0.186978053 + 0.193390598 + 0.203213504 + 0.211134516\\ &+ 0.220957422)\\ = \ &0.1887, \end{aligned}$$

$$
\begin{aligned}
AV(A_2) = & \frac{1}{36} \times (0.058279447 + 0.062651926 + 0.065924228 + 0.070296707 + 0.083091322 \\
& + 0.087463801 + 0.060360356 + 0.064732835 + 0.068005136 + 0.072377615 + 0.08517223 \\
& + 0.08954471 + 0.065706878 + 0.070079357 + 0.073351659 + 0.077724138 + 0.090518753 \\
& + 0.094891232 + 0.053375014 + 0.057747493 + 0.061019795 + 0.065392274 + 0.078186889 \\
& + 0.082559368 + 0.055455923 + 0.059828402 + 0.063100703 + 0.067473182 + 0.080267797 \\
& + 0.084640276 + 0.060802445 + 0.065174924 + 0.068447225 + 0.072819705 + 0.08561432 \\
& + 0.089986799) \\
= & \ 0.0695,
\end{aligned}
$$

$$
\begin{aligned}
AV(A_3) = & \frac{1}{36} \times (0.086188306 + 0.088252191 + 0.0883323 + 0.090396185 + 0.091305288 + 0.093369173 \\
& + 0.07568348 + 0.077747365 + 0.077827474 + 0.079891359 + 0.080800462 + 0.082864347 \\
& + 0.067341033 + 0.069404918 + 0.069485027 + 0.071548911 + 0.072458015 + 0.0745219 \\
& + 0.089550581 + 0.091614465 + 0.091694574 + 0.093758459 + 0.094667563 + 0.096731447 \\
& + 0.079045754 + 0.081109639 + 0.081189748 + 0.083253633 + 0.084162736 + 0.086226621 \\
& + 0.070703307 + 0.072767192 + 0.072847301 + 0.074911185 + 0.075820289 + 0.077884174) \\
= & \ 0.0794.
\end{aligned}
$$

Thus, the priority order of options is: $A_1 \succ A_3 \succ A_2$ where the sign "$\succ$" signifies "superior to." Hence, the optimal supplier is A_1, i.e., Poua Gostar Khorasan Company for Auto-making industry.

6 Results and validation

The outcomes with the validation are discussed in two ways: A sensitivity investigation of the proposed HF-DEA-FOCUM-MABAC approach considering diverse attribute weight sets values and the validation of the outcomes derived by proposed HF-DEA-FOCUM-MABAC approach

Table 9 The BAA matrix for SSS

ζ_1	ζ_2	ζ_3	ζ_4	ζ_5	ζ_6
{0.15234, 0.19193, 0.21221, 0.24292}	{0.21221, 0.174021, 0.12968, 0.19193, 0.15739, 0.11729}	{0.21361, 0.25098, 0.28823, 0.22699, 0.23618, 0.30629}	{0.16373, 0.19535, 0.24292}	{0.53011, 0.61374, 0.7023}	{0.08741, 0.16019}

Table 10 The degrees of BAA G for SSS

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	{0.13780, 0.16139, 0.18167, 0.19456}	{0.16665, 0.12845, 0.08412, 0.14637, 0.11182, 0.07172}	{0.15705, 0.17690, 0.231668}	{0.02553, 0.05715, 0.10472}	{0.47510, 0.54089, 0.59978}	{0.0638, 0.12275}
A_2	{0.09185}	{0.10126, 0.07183}	{0.02952, 0.04200, 0.07408}	{0.04298, 0.08885, 0.19186}	{0.0728}	{0.01121, 0.03744}
A_3	{0.04837, 0.06854}	{0.13486, 0.07183, 0.02178}	{0.02952}	{0.25102}	{0.04215, 0.05502, 0.0728}	{0.01121, 0.02359}

carried out by comparing them with corresponding HF-FOCUM-TOPSIS approach as follows:

6.1 Sensitivity investigation (SI)

Here, we use the SI to weigh the influence of the "most significant attribute" on outcomes of the introduced model. After calculating the attribute weights by FUCOM, the "most significant attribute" is recognized as the maximum weight. Kahraman (2002) suggested the weight proportionality procedure through the SI, given in Eq. (17) as follows:

$$w_c = (1 - w_s) \times \frac{w_c^0}{W_c^0} = w_c^0 - \alpha_c \times \Delta x \tag{17}$$

where w_c = Variation in attributes weights in sensitivity assessment, w_s = Weight of the most significant attribute, w_c^0 = Original values of the attribute weights, W_c^0 = Addition of the original values of attribute weights that are changed, α_c = weight coefficient of elasticity.

The relative compensation for diverse values of weight coefficients (α_c) can be estimated by the expression:

$$\alpha_c = \frac{w_c^0}{W_c^0} \tag{18}$$

The assumptions during the SI (Kahraman, 2002) are given by.

(i) The weight coefficients (α_c) is defined as one, which is given in Eq. (18);
(ii) The ratio of attribute weights remains unchanged through the SI.

From Eq. (18), it is observe that the variation degree to a set of weight coefficients is signified by the parameter Δx based on the coefficient (α_c). Now, we can estimate the limit values of Δx as follows:

$$-w_s^0 \le \Delta x \le \min\left\{\frac{w_c^0}{\alpha_c}\right\} \tag{19}$$

Next, we define the new attribute weights based on the pre-set attributes for SI. A set of weight coefficient values is computed by Eqs. (20) and (21).

$$w_s = w_s^0 + \alpha_s \times \Delta x \tag{20}$$

$$w_c = w_c^0 - \alpha_c \times \Delta x \tag{21}$$

where w_s^0 = original weight of the most influential attribute subjected to SI, w_c^0 = original value of attribute weights and $\sum w_s + \sum w_c = 1$.

In this assessment, we take the highest degree of attribute w_4 = 0.417, the C_4 attribute can be acknowledged as the most significant attribute. Afterward, the coefficients α_c are estimated in Table 11 and the limits of parameter Δx lie in $-0.417 \le \Delta x \le 0.586$ and obtained by Eq. (19). According to the defined limits for varying the most significant attribute weight, various attribute weight sets (S1, S2, …, S10) for sensitivity assessment are obtained. The interval $-0.417 \le \Delta x \le 0.586$ is categorized into 10 weight sets. For each set, the attribute weights are obtained by Eqs. (20) and (21), and are given in Table 12. Now, the overall assessment degree SS options are determined over diverse criteria weight sets and are depicted in Fig. 2 and the prioritization orders are given in Table 13. The outcomes (Fig. 2 and Table 13) display that allocating diverse weights to attributes indicate the variations in preference order of SS options, which validates that the presented approach is sensitive over the variations in attribute weights. Investigating the priority order, the option (A_1) has first place for each diverse sets of attribute weights, while A_2 is 2nd ranked in 50% cases and in the remaining cases it is 3rd ranked. The option A_3 is 2nd ranked in 50% cases, while in the remaining cases it is 3rd ranked. Next, we compute the "spearman rank correlation coefficient (SRCC)" values (r_A) (Ghorabaee et al. 2016; Mishra et al., 2019a, b) for diverse weight sets with the overall priority order and presented in Table 13. From Table 13, we obtain the average of the SRCC (r_A) values is 0.75, which shows a solid association (Ghorabaee et al. 2016) of priorities of SS options.

Table 11 weight coefficient (α_c) of attributes weights

	C_1	C_2	C_3	C_4	C_5	C_6
α_c	0.2372	0.3567	0.1433	1	0.0802	0.1826

6.2 Validation of the results based on different ranking methodology

To validate the outcomes, we discuss a comparison of presented HF-DEA-FUCOM-MABAC method with the corresponding HF-FOCUM-TOPSIS (Xu and Zhang, 2013). The TOPSIS method is chosen because it is one of the most renowned MADM models and it gives stable and reliable result. The algorithm of the HF-FOCUM-TOPSIS model is presented as.

Steps 1–5 Same as aforementioned model in Sect. 4

Step 6 Define the "hesitant fuzzy-positive ideal solution (HF-PIS" and "hesitant fuzzy-negative ideal solution (HF-NIS) as follows: $\Delta^+ = \{1\}$ and $\Delta^- = \{0\}$.

Step 7 Calculate the HF-distance measures $D^+\left(\vartheta_{ij}^h, \Delta^+\right)$ and $D^-\left(\vartheta_{ij}^h, \Delta^-\right)$, $i = 1, 2, , \ldots, r, j = 1, 2, \ldots\ldots, s$ using

Table 12 Ten set of attribute weights for SI

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
C_1	0.237	0.0854	0.0664	0.2372	0.2182	0.1992	0.1803	0.1613	0.1423	0.1233
C_2	0.3567	0.1284	0.0997	0.3567	0.3281	0.2996	0.2711	0.2425	0.2131	0.1855
C_3	0.1433	0.0516	0.0401	0.1433	0.1319	0.1204	0.1089	0.0975	0.0860	0.0745
C_4	0	0.64	0.72	0	0.0800	0.1600	0.2400	0.3200	0.4000	0.4800
C_5	0.0802	0.0289	0.0225	0.0802	0.0738	0.0674	0.0610	0.05454	0.0481	0.0417
C_6	0.1826	0.0657	0.0511	0.1826	0.1678	0.1534	0.1388	0.1242	0.1096	0.0949

Fig. 2 Final assessment values of options for different attribute weight sets

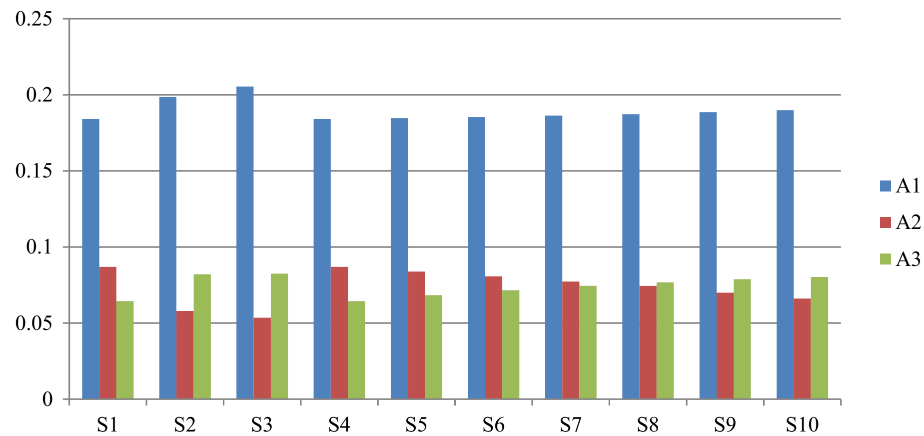

Table 13 Preference order of SSS with different attribute weight sets and the correlation values (r_A)

SSS	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Final ranking
A_1	1	1	1	1	1	1	1	1	1	1	1
A_2	2	3	3	2	2	2	2	3	3	3	3
A_3	3	2	2	3	3	3	3	2	2	2	2
Spearman's Correlation (r_A)	0.50	1.00	1.00	0.50	0.50	0.50	0.50	1.00	1.00	1.00	–

Table 14 Result by HF-FOCUM-TOPSIS method for SSS

SSS	$\mho_i^+$	$\mho_i^-$	λ_i	Final rank
A_1	0.8708	0.1631	0.1631	1
A_2	0.8560	0.1440	0.1440	2
A_3	0.8369	0.1292	0.1292	3

Eq. (4), where each value $D^+\left(\vartheta_{ij}^h, \Delta^+\right)$ and $D^-\left(\vartheta_{ij}^h, \Delta^-\right)$ is calculated.

Step 8 The discriminations of the options from HF-PIS and HF-NIS are estimated as follows:

$$\mho_i^+ = \sum_{j=1}^{s} D^+\left(\vartheta_{ij}^h, \Delta^+\right) \text{ and } \mho_i^- = \sum_{j=1}^{s} D^-\left(\vartheta_{ij}^h, \Delta^-\right),\ i = 1, 2, \ldots, r,\ j = 1, 2, \ldots, s.$$

Step 9 Obtain the "closeness index (CI)" for each option by utilizing the formula:

$$\lambda_i = \frac{\mho_i^-}{\mho_i^+ + \mho_i^-},\ i = 1, 2, 3, \ldots, r.$$

Step 10 The options are preferred based on their CI λ_i, $i = 1, 2, 3, \ldots, r$.

In Table 14, we depict the final outcomes of HF-FOCUM-TOPSIS method as follows:

Thus, the priority order of SS option is $A_1 \succ A_2 \succ A_3$ using HF-FOCUM-TOPSIS model. On the other hand, the developed HF-DEA-FOCUM-MABAC approach suggests a slightly different priority order which is $A_1 \succ A_3 \succ A_2$. However, both approaches have preferred SS option A_1 as the best option, which signifies that the preference order obtained by the HF-DEA-FOCUM-MABAC method is validated and credible.

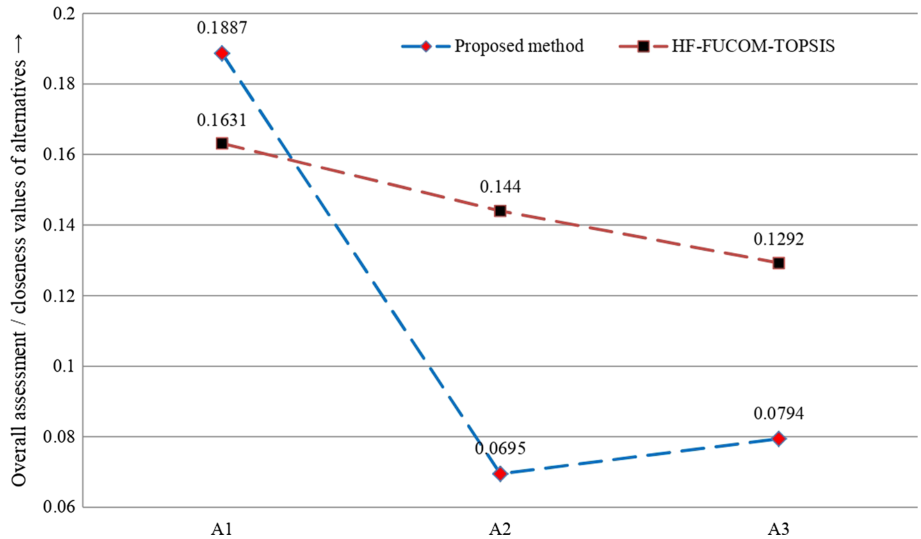

Fig. 3 Comparison of the overall assessment degree/CI of the presented approach with extant method

Here, Fig. 3 demonstrates the variation of overall assessment degree and CI of SS options obtained by the presented and extant methods. Overall, the benefits of the HF-DEA-FUCOM-MABAC method over the extant method are given as follows (see Fig. 3):

- The MABAC is distance-based method. The core is to establish the BAA as the benchmark, and to choose the optimal option by assessing the relative association between each option and the BAA, while The TOPSIS model provides an outcome with the smallest discrimination degree from the HF-PIS and the highest discrimination from the HF-NIS, but it does not consider the relative significance of these discriminations.
- In MABAC approach, we utilize the hesitant fuzzy aggregation operators as well as distance measure to estimate the overall assessment degree of options. In the facet of MABAC, the BAA matrix is computed by the HFWG operator, which is closer to theoretical degree than that essential from average operator. In TOPSIS, the implementation of only distance measure may lead to information loss and alteration, which can be evaded by the presented HF-DEA-FUCOM-MABAC approach.

7 Conclusions

The concern of sustainability in the SCM has become an important concern that is getting substantial consideration. In this paper, a combined methodology with DEA-FUCOM and MABAC approaches is implemented for the first time for assessing the suitable sustainable supplier, using a case study for an Auto-making industry. Considering the concern of imprecision and uncertainty of practical MADM problems, we represent the attribute values in terms of the HFSs at the time of formation of MADM. In this presented methodology, efficient alternatives are identified by the DEA tool, aggregation is done using hesitant fuzzy weighted aggregation operators, subjective weight of attributes are calculated using the FUCOM and final ranks of the alternatives are obtained using the HF-MABAC method. For better understanding the method, we have demonstrated a case study of SSS problem for an Auto-making industry is considered and the corresponding outcomes are compared with the extant model which truly allows of its efficiency and strength.

The proposed HF-DEA-FUCOM-MABAC approach has some advantage as follows:

(i) As HFSs can tackle more uncertain data as a generalizations of FSs that occurs in realistic MADM. Thus, the developed approach is more general.

(ii) In our developed method, DEA is used to identify the efficient alternatives at the 1st stage and these efficient alternatives are evaluated further by decision experts based on certain attributes. Thus DEA technique reduces our aggregation computation complexity as it reduces the number of alternatives before the aggregation process starts.

(iii) The presented method computes the attribute weights by the FUCOM. It belongs to the group of subjective procedures for computing attribute weights, as well as the AHP tool (Saaty, 1980) and the BWM (Rezaei, 2015). Like the AHP and BWM methods, FUCOM is based on the pairwise comparison of attributes doctrine and validate the outcomes with DFC. However, in contrast to different subjective procedures, FUCOM shows smaller DFC while obtaining the degree of the attributes from the optimal degrees (Pamucar et al., 2018a, b, c, d).

(iv) To increase the robustness of the fuzzy-MABAC, we have developed HF-MABAC with the DEA and FUCOM. Compared to the existing tools like VIKOR, ELECTRE, TOPSIS, PROMETHEE and others, the key concept of the MABAC approach is that it considers the discrimination between the attribute degree of options and the BAA, and considers the fuzziness of the decision settings, to provide more precise and efficient MADM outcomes. Thus, the introduced approach is bridging the extant research gap of sustainable supplier assessment.

For further study, the presented approach can be used to various MADM problems such as energy investment evaluation, project selection, low-carbon tourism strategy selection and risk assessment. It may be suggested to consider different criteria and alternatives for SSS or other types of supplier assessment for a more comprehensive solution. The developed methods can be extended by "hesitant fuzzy soft sets (HFSs)," "neutrosophic sets (NSs)," "picture fuzzy sets (PiFSs)," "spherical fuzzy sets (SFSs)" and "intuitionistic 2-tuple fuzzy linguistic term sets (I2TFLTSs)" settings.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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