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A sophisticated decision paradigm for the assessment of hydrogen storage technologies for mobility applications

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A B S T R A C T

In the pursuit of sustainable transportation, hydrogen emerges as a promising zero-emission alternative, offering greater efficiency compared to conventional fuels. However, achieving widespread adoption of hydrogen transportation necessitates a focus on developing efficient onboard storage systems. Therefore, the evaluation of various storage methods becomes pivotal in determining a viable solution for vehicle use, constituting a multi-attribute decision-making challenge. This study aims to create a structured decision-making model employing bipolar linear diophantine fuzzy logic, specifically applied to assess hydrogen storage technologies. Bipolar linear diophantine fuzzy sets are introduced to address the inherent uncertainty in decision-making. The framework evaluates the feasibility of four storage systems across ten sustainability criteria. An enhanced LOPCOW-OPA model based on bipolar linear diophantine fuzzy logic is proposed to assess the significance of criteria, while the bipolar linear diophantine fuzzy-based MACONT-MARCOS-ELECTRE-III approach ranks storage technologies. The findings indicate compressed hydrogen storage as an optimal onboard solution for mobile applications. Sensitivity analysis is conducted to gauge how attribute weights and other variables influence the decision-making process. Furthermore, validation of the results obtained through the proposed method is performed via comparative analysis. Moreover, the results obtained can offer valuable insights for the development of hydrogen storage solutions aimed at sustainable and efficient transportation.

1. Introduction

Growing human activities and improved living standards are driving an increasing demand for energy. The primary energy sources, fossil fuels, which currently meet these demands, are depleting and causing severe negative impacts on society and the environment. The automotive industry, the second-largest energy consumer at 29% of total energy consumption [1], heavily relies on liquid fuels from crude oil refining. The high energy density, transport convenience, and well-established storage infrastructure make these fuels the preferred choice, resulting in significant greenhouse gas (GHG) emissions, contributing to 37% of global CO_2 emissions [1]. As populations and vehicle numbers rise, traffic congestion increases, leading to elevated emissions and deteriorating air quality. This underscores the urgency for sustainable transportation, particularly in terms of energy independence. Countries like the US, UK, Germany, Korea, and China are already making substantial strides in sustainable mobility, serving as examples for others [2]. Table 1 presents the nomenclature used in the study.

In India, the transportation sector consumes 25% of overall energy, significantly impacting the country's energy infrastructure and socio-economic growth [2]. Achieving a sustainable economy highlights the crucial need for smart and sustainable transportation infrastructure to reduce emissions and optimize energy demand. Electric vehicles (EVs) have emerged as promising choices for environmentally friendly transportation due to minimal emissions, affordable refueling, and

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Table 1
Abbreviations.

EVs	Electric vehicles
FCVs	Fuel cell vehicles
GH	Green hydrogen
HFCVs	Hydrogen fuel cell vehicles
HST	Hydrogen storage technology
MADM	Multi-Attribute decision making
BFS	Bipolar fuzzy set
IFS	Intuitionistic fuzzy set
PyFS	Pythagorean fuzzy sets
q-ROFS	q-rung orthopair fuzzy set
LDFS	Linear diophantine fuzzy set
BLDFS	Bipolar linear diophantine fuzzy set
LOPCOW	Logarithmic Percentage Change-driven Objective Weighting
OPA	Ordinal Priority Approach
MARCOS	Measurement of alternatives and ranking according to COmpromise solution
MACONT	Mixed Aggregation by Comphrehensive Normalization Technique for Multi-Criteria Analysis
ELECTRE	ELimination Et Choice Translating REality

reduced maintenance costs. Nevertheless, the long battery charging time, limited driving range, and high purchasing costs accompanied with the EVs led to the groundbreaking progressions in vehicle technology, such as hybrid electric vehicles (HEVs), and fuel cell electric vehicles (FCEVs) [3]. Within these, hydrogen-based fuel cell technology (HFCV) for EVs has exhibited considerable promise in storing and converting chemical energy into electricity [4]. This innovation presents distinct benefits such as superior energy conversion rates, an effective drivetrain, and zero CO_2 emissions, surpassing the performance of conventional gasoline vehicles [4].

Unlike the EVs, which are expected to dominate in the vehicular market, HFCVs are also looked upon as equal significance as they possess the ability to be fueled using renewable and sustainable energy sources, and use electric motors. However, the notable difference between them lies with the driving range and the refueling style. In the commercial scale, EVs are found to be well suitable for short-range and small vehicles and FCVs for medium–large and long-range vehicles. Globally around 6500 FCV are sold to the consumers with California occupying a leading market in the FCVs [3]. In this line, India is beginning to consider using hydrogen as a clean fuel in fuel cell electric vehicles and is preparing to adopt hydrogen as a fuel. Variable Renewable Energy Sources (VRES) yield significant influence in the Indian energy landscape, presenting the capability to produce green hydrogen at a scale sufficient to power 92,000 fuel cell buses. Despite advancements in hydrogen vehicle technology, the main obstacle to their widespread adoption in India continues to be the initial cost associated with importing fuel cells and electrolysers.

However, as research, development, and scaled manufacturing of electrolysers become a global technological competition, India has a significant opportunity to benefit by promoting domestic production of these essential components. By doing so, the country can attain technical prowess, participate actively in the burgeoning global market driving the clean energy transition, and capture a larger share of the economic benefits associated with this transition. Additionally, anticipated cost reductions in hydrogen production through solar PV or wind-based electrolysis by 2030, ranging from $1.5/\text{kg} – 2.3/\text{kg}$, are poised to enhance the competitiveness of hydrogen fuel cell vehicles (HFCVs) against conventional fossil fuel-based combustion engines [3]. By supporting the integration of renewable energy into the grid, the model can help accelerate the transition to a low-carbon energy system and reduce dependence on fossil fuels. Consequently, various on-board hydrogen storage technologies (HST) are under development to make vehicular applications technologically viable.

With several Hydrogen Storage Technologies (HST) already deployed and in the pipeline for further development, the need arises to address the issues that intersects with conditions like geographical, economic, and developmental factors in determining the feasibility and viability of the storage techniques. This comprehensive examination, facilitated by Multiple Attribute Decision Making (MADM), has assisted decision-makers in evaluating these various factors to pinpoint the most efficient and sustainable solutions. Given the variability in human preferences, integrating fuzzy logic into decision-making processes has become indispensable for achieving optimal outcomes. Numerous researchers have investigated sustainable Hydrogen Storage Technologies (HST) tailored to specific applications using fuzzy MADM methodologies. These investigations encompass subjective techniques such as Analytic Hierarchy Process (AHP) and Decision Making Trial and Evaluation Laboratory (DEMATEL), as well as traditional ranking approaches like VIKOR and TOPSIS, to address inherent subjectivity and trade-offs among conflicting attributes. With various methods suggesting different hydrogen storage options, a more thorough analysis is needed to enable decision-makers to make choices based on objective criteria rather than subjective biases, thus ensuring consistency in evaluation methods.

Consequently, the study aims to offer a dependable and comprehensive decision-making tool for selecting the most sustainable hydrogen storage methods for mobile applications in India. To achieve this, a combination of hybrid methods, including MACONT-MARCOS-ELECTRE-III techniques enriched by bipolar linear diophantine fuzzy sets (BLDFS), is proposed to handle diverse information and streamline decision-making, with the goal of realizing effective solutions in HST to drive the commercialization of hydrogen-powered vehicles in Indian road transportation. Additionally, an integrated weighting method, incorporating LOPCOW-OPA extended using BLDFS, is suggested for analyzing influential parameters in the decision-making process.

This proposed work makes a significant contribution to existing literature, as no previous study has considered a combination of diverse ranking methods for analyzing hydrogen storage options. The study's findings can provide valuable insights for policymakers and stakeholders, helping them understand the factors that shape the development of hydrogen storage systems. By systematically examining multiple parameters, the study offers insights into the complex landscape of hydrogen storage, which is crucial for establishing a sustainable energy storage infrastructure.

1.1. Hydrogen storage technologies

The potential of HFC compared to battery systems highlights the future role of H_2 in sustainable transport. Presently, companies like Toyota Mirai, Hyundai, Renault, and Honda are key players in producing HFCVs commercially [3,5]. Numerous countries are actively researching the development of GH ecosystems, aiming to replace fossil fuels. India, aligning with this trend, has launched a national strategy for GH, aiming to transition to an independent economy powered by sustainable, hydrogen-based energy. This strategy includes establishing India as a leading nation in GH technology, with various pilot projects and studies underway to address the challenges of creating a hydrogen-based economy. However, as the growth of hydrogen economy is the country is reliant on the RES, developing storage technologies can enable the storage and utilization of renewable energy sources such as wind and solar power which can help in energy sustainability, grid stability and energy independence. This can help in the reduction of import cost spent on conventional fuels and helps in the cost effective production of hydrogen from the renewables.

The challenges in storing and transporting hydrogen, due to its gaseous state, hinder its practicality in mobile uses. Hydrogen's low energy density poses a storage challenge in vehicles, needing to balance storage capacity with driving range. Given hydrogen's low volumetric energy density – approximately 0.083 kg per cubic meter under atmospheric conditions – a vehicle needs a storage system capable of holding about 6 to 7 kg of H_2 to ensure reasonable autonomy [6]. Consequently, to improve hydrogen's energy density both gravimetrically and volumetrically, four storage methods are being explored [1,4,7,8].

- **Compressed Storage:** Here H_2 is pressurized and stored in high-pressure tanks, typically ranging from 350 to 700 bar [8]. These tanks are constructed using carbon fiber-reinforced polymers, which are able to withstand the internal pressure, reducing the risk of gas leakage and explosions when subjected to strain. The tanks are classified into types I, II, III, and IV, depending on the materials utilized and the internal pressure [8]. Type III or IV vessels, capable of storing H_2 at 700 bars, are considered practical options, offering rapid refueling times (<3 min) and a driving range of up to 500 km [1,8]. This method has already demonstrated success and is promising, with major manufacturers of HFCVs already employing it commercially.
  From a safety perspective, the materials commonly used in these tanks, such as carbon fiber and nylon-6, are non-toxic and environmentally benign. However, a significant amount of energy is required to compress the hydrogen from 20 to 700 bars. While high pressure poses inherent risks, considerable efforts are made to safeguard the pressure vessel in the event of an accident. This technology improves storage performance by providing high strength at a reduced weight. The cost of carbon fiber constitutes a significant portion of the total expenses, followed by the balance of the plant.
  For instance, major car manufacturers like Maruti Suzuki and Hyundai produce approximately 500,000 units in India. However, if they were to manufacture FCEVs, their combined demand for type-IV tanks would be substantially higher. This increased demand would result in a considerable reduction in carbon fiber and other raw material costs, leading to significant growth in compressed storage and its applications.
- **Liquid Storage:** Due to the low energy density of hydrogen in its gaseous state, which necessitates large storage volumes, storing it in the form of liquid is possible. In this technology, H_2 is cooled below its boiling point of 20 K [9] to liquefy it, and the resulting liquid H_2 is stored in heavily insulated containers. Liquid storage offers higher volumetric and gravitational density compared to compressed storage, making it more efficient for transport and distribution. However, liquefaction entails energy losses from boil-off, requiring further research for vehicular applications [7]. Additionally, vehicles equipped with such tanks need regular refilling, even when not in use.
  Therefore, this storage concept is most effectively utilized for commercial applications with consistent and predictable demand. Liquefaction consumes approximately 35% of the energy stored within hydrogen, resulting in a storage efficiency of around 22.3% [7]. It is anticipated that the cost associated with such storage processes (liquefaction, storage, re-gasification) will exceed that of high-pressure storage, even at pressure levels of 700 bar and above.
- **Cryo-compressed Storage:** Combining the advantages of both compressed gas and liquid storage, cryo-compressed storage entails storing H_2 at cryogenic temperatures within a pressurizable vessel, typically operating at around 350 bar and below 20 K [7]. In this approach, the insulated vessel utilized for hydrogen storage is designed to withstand both cryogenic temperatures and high pressures, thereby enhancing volumetric storage capacity and safety compared to compressed hydrogen or cryogenic liquid hydrogen alone. This method enables various forms of H_2 fueling, including liquid, cold-compressed, ambient-temperature compressed, and cryo-compressed hydrogen.
  The use of lower pressures in cryo-compressed hydrogen storage, typically below 300 bar, in contrast to compressed hydrogen storage at 700 bar, may reduce the need for more expensive carbon fiber composites. However, challenges related to infrastructure availability and cost remain significant barriers to the widespread adoption of this storage method, thereby limiting its viability.
- **Material-based Storage:** In this type of storage, H_2 is stored in a solid state, achieved either by physically adsorbing it onto materials with high surface areas such as carbon nanotubes and metal–organic frameworks, or by chemically bonding it with substrates like metal hydrides and complex hydrides, which release hydrogen through thermal decomposition [5]. Solid storage, particularly utilizing metal hydrides, provides compact, long-term storage with high density, making it well-suited for fuel cell vehicles.
  Compared to physical storage methods, material-based storage is anticipated to offer higher hydrogen storage capacity at room temperature and enhanced safety due to lower hydrogen storing pressure and a slower hydrogen release rate. However, the need to maintain specific temperatures during refueling and operation results in energy losses and requires bulky insulation. Additionally, metal hydrides present challenges related to the weight of hydrogen on-board storage, which may potentially affect vehicle performance and efficiency.
  Various metal combinations, such as zirconium (Zr), lanthanum (La), titanium (Ti), and magnesium (Mg), have been developed as materials for hydrogen storage [5]. Unlike methods that store hydrogen in its gaseous state, material-based storage eliminates the need for additional processes for conversion or purification. However, desorbing or releasing hydrogen from the material may require additional steps or energy input, which could impact overall efficiency and practicality.

The paper's layout is as follows: In Section 1, the importance of hydrogen storage technologies and the examination of current methods are introduced. Section 2 establishes the literature review. The concept of BLFS is introduced in Section 3, with a decision algorithm outlined in Sections 4 and 4.1. A numerical example is presented in Section 5. Sections 6 and 7 discuss result validation and findings, respectively. Lastly, Section 8 provides a conclusion.

2. Background of the study

Multi attribute decision making (MADM) frameworks are crucial for evaluating diverse alternatives, especially in conflicting circumstances. Decisions often involve expert perspectives, requiring a specialized tool for subjective assessments and measuring ambiguity in human judgment data. Fuzzy logic, with its unique ability to convey logical reasoning through linguistic expressions and a continuum of values between 0 and 1, is indispensable in this context. The increasing recognition of synergies between fuzzy logic and MADM has led to a rising trend of integrating these approaches, enhancing decision-making effectiveness across a wide range of diverse problems [10]. Researchers have introduced various extensions of fuzzy sets by modifying the number of elements used to describe imprecision and the associated range of values. Among these extensions is the Bipolar fuzzy sets (BFS) developed by Zhang et al. [11], which has the capability to represent bipolar information, considering positive and negative aspects within the range of $[-1, 1]$. This two-way assessment provides a broader framework for expressing information, thereby improving the decision-making process. Consequently, Alghamdi et al. [12] introduced BFS-based modifications to ELECTRE-I and TOPSIS methodologies for addressing Multiple Attribute Decision Making (MADM) situations. Additionally, Akram et al. [13] applied this model to diagnose patients' health status. The concept of bipolar soft rough sets was initiated by Gul et al. [14], and Sindhu et al. [15] proposed the Bipolar Picture Fuzzy Set to handle the judgmental thinking of experts in decision-making scenarios. As a result, a multitude of extended fuzzy sets have been established, coupled with BFS serving as an excellent tool for expressing the reasoning behind human cognition and dealing with the inherent fuzziness in analyzing decision scenarios [16–18].

In a manner comparable to intuitionistic fuzzy sets (IFS), pythagorean fuzzy sets (PyFS), and q-rung orthopair fuzzy sets (q-ROFS), Riaz et al. [19] presented the ideology of linear diophantine fuzzy sets (LDFS), wherein control parameters are entailed into the current framework of IFS. This integration of control parameters removes the limits associated with membership and non-membership grades, allowing for greater flexibility in selecting these grades within a range of values. This motivated further research using LDFS and several extensions of these set has been proposed for capturing uncertainty and fuzziness arising in MADM problems. Riaz et al. [20] proposed spherical LDFS in dealing with ambiguity in emergency decision making scenarios. Kamaci et al. [21] incorporated complex LDFS and its cosine similarity measures in assessing medical diagnosis problems. Further, q-LDFS [22], dual hesitant LDFS [23], interval valued LDFS [24] are proposed as prominent tools for hesitancy management for optimal decision making. Thus, the benefits offered by both LDFS and BFS promote their integration for data curation, particularly in scenarios where a comprehensive assessment involving both fuzziness and bipolarity is necessary.

In the decision-making process, assessing alternatives in the presence of conflicting factors is pivotal. Yet, allocating attribute weights exclusively through either systematic data analysis or subjective opinions may yield inappropriate outcomes. Acknowledging the constraints of each method, a blended approach becomes valuable, ensuring a more precise representation of the relative importance of each criterion. Ecer et al. [25] introduced Logarithmic Percentage Change-driven Objective Weighting (LOPCOW), a method that gauges the significance of each attribute through a logarithmic function and variability distribution measure. In contrast to entropy [26] and MEREC [27] methods that employ logarithmic functions for criteria weight estimation, LOPCOW distinguishes itself by effectively managing both positive and negative data, thereby producing more rational and balanced weights [25]. The approach has been integrated with ranking methods such as MACONT, CoCoSo, MAIRCA, VIKOR, and ARAS to address diverse problems, including the selection of third-party logistics providers [28], micro-mobility options in urban transportation [29], performance analysis [30] and unmanned aerial vehicle selection for precision agriculture [31].

Among the subjective evaluations used in the allocation of attribute weights, Ordinal Priority Approach (OPA) serves as a mathematical programming method for indicating attribute importance based on expert suggestions [32]. This technique has been combined with the WINGS method for planning undergraduate elective courses [33], the MARCOS method for sustainable supplier selection [34], last-mile delivery selection [35], the RAFSI method for autonomous vehicle selection [36], and the EDAS method for assessing production strategies [37]. In settings requiring group decision-making, the priority assigned to experts can have a significant impact on the practicality of the decisions. Using a systematic technique, rather than allocating weights to experts at arbitrary can improve the decision-making process's rationality. In light of this aspect, Wang et al. [38] introduced a mean deviation-based approach that utilizes a fuzzy preference relation matrix to prioritize experts. Similarly, Ecer et al. [31] proposed an algorithm grounded in regret theory to analyze the behavioral attitudes of experts.

In recent times, numerous MADM techniques have gained importance as valuable tools for assessing options based on different attributes. Measurement of alternatives and ranking according to COmpromise solution (MARCOS) is one such method developed by Stević et al. [39] for ranking alternatives, based on the distance between the alternatives and the reference alternative. The simplicity, efficiency, and flexibility of the algorithm compelled the decision-makers to adopt the suggested method. Furthermore, an assortment of expanded frameworks for the established model have been put forward including fuzzy logic [40], grey numbers [41], and D-numbers [42], to handle the uncertainty and ambiguity encountered by decision-makers when evaluating options based on a set of qualitative criteria. Similarly, the approach has been merged with two or more methods, resulting in integrated ranking outcomes and further refining judgment in problem analysis. Mitrović et al. [43] combined fuzzy MARCOS with CRITIC, FUCOM and DEA methods for the assessment of road safety parameters. Further the method has been extended using the spherical fuzzy sets and been fused with CRITIC method for smart phone selection [44]. Büyüközkan et al. [45] presented SWOT based fuzzy AHP method coupled with fuzzy MARCOS method for the assessment of digital technologies. Nonetheless, the fuzzy MARCOS encounters limitations in information normalization and the permissible trade-offs between diverse criteria. To overcome this constraint, employing integrated frameworks that yield integrated ranking results will augment judgment in problem analysis [46].

Mixed Aggregation by Comprehensive Normalization Technique for Multi-Criteria Analysis (MACONT) is also a recently developed MADM technique designed to pinpoint potential alternatives [47]. What sets this technique apart is its incorporation of multistage normalization and distance-based ranking, which accommodates both compensatory and non-compensatory elements of criteria. Aksakal et al. [48] combined MACONT with the fuzzy BWM-CRITIC methods to choose thermal insulation materials. Furthermore, its efficacy has been showcased in achieving sustainable solutions across diverse applications, including strategy selection [49], sustainable supplier selection [50], transportation company selection [51], and sorting problems [52].

The ELimination Et Choice Translating REality (ELECTRE) is a non-compensatory technique that establishes the outranking relation among alternatives through concordance and discordance indices [53]. Various extensions of this method have been introduced, differing in both their operations and the nature of the decision problem considered [54]. Notably, the ELECTRE-III method has gained widespread use owing to its capability to handle fuzzy data [55]. Movahedi et al. [56] incorporated this method with FCM-LA techniques for the sequencing of stock exchanging industries in Tehran. Dortaj et al. [57] devised a modified ELECTRE-III approach for solving site selection problems. Mohamadghasemi et al. [58] proposed an interval type-2 fuzzy-based ELECTRE-III method for material handling equipment selection, while Liang et al. [59] suggested a picture fuzzy-based hybrid model for cleaner production assessment in gold mines.

The sporadic nature of RES underscores the pivotal importance of energy storage systems in bolstering the dependability and safety of the power grid. Employing hydrogen as a storage medium for surplus energy emerges as an eco-friendly solution, maximizing the utilization of clean energy and fostering the growth of a low-carbon economy [66]. In recent times, there has been a notable uptick in the utilization of Multi Attribute Decision Making (MADM) models to streamline decision-making processes concerning energy-related issues.

For instance, Mostafaeipour et al. [67] conducted a study utilizing several decision-making models to evaluate potential locations for wind-based hydrogen projects in Uzbekistan. Similarly, Gao et al. [68] employed the TODIM model to assess suitable sites for integrating hydrogen storage with existing photovoltaic power generation in China. Sun et al. [69] investigated risk factors associated with hydrogen storage and distribution using the ANP-DEMATEL approach. Additionally, Colak et al. [70] conducted a comprehensive analysis of various energy storage systems using hesitant fuzzy AHP-VIKOR methods, considering both qualitative and quantitative parameters.

Furthermore, Guo et al. [71] utilized a probabilistic hesitant fuzzy-based DEMATEL-PROMETHEE-II approach to assess the investment feasibility of hybrid storage projects incorporating hydrogen in China. Similarly, Wu et al. [72] employed a triangular intuitionistic fuzzy-based DEMATEL-TODIM approach to assess similar projects in the Mongolia region of China. Albawab et al. [73] highlighted influential parameters for assessing the performance of various energy storage systems using SWARA-ARAS techniques.

Table 2
MADM approaches in HST selection.

Authors	Methodology	Application	Preferred option
Gumus et al. [60]	Fuzzy AHP-GRA	Portable and stationary storage in Turkey	Metal hydride
Ilahar et al. [61]	Z fuzzy DEMATEL-VIKOR	Stationary	Carbon nanotubes
Sharaf et al. [6]	Spherical fuzzy VIKOR	Automobiles	Compressed hydrogen gas at 350 bar
Haktanır et al. [62]	Triangular intuitionistic Z number based AHP-TOPSIS	–	Chemical storage
Karatas et al. [63]	Fuzzy AHP and weighted Fuzzy axiomatic design	–	Metal hydride
Acar et al. [64]	Interval valued intuitionistic AHP	Stationary	Compressed hydrogen
Oner et al. [65]	AHP-VIKOR	HFC vehicles	Methanol

In the mean time, Mohamed et al. [74] developed a multi-stage decision model using the interval-valued neutrosophic fuzzy CODAS method to address complexities in renewable energy source selection. Sallam et al. [75] assessed potential factors for onshore wind energy generation using an interval-valued neutrosophic fuzzy WSM model under sustainable indicators. Furthermore, as awareness of the vital importance of hydrogen storage in diverse fields has increased, researchers have heightened their endeavors to develop sustainable HST tailored to specific applications. The combined results of investigations aimed at pinpointing appropriate HSTs for distinct purposes, along with the methodologies employed, are consolidated in Table 2.

Considering that AHP, VIKOR, TOPSIS, SWARA, DEMATEL, TODIM, ARAS, and WSM are commonly utilized compensatory methods in hydrogen and energy-related decision-making models, it becomes crucial to assess the effectiveness of alternative well-established techniques to address such issues comprehensively. These methods entail trade-offs among criteria while ranking alternatives against multiple constraints, highlighting the necessity for models that can handle such limitations effectively to facilitate efficient decision-making in such contexts. Furthermore, although reviewed studies frequently employ hybrid methodological frameworks by combining fuzzy sets or weight estimation methods, they often overlook the potential of combining two or more methods for criteria weight estimation or alternative prioritization. Hybrid methods have demonstrated greater effectiveness in navigating complexities, offering more realistic solutions compared to standalone techniques.

Therefore, this study proposes a bipolar linear diophantine fuzzy-based integrated framework for criteria assessment and ranking of alternatives. When dealing with group decision-making processes, assigning weights to experts to signify their influence on the decision process is crucial. Instead of arbitrarily assigning weights, employing a methodological procedure can enhance result accuracy. This study utilizes the mean deviation method to allocate experts' significance and proposes the LOPCOW-OPA method for attribute weight assignment. Furthermore, three ranking models (MACONT, MARCOS, and ELECTRE-III) i.e., the combination o are employed to identify the optimal choice.

2.1. Motivation

- Limited research exists in assessing diverse HST through the MADM approach. This emphasizes the requirement for comprehensive frameworks considering multiple factors associated with evolving sustainability trends to attain effective solutions.
- Combining BFS and LDFS provides considerable benefits in handling uncertainty and imprecision, resulting in a powerful technique for improving data accuracy and management in group decision-making processes. A thorough investigation of BLDFS is required to fully realize its potential for boosting group decision-making efficiency.
- Using combined ranking strategies is beneficial for assessing the complex and varied information that comes up when tackling more complicated problems [10]. Table 2 showcases a research void and highlights the importance of developing sophisticated decision frameworks essential for evaluating HST for their potential applications.

2.2. Contribution

- Recognizing the difficulty in evaluating various HST for specific applications, this study presents a decision-making model for selecting optimal hydrogen carriers for HFC vehicles.
- BLDFS is proposed as a combination of LDFS and BFS to proficiently capture and address the inherent ambiguity and fuzziness in the decision-making process.
- For systematic attribute weighing, objective-subjective LOPCOW-OPA model enhanced using the BLDF logic is developed to highlight the importance of attributes in decision-making.
- To prioritize storage systems, the article suggests integrating three MADM models (MACONT, MARCOS, and ELECTRE-III) with BLDFS.

3. Preliminaries

Definition 1. A bipolar linear diophantine fuzzy set (BLDFS) $\mathfrak{S}$ on the reference set Ω is defined as

$$\mathfrak{S} = \Big\{\Big(\kappa, \left\langle \Upsilon^+_{\mathfrak{S}}(\kappa), \Upsilon^-_{\mathfrak{S}}(\kappa), \Psi^+_{\mathfrak{S}}(\kappa), \Psi^-_{\mathfrak{S}}(\kappa)\right\rangle, \left\langle \zeta^+_{\mathfrak{S}}(\kappa), \zeta^-_{\mathfrak{S}}(\kappa), \xi^+_{\mathfrak{S}}(\kappa), \xi^-_{\mathfrak{S}}(\kappa)\right\rangle\Big) : \kappa \in \Omega\Big\}. \tag{1}$$

Here, $\Upsilon^+_{\mathfrak{S}}(\kappa), \Psi^+_{\mathfrak{S}}(\kappa), \zeta^+_{\mathfrak{S}}(\kappa), \xi^+_{\mathfrak{S}}(\kappa)$ represent the positive degrees of satisfaction, dissatisfaction and the control parameters of an element $\kappa \in \Omega$ corresponding to $\mathfrak{S}$ whereas $\Upsilon^-_{\mathfrak{S}}(\kappa), \Psi^-_{\mathfrak{S}}(\kappa), \zeta^-_{\mathfrak{S}}(\kappa), \xi^-_{\mathfrak{S}}(\kappa)$ are the negative grades of satisfaction, dissatisfaction and the control parameters of $\kappa \in \Omega$ describing a few implicit counter property corresponding to $\mathfrak{S}$ satisfying:

(i) $0 \le \Upsilon^+_{\mathfrak{S}}(\kappa), \Psi^+_{\mathfrak{S}}(\kappa), \zeta^+_{\mathfrak{S}}(\kappa), \xi^+_{\mathfrak{S}}(\kappa) \le 1$
(ii) $-1 \le \Upsilon^-_{\mathfrak{S}}(\kappa), \Psi^-_{\mathfrak{S}}(\kappa), \zeta^-_{\mathfrak{S}}(\kappa), \xi^-_{\mathfrak{S}}(\kappa) \le 0$
(iii) $\zeta^+_{\mathfrak{S}}(\kappa)\Upsilon^+_{\mathfrak{S}}(\kappa) + \xi^+_{\mathfrak{S}}(\kappa)\Psi^+_{\mathfrak{S}}(\kappa) \le 1$
(iv) $0 \le \zeta^-_{\mathfrak{S}}(\kappa)\Upsilon^-_{\mathfrak{S}}(\kappa) + \xi^-_{\mathfrak{S}}(\kappa)\Psi^-_{\mathfrak{S}}(\kappa) \le 1$
(v) $0 \le \zeta^+_{\mathfrak{S}}(\kappa) + \xi^+_{\mathfrak{S}}(\kappa) \le 1$
(vi) $-1 \le \zeta^-_{\mathfrak{S}}(\kappa) + \xi^-_{\mathfrak{S}}(\kappa) \le 0$

Furthermore, the positive hesitation or the indeterminancy degree is determined as $\chi^+_{\mathfrak{S}}(\kappa) = 1 - \left(\zeta^+_{\mathfrak{S}}(\kappa)\Upsilon^+_{\mathfrak{S}}(\kappa) + \xi^+_{\mathfrak{S}}(\kappa)\Psi^+_{\mathfrak{S}}(\kappa)\right)$ and the negative degree is defined as $\chi^-_{\mathfrak{S}}(\kappa) = -1 - \left(\zeta^+_{\mathfrak{S}}(\kappa)\Upsilon^+_{\mathfrak{S}}(\kappa) + \xi^+_{\mathfrak{S}}(\kappa)\Psi^+_{\mathfrak{S}}(\kappa)\right)$. Simply, $_F = \left\{\left\langle \Upsilon^+_F, \Upsilon^-_F, \Psi^+_F, \Psi^-_F\right\rangle, \left\langle \zeta^+_F, \zeta^-_F, \xi^+_F, \xi^-_F\right\rangle\right\}$ is called the bipolar linear diophantine fuzzy number (BLDFN). Also, the collection of all BLDFS over Ω is denoted as BLDFS(Ω).

Fig. 1 depicts a contrast among IFS, LDFS, and BLDFS. The visualization emphasizes BLDFS's superior capability in extending the range of both satisfaction and dissatisfaction grades compared to other expanded fuzzy sets. This guarantees a more meticulous and accurate examination of fuzzy data, allowing for the inclusion of both positive and negative opinions while upholding mathematical precision.

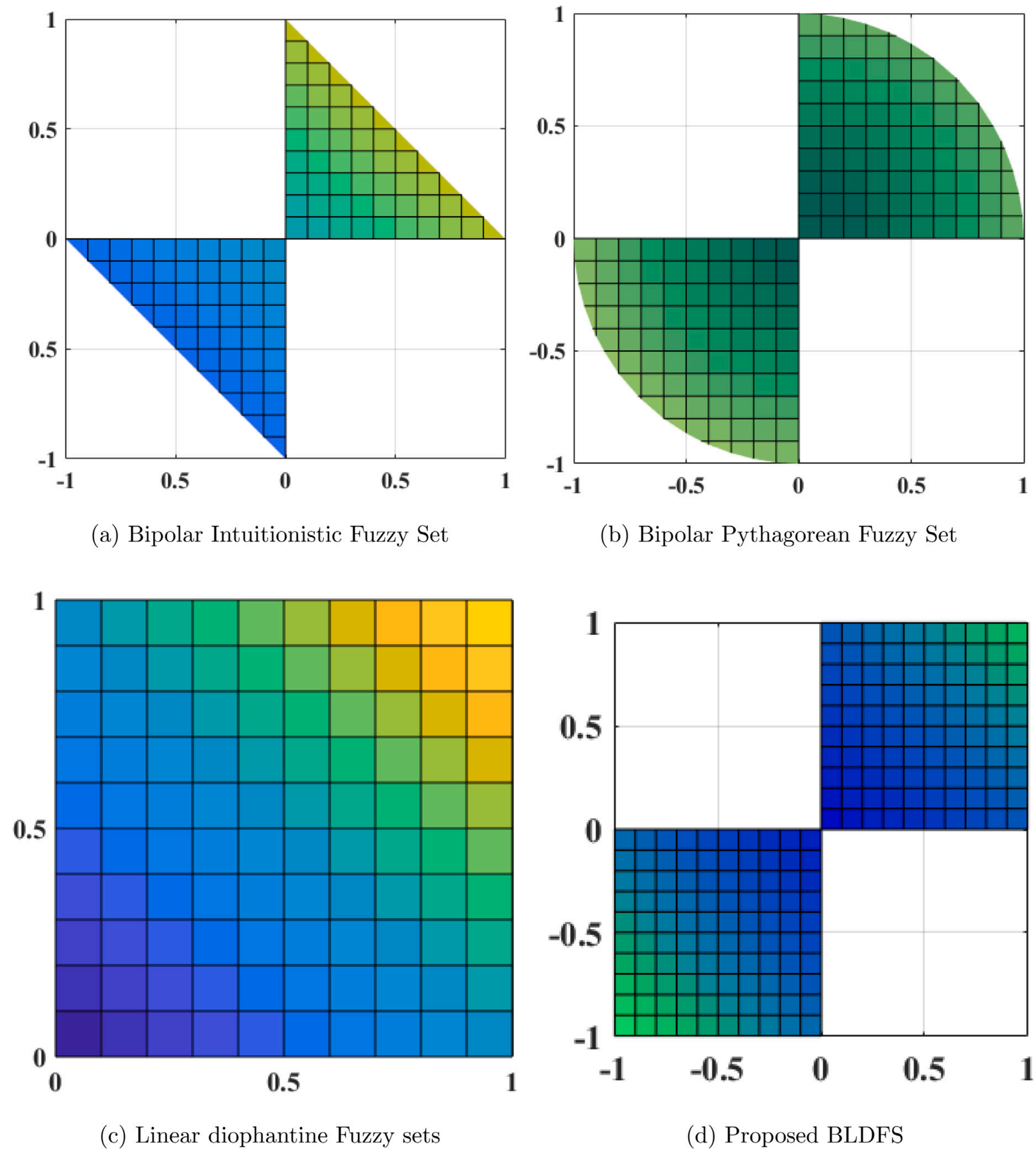


Fig. 1. Comparison of BLDFS with other existing fuzzy sets.

Definition 2. For $\mathcal{F}_{\mathfrak{b}} = \left\{\left\langle \Upsilon^{+}_{\mathcal{F}_{\mathfrak{b}}}, \Upsilon^{-}_{\mathcal{F}_{\mathfrak{b}}}, \Psi^{+}_{\mathcal{F}_{\mathfrak{b}}}, \Psi^{-}_{\mathcal{F}_{\mathfrak{b}}} \right\rangle, \left\langle \zeta^{+}_{\mathcal{F}_{\mathfrak{b}}}, \zeta^{-}_{\mathcal{F}_{\mathfrak{b}}}, \xi^{+}_{\mathcal{F}_{\mathfrak{b}}}, \xi^{-}_{\mathcal{F}_{\mathfrak{b}}} \right\rangle\right\}$ with $\mathfrak{b} = 1, 2$ and $\mathfrak{e} > 0$ we define the following:

- $\mathcal{F}_1 \oplus \mathcal{F}_2 = (\langle \Upsilon^{+}_{\mathcal{F}1} + \Upsilon^{+}_{\mathcal{F}2} - \Upsilon^{+}_{\mathcal{F}1}\Upsilon^{+}_{\mathcal{F}2}, -((-\Upsilon^{-}_{\mathcal{F}1})(-\Upsilon^{-}_{\mathcal{F}2})), \Psi^{+}_{\mathcal{F}1}\Psi^{+}_{\mathcal{F}2}, -((-\Psi^{-}_{\mathcal{F}1}) + (\Psi^{-}_{\mathcal{F}2}) - (-\Psi^{-}_{\mathcal{F}1})(-\Psi^{-}_{\mathcal{F}1}))\rangle, \langle \zeta^{+}_{\mathcal{F}1} + \zeta^{+}_{\mathcal{F}2} - \zeta^{+}_{\mathcal{F}1}\zeta^{+}_{\mathcal{F}2}, -((-\zeta^{-}_{\mathcal{F}1})(-\zeta^{-}_{\mathcal{F}2})), \xi^{+}_{\mathcal{F}1}\xi^{+}_{\mathcal{F}2}, -((-\xi^{-}_{\mathcal{F}1}) + (\xi^{-}_{\mathcal{F}2}) - (-\xi^{-}_{\mathcal{F}1})(-\xi^{-}_{\mathcal{F}1}))\rangle)$
- $\mathcal{F}_1 \otimes \mathcal{F}_2 = (\langle \Upsilon^{+}_{\mathcal{F}1}\Upsilon^{+}_{\mathcal{F}2}, -((-\Upsilon^{-}_{\mathcal{F}1}) + (\Upsilon^{-}_{\mathcal{F}2}) - (-\Upsilon^{-}_{\mathcal{F}1})(-\Upsilon^{-}_{\mathcal{F}1})), \Psi^{+}_{\mathcal{F}1} + \Psi^{+}_{\mathcal{F}2} - \Psi^{+}_{\mathcal{F}1}\Psi^{+}_{\mathcal{F}2}, -((-\Psi^{-}_{\mathcal{F}1})(-\Psi^{-}_{\mathcal{F}2}))\rangle, \langle \zeta^{+}_{\mathcal{F}1}\zeta^{+}_{\mathcal{F}2}, -((-\zeta^{-}_{\mathcal{F}1}) + (\zeta^{-}_{\mathcal{F}2}) - (-\zeta^{-}_{\mathcal{F}1})(-\zeta^{-}_{\mathcal{F}1})), \xi^{+}_{\mathcal{F}1} + \xi^{+}_{\mathcal{F}2} - \xi^{+}_{\mathcal{F}1}\xi^{+}_{\mathcal{F}2}, -((-\xi^{-}_{\mathcal{F}1})(-\xi^{-}_{\mathcal{F}2}))\rangle)$
- $\mathfrak{e}\mathcal{F} = (\langle 1 - (1 - \Upsilon^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(-\Upsilon^{-}_{\mathcal{F}1})^{\mathfrak{e}}, (\Psi^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(1 - (1 - (-\Psi^{-}_{\mathcal{F}1}))^{\mathfrak{e}})\rangle, \langle 1 - (1 - \zeta^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(-\zeta^{-}_{\mathcal{F}1})^{\mathfrak{e}}, (\xi^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(1 - (1 - (-\xi^{-}_{\mathcal{F}1}))^{\mathfrak{e}})\rangle)$
- $\mathcal{F}_1^{\mathfrak{e}} = (\langle (\Upsilon^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(1 - (1 - (-\Upsilon^{-}_{\mathcal{F}1}))^{\mathfrak{e}}), 1 - (1 - \Psi^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(-\Psi^{-}_{\mathcal{F}1})^{\mathfrak{e}}\rangle, \langle (\zeta^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(1 - (1 - (-\zeta^{-}_{\mathcal{F}1}))^{\mathfrak{e}}), 1 - (1 - \xi^{+}_{\mathcal{F}1})^{\mathfrak{e}}, -(-\xi^{-}_{\mathcal{F}1})^{\mathfrak{e}}\rangle)$

Definition 3. Let $\mathcal{F} = \{\langle \Upsilon^{+}_{\mathcal{F}}, \Upsilon^{-}_{\mathcal{F}}, \Psi^{+}_{\mathcal{F}}, \Psi^{-}_{\mathcal{F}} \rangle, \langle \zeta^{+}_{\mathcal{F}}, \zeta^{-}_{\mathcal{F}}, \xi^{+}_{\mathcal{F}}, \xi^{-}_{\mathcal{F}} \rangle\}$ be a BLDFN on Ω. Then the score function $\mathfrak{H}$, on $\mathcal{F}$ is a mapping $\Lambda : BLDFN(\Omega) \rightarrow [-1, 1]$ defined as

$$\Lambda(\mathcal{F}) = \frac{1}{4}[\{(\Upsilon^{+}_{\mathcal{F}} - \Psi^{+}_{\mathcal{F}}) + (\zeta^{+}_{\mathcal{F}} - \xi^{+}_{\mathcal{F}})\} - \{(\Upsilon^{-}_{\mathcal{F}} - \Psi^{-}_{\mathcal{F}}) + (\zeta^{-}_{\mathcal{F}} - \xi^{-}_{\mathcal{F}})\}] \tag{2}$$

Also, the accuracy function $\mathfrak{T}$ on $\mathcal{F}$ is a mapping $\mathfrak{T} : BLDFN(\omega) \rightarrow [0, 1]$

$$\mathfrak{T}(\mathcal{F}) = \frac{1}{4}\left[\left\{\left(\frac{\Upsilon^{+}_{\mathcal{F}} + \Psi^{+}_{\mathcal{F}}}{2}\right) + (\zeta^{+}_{\mathcal{F}} + \xi^{+}_{\mathcal{F}})\right\} - \left\{\left(\frac{\Upsilon^{-}_{\mathcal{F}} + \Psi^{-}_{\mathcal{F}}}{2}\right) + (\zeta^{-}_{\mathcal{F}} + \xi^{-}_{\mathcal{F}})\right\}\right] \tag{3}$$

Subsequently, the contrasting laws utilized to compare two BLDFS are given as follows:

(1) If $\Lambda_{\mathcal{F}_1} < \Lambda_{\mathcal{F}_2} \Rightarrow \mathcal{F}_1 < \mathcal{F}_2$

(2) If $\Lambda_{F_1} > \Lambda_{F_2} \Rightarrow F_1 > F_2$
(3) If $\Lambda_{F_1} = \Lambda_{F_2}$, then

(i) If $\mathfrak{T}_{F_1} < \mathfrak{T}_{F_2} \Rightarrow F_1 < F_2$
(ii) If $\mathfrak{T}_{F_1} > \mathfrak{T}_{F_2} \Rightarrow F_1 > F_2$
(iii) If $\mathfrak{T}_{F_1} = \mathfrak{T}_{F_2} \Rightarrow F_1 \approx F_2$

Theorem 1. *For a family of BLDFNs,* $F_t = \left\{\left\langle \Upsilon^+_{F_t}, \Upsilon^-_{F_t}, \Psi^+_{F_t}, \Psi^-_{F_t}\right\rangle, \left\langle \zeta^+_{F_t}, \zeta^-_{F_t}, \xi^+_{F_t}, \xi^-_{F_t}\right\rangle\right\}$, $t = 1,2,\dots,k$ *on* Ω *with* $\tau = (\tau_1, \tau_2, \dots, \tau_t)^T$ *being the weight vectors associated with each* $F_t, \tau_k > 0$ *and* $\sum_{k=1}^{t}\tau_k = 1$, *then the bipolar linear diophantine fuzzy weighted geometric aggregation operator (BLDFWGAO) is a mapping* $\Theta : BLDFN(\Omega) \to BLDFN(\Omega)$ *defined as*

$$\text{BLDFWGAO}(F_1, F_2, \dots, F_t) = \Bigg(\Bigg\langle \prod_{k=1}^{t}\left(\Upsilon^+_{F_k}\right)^{\tau_k}, -\left(1-\prod_{k=1}^{t}\left(1-\left(-\Upsilon^-_{F_k}\right)\right)^{\tau_k}\right) 1-\prod_{k=1}^{t}\left(1-\Psi^+_{F_k}\right)^{\tau_k}, -\left(\prod_{k=1}^{t}\left(-\Psi^-_{F_k}\right)^{\tau_k}\right)\Bigg\rangle, \Bigg\langle \prod_{k=1}^{t}\left(\zeta^+_{F_k}\right)^{\tau_k}, -\left(1-\prod_{k=1}^{t}\left(1-\left(-\zeta^-_{F_k}\right)\right)^{\tau_k}\right), 1-\prod_{k=1}^{t}\left(1-\xi^+_{F_k}\right)^{\tau_k}, -\left(\prod_{k=1}^{t}\left(-\xi^-_{\aleph_1}\right)^{\tau_k}\right)\Bigg\rangle\Bigg) \quad (4)$$

Proof. The proof follows using a mathematical induction process as in [16]. □

4. Methodological framework

A comprehensive framework has been developed for evaluating HST for mobility applications, organized into six distinct phases as shown in Fig. 2. Initially, the alternatives and evaluation criteria are established through a review of existing literature and input from experts. We approach the problem as a group decision-making scenario involving a committee comprising three experts. Assigning weights to these experts is crucial for accurately weighing their opinions and perspectives. So in Phase I, the focus lies on assessing the role of experts in decision-making, introducing an algorithm to analyze their potential impact. This approach enhances decision-making credibility and accuracy by avoiding subjectivity in weight allocations.

Based on the reviewed literature and experts suggestions, Phase II involves gathering fuzzy information about each alternative based on attributes, leading to the creation of decision matrices and a combined matrix. Phase III then determines the importance of these attributes. Objective analysis employs the BLDF-LOPCOW method, while subjective analysis utilizes the OPA method, with integrated weights established during this stage.

The subsequent three phases are dedicated to ranking of the alternatives. Phase IV presents the normalization procedures from the MACONT method for the normalization of the decision matrix from Phase II. Next, a utility matrix is constructed using the Phase V using the steps of the BLDF-based MARCOS method. Finally the ranking of the alternatives in done in Phase VII by determining the relation between each alternative using the credibility index as defined in the ELECTRE-III approach. The detailed algorithm of the developed methodology is presented in the following sections.

4.1. Algorithm of the proposed framework

A MAGDM problem consists of $\mathfrak{s}$ alternatives $(\mathcal{D}_i, 1 \le i \le \mathfrak{s})$ which are to be evaluated based on t attributes $(\beth_{\mathfrak{k}}, 1 \le \mathfrak{k} \le t)$ with $\varsigma = (\varsigma_1, \varsigma_2, \dots, \varsigma_t)^T$ representing the weights of the attributes. Let $\beth^+_{\mathfrak{k}}$ represent the positive set of attributes and $\beth^-_{\mathfrak{k}}$ be the negative set of attributes. The input data is provided by the committee of $\mathfrak{p}$ experts $\Xi_q, (1 \le q \le \mathfrak{p})$ taking part in the decision process and letting ν_q represent their associated weight vectors with each $\nu_j > 0$ and $\sum_{q=1}^{p}\nu_q = 1$.

Then the steps of the proposed methodology is given as follows:

Phase I: Determination of expert weights:

Step 1. Pairwise comparisons between the alternatives are conducted by each expert, and their estimated values are provided in an acceptable complete BLDF preference relation

$$\mathfrak{F}^q = [\mathfrak{F}^q_{i\mathfrak{l}}]_{\mathfrak{s}\times\mathfrak{s}} \quad (5)$$

Here, each $\mathfrak{F}^q_{i\mathfrak{l}} = \left\{\left\langle {}^q\zeta^+_{i\mathfrak{l}}, {}^q\zeta^-_{i\mathfrak{l}}, {}^q\chi^+_{i\mathfrak{l}}, {}^q\chi^-_{il}\right\rangle, \left\langle {}^q\phi^+_{i\mathfrak{l}}, {}^q\phi^-_{i\mathfrak{l}}, {}^q\psi^+_{il}, {}^q\psi^-_{il}\right\rangle\right\}$ represents the preference degree of alternative $\mathcal{A}_i$ over $\mathcal{A}_{\mathfrak{l}}$ with respect to an expert Ξ_q.

Step 2. Determine the scoring matrix $\mathfrak{S}^q = \mathfrak{S}(\mathfrak{F}^q_{i\mathfrak{l}})$ using Definition 3. Then obtain the mean scoring matrix $\mathcal{M} = [\mathcal{M}_{i\mathfrak{l}}]_{\mathfrak{s}\times\mathfrak{s}}$ using the Eq. (6) .

$$\mathcal{M}_{i\mathfrak{l}} = \frac{1}{\mathfrak{p}}\sum_{q=1}^{\mathfrak{p}}\mathfrak{S}(\mathfrak{F}^q_{i\mathfrak{l}}) \quad (6)$$

Step 3. The weights of the experts (ν_q) are calculated using the Eq. (7).

$$\nu_q = \frac{1-\mathcal{W}_q}{\sum_{q=1}^{p}(1-\mathcal{W}_q)} \quad (7)$$

where $\mathcal{W}_q$ is the deviation index which is obtained as

$$\mathcal{W}_q = \frac{1}{\mathfrak{s}^2}\sum_{i=1}^{\mathfrak{s}}\sum_{l=1}^{\mathfrak{s}}\left|\mathfrak{S}(\mathfrak{F}^q_{i\mathfrak{l}}) - \mathcal{M}_{i\mathfrak{l}}\right| \quad (8)$$

Phase II: Construction of decision matrix:

Step 1. Based on the evaluation information provided by the experts Ξ_q, the initial decision matrix $\aleph^q$ is developed as in Eq. (9).

$$\aleph^q = [\aleph^q_{i\mathfrak{k}}]_{\mathfrak{s}\times t} = \begin{array}{c} \\ \mathcal{A}_1 \\ \mathcal{A}_2 \\ \vdots \\ \mathcal{A}_{\mathfrak{s}} \end{array}\begin{array}{c} \beth_1 \quad \beth_2 \quad \cdots \quad \beth_t \\ \begin{pmatrix} \aleph^q_{11} & \aleph^q_{12} & \cdots & \aleph^f_{1t} \\ \aleph^q_{21} & \aleph^q_{22} & \cdots & \aleph^q_{2t} \\ \vdots & \vdots & \cdots & \vdots \\ \aleph^q_{\mathfrak{s}1} & \aleph^q_{\mathfrak{s}2} & \cdots & \aleph^q_{\mathfrak{s}t} \end{pmatrix} \end{array}, \quad (9)$$

where each $\aleph^q_{\mathfrak{s}t}$ is a BLDFN expressed as $\aleph^q_{ik} = \left\{\left\langle {}^q\zeta^+_{i\mathfrak{k}}, {}^q\zeta^-_{i\mathfrak{k}}, {}^q\chi^+_{i\mathfrak{k}}, {}^q\chi^-_{i\mathfrak{k}}\right\rangle, \left\langle {}^q\phi^+_{i\mathfrak{k}}, {}^q\phi^-_{i\mathfrak{k}}, {}^q\psi^+_{i\mathfrak{k}}, {}^q\psi^-_{i\mathfrak{k}}\right\rangle\right\}$

Step 2. The individual matrices are integrated into an aggregated decision matrix $\aleph = [\aleph_{it}]_{\mathfrak{s}\times t}$ by combining the weights of the experts obtained from Phase-I using the BLDFWGAO defined in Eq. (4).

Step 3. Calculate the scoring matrix $\mathcal{F} = [\mathcal{F}_{i\mathfrak{k}}]_{\mathfrak{s}\times t}$ using the BLDF score function defined in Definition 3.

Phase III: Integrated Criteria weight Estimation

(i.) Estimation of $\varsigma^o_{\mathfrak{k}}$ using fuzzy LOPCOW method:

Step 6.1. Normalize the score values using the Eq. (10)

$$\mathcal{Q}_{i\mathfrak{k}} = \begin{cases} \dfrac{\mathcal{F}_{i\mathfrak{k}} - \min_i \mathcal{F}_{i\mathfrak{k}}}{\max_i \mathcal{F}_{i\mathfrak{k}} - \min_i \mathcal{F}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^+ \\ \dfrac{\max_i \mathcal{F}_{i\mathfrak{k}} - \mathcal{F}_{i\mathfrak{k}}}{\max_i \mathcal{F}_{i\mathfrak{k}} - \min_i \mathcal{F}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^- \end{cases} \quad (10)$$

Step 6.2. For each criteria $\beth_{\mathfrak{k}}$, the standard deviation $\sigma_{\mathfrak{k}}$ and the percentage values $\mathcal{P}_{i\mathfrak{k}}$ are calculated as

$$\sigma_{\mathfrak{k}} = \sqrt{\frac{\sum_{i=1}^{\mathfrak{s}}\left(\mathcal{Q}_{i\mathfrak{k}} - \frac{\sum_{i=1}^{\mathfrak{s}}\mathcal{Q}_{i\mathfrak{k}}}{\mathfrak{s}}\right)^2}{\mathfrak{s}}} \quad (11)$$

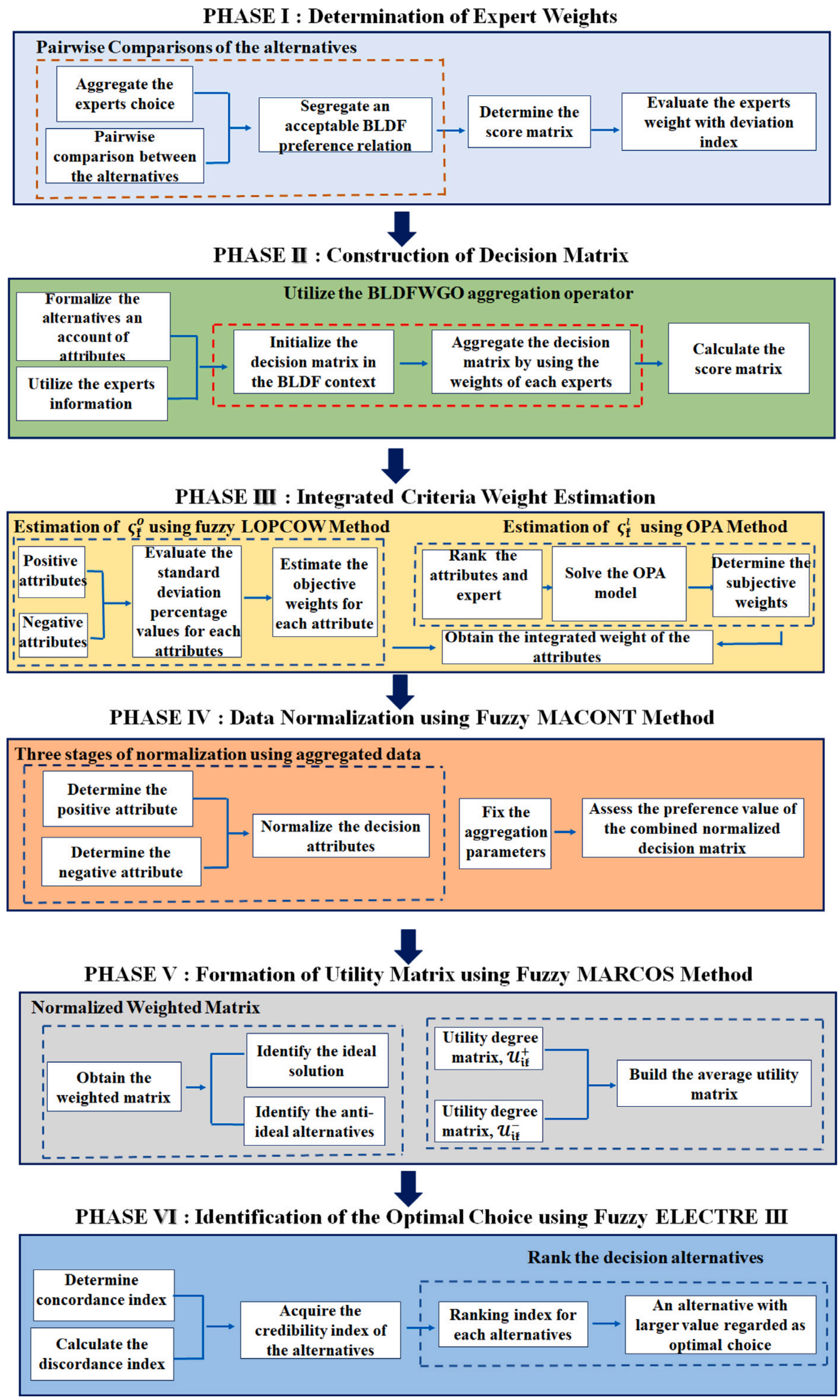


Fig. 2. Hierarchical structure of the proposed algorithm.

$$\mathcal{P}_{i\mathfrak{k}} = \left| \ln \left(\frac{\frac{\sum_{i=1}^{\mathfrak{s}} (\mathcal{Q}_{i\mathfrak{k}})^2}{\mathfrak{s}}}{\sigma_{\mathfrak{k}}} \right) \right| \tag{12}$$

Step 6.3. Further, using Eq. (13), the objective criteria weights $(\zeta_{\ell}{}^{\alpha})$ are estimated as

$$\varsigma_{\mathfrak{k}}^{o} = \frac{\mathcal{P}_{i\mathfrak{k}}}{\sum_{\mathfrak{k}=1}^{\mathfrak{t}} \mathcal{P}_{i\mathfrak{k}}} \tag{13}$$

(ii.) Estimation of $\varsigma_{\mathfrak{k}}^{\prime}$ using OPA method:

Step 7.1. Ranking of experts and criteria

The experts' are ranked based on their significance i.e., years of experience or academic degree and the criteria are ranked based on expert suggestions

Step 7.2. Solving of the OPA model

The subjective evaluation of the attributes are done by solving the linear programming model

$$\begin{aligned} &\text{Maximize } \mathcal{O} \\ &\text{such that, } \quad \mathcal{O} \le \mathfrak{q}\left(\mathfrak{k}\left(\varsigma_{\mathfrak{q}\mathfrak{k}}^{\mathfrak{f}} - \varsigma_{\mathfrak{q}j}^{\mathfrak{f}+1}\right)\right) \\ &\sum_{\mathfrak{q}=1}^{\mathfrak{p}} \sum_{\mathfrak{k}=1}^{\mathfrak{t}} \varsigma_{\mathfrak{q}\mathfrak{k}} = 1 \\ &\varsigma_{\mathfrak{q}\mathfrak{k}} \ge 0 \quad \forall \quad \mathfrak{q}, \mathfrak{k} \end{aligned} \tag{14}$$

Here $\varsigma_{\mathfrak{q}\mathfrak{k}}^{\mathfrak{f}}$ denotes the importance of $\mathfrak{k}$th criteria by $\mathfrak{q}$th expert at $\mathfrak{f}$th rank. Also, $\mathcal{O}$ is unrestricted to sign. After solving Eq. (14), in order to determine the subjective weights of the attributes, the following Eq. (15) is utilized

$$\zeta_{\mathfrak{k}}^{\prime} = \sum_{\mathfrak{q}=1}^{\mathfrak{p}} \zeta_{\mathfrak{q}\mathfrak{t}} \tag{15}$$

Step 8. The integrated weights of the attributes are determined using the Eq. (16)

$$\varsigma_{\mathfrak{k}} = \epsilon \zeta_{\mathfrak{k}}^{o} + (1-\epsilon)\zeta_{\mathfrak{k}}^{\prime} \tag{16}$$

Here ϵ is a aggregation parameter lying in $[0, 1]$.

Phase IV: Data normalization using fuzzy MACNOT method:

Step 4. Perform the three stage normalization of the aggregated data following the Eqs. (17)–(19).

$$\tilde{\mathcal{F}}_{i\mathfrak{k}}^{(1)} = \begin{cases} \dfrac{\tilde{\mathcal{F}}_{i\mathfrak{k}}}{\sum_{i=1}^{\mathfrak{t}} \tilde{\mathcal{F}}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^{+} \\ \dfrac{\frac{1}{\tilde{\mathcal{F}}_{i\mathfrak{k}}}}{\sum_{i=1}^{\mathfrak{t}} \frac{1}{\tilde{\mathcal{F}}_{i\mathfrak{k}}}} & \text{for} \quad \mathfrak{k} \in \beth^{-} \end{cases} \tag{17}$$

$$\tilde{\mathcal{F}}_{i\mathfrak{k}}^{(2)} = \begin{cases} \dfrac{\tilde{\mathcal{F}}_{i\mathfrak{k}}}{\max_i \tilde{\mathcal{F}}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^{+} \\ \dfrac{\min_i \tilde{\mathcal{F}}_{i\mathfrak{k}}}{\tilde{\mathcal{F}}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^{-} \end{cases} \tag{18}$$

$$\tilde{\mathcal{F}}_{i\mathfrak{k}}^{(3)} = \begin{cases} \dfrac{\tilde{\mathcal{F}}_{i\mathfrak{k}} - \min_i \tilde{\mathcal{F}}_{i\mathfrak{k}}}{\max_i \tilde{\mathcal{F}}_{i\mathfrak{k}} - \min_i \tilde{\mathcal{F}}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^{+} \\ \dfrac{\max_i \tilde{\mathcal{F}}_{i\mathfrak{k}} - \tilde{\mathcal{F}}_{i\mathfrak{k}}}{\max_i \tilde{\mathcal{F}}_{i\mathfrak{k}} - \min_i \tilde{\mathcal{F}}_{i\mathfrak{k}}} & \text{for} \quad \mathfrak{k} \in \beth^{-} \end{cases} \tag{19}$$

Step 5. The preference values of the combined normalized decision matrix $\tilde{\mathcal{F}} = \left[\tilde{\mathcal{F}}_{i\mathfrak{k}}\right]_{\mathfrak{s}\times\mathfrak{t}}$ are calculated based on Eq. (20).

$$\tilde{\mathcal{F}}_{\mathrm{li}} = \alpha \tilde{\mathcal{F}}_{i\mathfrak{k}}^{(1)} + \beta \tilde{\mathcal{F}}_{i\mathfrak{k}}^{(2)} + (1-\alpha-\beta)\tilde{\mathcal{F}}_{i\mathfrak{k}}^{(3)} \tag{20}$$

where $\alpha, \beta \in [0, 1]$ are the adjustment parameter used to determine the relative importance between the normalized data from three stages.

Phase V: Formation of utility matrix using fuzzy MARCOS method

Step 5. Determine the values of the weighted matrix $\mathcal{X} = \left[\mathcal{X}_{i\mathfrak{k}}\right]_{\mathfrak{s}\times\mathfrak{t}}$ following Eq. (21),

$$\mathcal{X}_{i\mathfrak{k}} = \tilde{\mathcal{F}}_{i\mathfrak{k}} \times \varsigma_{\mathfrak{k}} \tag{21}$$

where $\varsigma_{\mathfrak{k}}$ represents the weights of the attributes evaluated using Eq. (16).

Step 6. Identify the ideal and anti-ideal solution values based on the attributes using (22)–(23)

$$\mathcal{C}_{B\mathfrak{k}} = \max_{i} \mathcal{X}_{i\mathfrak{k}} \text{ if } \quad \mathfrak{k} \in \beth_{\mathfrak{k}}^{+} \text{and } \min_{i} \mathcal{X}_{i\mathfrak{k}} \text{ if } \mathfrak{k} \in \beth_{\mathfrak{k}}^{-} \tag{22}$$

$$\mathcal{C}_{w\mathfrak{k}} = \min_{i} \mathcal{X}_{i\mathfrak{k}} \text{ if } \quad \mathfrak{k} \in \beth_{\mathfrak{k}}^{+} \text{and } \max_{i} \mathcal{X}_{i\mathfrak{k}} \text{ if } \mathfrak{k} \in \beth_{\mathfrak{k}}^{-} \tag{23}$$

Step 7. With respect to ideal and anti-ideal values determine the utility degree matrices $\mathcal{U}_{i\mathfrak{k}}^{+}$ and $\mathcal{U}_{i\mathfrak{k}}^{-}$ applying Eq. (24).

$$\mathcal{U}_{i\mathfrak{k}}^{+} = \frac{\mathcal{X}_{i\mathfrak{k}}}{\sum_{\mathfrak{k}=1}^{\mathfrak{s}} \mathcal{C}_{B\mathfrak{k}}}; \quad \mathcal{U}_{i\mathfrak{k}}^{-} = \frac{\mathcal{X}_{i\mathfrak{k}}}{\sum_{\mathfrak{k}=1}^{\mathfrak{s}} \mathcal{C}_{w\mathfrak{k}}} \tag{24}$$

Step 8. Build the average utility matrix $\mathcal{U}_{i\mathfrak{k}}$ as in Eq. (25).

$$\mathcal{U}_{it} = \frac{1}{2}\left(\mathcal{U}_{it}^{+} + \mathcal{U}_{it}^{-}\right) \quad (1 \le i \le \mathfrak{s}, 1 \le \mathfrak{k} \le \mathfrak{t}) \tag{25}$$

Phase VI: Identification of the optimal choice using fuzzy ELECTRE-III approach

Step 7. The concordance index $\mathcal{Y}$ between the alternative $\mathcal{A}_i$ and $\mathcal{A}_{\mathfrak{l}}$ is found using Eq. (26).

$$\mathcal{Y}\left(\mathcal{A}_i, \mathcal{A}_{\mathfrak{l}}\right) = \sum_{\mathfrak{k}=1}^{\mathfrak{t}} \left(\varsigma_j \cdot \mu\left(\mathcal{U}_{i\mathfrak{k}}, \mathcal{U}_{\mathfrak{l}\mathfrak{k}}\right)\right) \tag{26}$$

where

$$\mu(\mathcal{U}_{i\mathfrak{k}}, \mathcal{U}_{\mathfrak{l}\mathfrak{k}}) = \begin{cases} 0, & \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \mathcal{U}_{i\mathfrak{k}} > \varrho_{\mathfrak{k}} \\ \frac{\varrho_{\mathfrak{k}} + \mathcal{U}_{i\mathfrak{k}} - \mathcal{U}_{\mathfrak{l}\mathfrak{k}}}{\varrho_{\mathfrak{k}} - \pi_{\mathfrak{k}}} & \varrho_{\mathfrak{k}} < \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \mathcal{U}_{i\mathfrak{k}} < \pi_{\mathfrak{k}} \\ 1 & \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \mathcal{U}_{i\mathfrak{k}} \le \pi_{\mathfrak{k}} \end{cases} \tag{27}$$

Here, $\pi_{\mathfrak{k}}$ and $\varrho_{\mathfrak{k}}$ represent the indifference and preference thresholds against criterion $\beth_{\mathfrak{k}}$ respectively, with $0 \le \pi_{\mathfrak{k}} \le \varrho_{e}$.

Likewise, the discordance index $\mathcal{R}$ subject to the alternatives is determined as in Eq. (28)

$$\mathcal{R}\left(\mathcal{A}_i, \mathcal{A}_{\mathfrak{l}}\right) = \sum_{\mathfrak{k}=1}^{\mathfrak{t}} \left(\varsigma_j \cdot \xi\left(\mathcal{U}_{i\mathfrak{k}}, \mathcal{U}_{\mathfrak{l}\mathfrak{k}}\right)\right) \tag{28}$$

where the discordance degree ξ is determined as

$$\xi(\mathcal{U}_{i\mathfrak{k}}, \mathcal{U}_{\mathfrak{l}\mathfrak{k}}) = \begin{cases} 0, & \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \mathcal{U}_{i\mathfrak{k}} < \varrho_{\mathfrak{k}} \\ \frac{\mathcal{U}_{i\mathfrak{k}} - \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \varrho_{\mathfrak{k}}}{Y_{\mathfrak{k}} - \varrho_{\mathfrak{k}}} & \varrho_{\mathfrak{k}} < \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \mathcal{U}_{i\mathfrak{k}} < Y_{\mathfrak{k}} \\ 1 & \mathcal{U}_{\mathfrak{l}\mathfrak{k}} - \mathcal{U}_{i\mathfrak{k}} \ge Y_{\mathfrak{k}} \end{cases} \tag{29}$$

where, $Y_{\mathfrak{k}}$ correspond to the veto threshold against criterion $\beth_{\mathfrak{k}}$ respectively, with $0 \le \varrho_{\mathfrak{k}} \le Y_{\mathfrak{k}}$.

Step 8. Acquire the credibility index between the alternative $\mathcal{A}_i$ and $\mathcal{A}_{\mathfrak{l}}$ is computed as

$$\mathcal{T}\left(\mathcal{A}_i, \mathcal{A}_{\mathfrak{l}}\right) = \mathcal{Y}\left(\mathcal{A}_i, \mathcal{A}_{\mathfrak{l}}\right) \cdot \mathcal{R}\left(\mathcal{A}_i, \mathcal{A}_{\mathfrak{l}}\right) \tag{30}$$

Step 9. The ranking index for each alternative $\mathcal{A}_i, (1 \le i \le \mathfrak{s})$ is calculated as

$$\Lambda\left(\mathcal{A}_i\right) = \sum_{\mathfrak{l}=1}^{\mathfrak{s}} \mathcal{T}\left(\mathcal{A}_i, \mathcal{A}_{\mathfrak{l}}\right) - \sum_{\mathfrak{l}=1}^{\mathfrak{s}} \mathcal{T}\left(\mathcal{A}_{\mathfrak{l}}, \mathcal{A}_i\right) \tag{31}$$

From Eq. (31), the alternative with larger $\Lambda\left(\mathcal{A}_i\right)$ value is regarded as the optimal choice.

5. Numerical illustration

Hydrogen, when employed as a fuel, represents a potential solution for achieving environmentally friendly transportation. Unlike conventional fuels, the utilization of hydrogen as an energy carrier necessitates

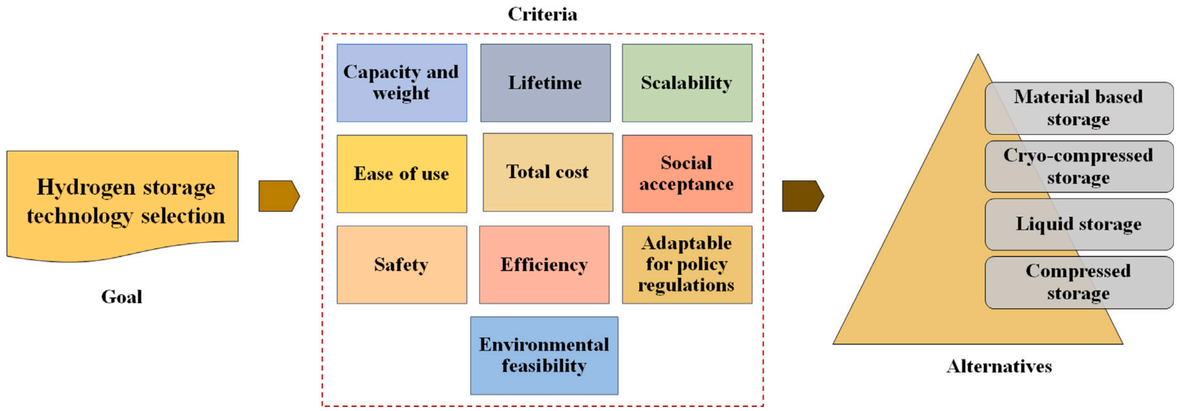


Fig. 3. Framework of the problem.

Table 3
Linguistic rating.

Linguistic term	Positive membership	Negative membership	Positive non-membership	Negative non-membership
Absolutely desirable	[1,0.87]	[−0.95, −0.75]	[0.03, 0.26]	[−0.24,−0.35]
Highly desirable	(0.87, 0.74]	(−0.75, −0.65]	(0.26, 0.41]	(−0.35,−0.43]
Moderately desirable	(0.74, 0.61]	(−0.65, −0.55]	(0.41, 0.53]	(−0.43,−0.56]
Equally desirable	(0.61, 0.48]	(−0.55, −0.45]	(0.53, 0.62]	(−0.56,−0.64]
Moderately undesirable	(0.48, 0.34]	(−0.45, −0.35]	(0.62, 0.71]	(−0.64, −0.76]
Highly undesirable	(0.34, 0.22]	(−0.35, −0.25]	(0.71, 0.84]	(−0.76, −0.88]
Absolutely undesirable	(0.22, 0.00]	(−0.25, −0.15]	(0.84, 0.93]	(−0.88, −0.99]

Linguistic term	Reference parameters			
	1	2	3	4
Absolutely desirable	[0.90, 0.70]	[−0.75, −0.65]	[0.05,0.10]	[−0.15, −0.25]
Highly desirable	(0.70, 0.60]	(−0.65, −0.55]	(0.10, 0.30]	(−0.25, −0.35]
Moderately desirable	(0.60, 0.40]	(−0.55, −0.45]	(0.30, 0.40]	(−0.35, −0.45]
Equally desirable	(0.40, 0.30]	(−0.45, −0.35]	(0.40, 0.60]	(−0.45, −0.55]
Moderately undesirable	(0.30, 0.10]	(−0.35, −0.25]	(0.60, 0.70]	(−0.55, −0.65]
Highly undesirable	(0.10, 0.05]	(−0.25, −0.15]	(0.70, 0.90]	(−0.65, −0.75]
Absolutely undesirable	(0.05, 0]	(−0.15, 0]	(0.90, 1]	(−0.75, −0.85]

secure and efficient storage technologies. Addressing the challenges posed by technological, economic, and environmental constraints becomes imperative in this context. Within the various on-board hydrogen storage (HST) alternatives discussed, the selection of a sustainable, safe, and economically viable technique poses a strategic challenge for decision-makers. The structural framework of this challenge is outlined in Fig. 3.

To guide the decision-making process, a committee comprising three experts contributes recommendations expressed in linguistic terms, each accompanied by a quantifying value in the form of introduced BLDFS. The incorporation of positive and negative grades, along with the flexibility to choose between $[-1, 1]$ within specific constraints, enhances the ability to closely capture incomplete information and ambiguity inherent in diverse opinions during the group decision process.

The linguistic scale relevant to the evaluation is detailed in the presented table. Drawing from both existing literature and expert suggestions, the assessment of storage alternatives focuses on ten specific parameters, with a comprehensive description of these attributes provided in Table 3. Here the criteria 5 is regarded as the cost criteria (see Table 4).

5.1. Adaptation to the problem

Initially, as in Phase I to assess the impact of each expert on the decision-making process, we conduct pairwise comparisons between each alternative based on individual expert judgments. By employing Definition 3, we derive the scoring matrices associated to expert, as outlined in Eqs. (32)–(34). Subsequently, using Eqs. (6) to (8), the weights of the experts are determined as 0.3420, 0.3341, and 0.3239.

$$\mathfrak{S}_1 = \begin{pmatrix} 0 & -0.0250 & -0.1250 & 0.0500 \\ 0.0250 & 0 & 0.1500 & 0.1000 \\ 0.1250 & -0.1500 & 0 & 0.0750 \\ 0.0500 & -0.1000 & -0.0750 & 0 \end{pmatrix} \tag{32}$$

$$\mathfrak{S}_2 = \begin{pmatrix} 0 & 0.1375 & -0.1250 & 0.0500 \\ -0.1375 & 0 & 0.1500 & 0.0750 \\ 0.1250 & -0.1500 & 0 & 0.0250 \\ -0.0500 & -0.0750 & -0.0250 & 0 \end{pmatrix} \tag{33}$$

$$\mathfrak{S}_3 = \begin{pmatrix} 0 & -0.4025 & -0.0075 & 0.2650 \\ 0.4025 & 0 & -0.0250 & 0.0625 \\ 0.0075 & 0.0250 & 0 & 0.2500 \\ -0.2650 & -0.0625 & -0.2500 & 0 \end{pmatrix} \tag{34}$$

Conversely, when assessing the alternative storage options based on the considered attributes according to each expert, decision matrices are generated as in Phase-II, as depicted in Tables 5–7. Employing Eq. (4), we derive the collective decision matrix, and subsequently, using Definition 3, the resulting scoring matrix is presented in Table 8.

Moving on to Phase III, the process of determining the criteria weights involves utilizing the matrix in Table 8. Following Eqs. (10)–(13), we initially present the objective weights of the attributes obtained in Table 10. Concurrently, for subjective evaluation, the experts are ranked as $\Xi_1 > \Xi_2 > \Xi_3$. Subsequently, based on expert opinions, the preferences for each criterion are provided and presented in Table 9.

Table 4
Criteria description.

Criteria	Description	Supporting studies
Capacity and Weight ($\beth_1$)	It signifies the storage container's weight and its fuel capacity, enabling a vehicle to operate without the need for frequent refueling.	[6,63]
Lifetime ($\beth_2$)	It pertains to the refueling cycle of the storage medium, indicating the duration it can undergo refueling before experiencing material degradation.	[6,63,64]
Scalability ($\beth_3$)	It signifies the maturity of the technology for commercial deployment, its reliability at scale, and its ability to adapt to the existing geographical infrastructure.	[6,64]
Ease of use ($\beth_4$)	It signifies the degree of complexity involved in operating and managing the system in conjunction with human interactions.	[64]
Total cost ($\beth_5$)	It is the measure of the total cost spent on developing, deploying, operating, and maintaining the storage system.	[6,63,64]
Social Acceptance ($\beth_6$)	It signifies the extent to which the community is open to accepting and integrating the technology.	[64]
Safety ($\beth_7$)	It indicates the potential risks associated with the implementation of the technology which might impact both workers and the broader society.	[6,64]
Efficiency ($\beth_8$)	It compares the input energy used for hydrogen storage to the output energy produced when the hydrogen is reclaimed.	[64]
Adaptable for policy regulations ($\beth_9$)	It assesses the technology's adaptability to comply with policy regulations, facilitating the attraction of foreign investments and contributing to the sustainable development of the hydrogen economy.	Expert opinion
Environmental feasibility ($\beth_{10}$)	It represents the technology's ability to eliminate detrimental emissions, alleviate resource depletion, and improve overall environmental quality.	[64]

Table 5
The initial BLDF decision matrix for expert Ξ_1.

	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$
$\mathcal{D}_1$	⟨⟨0.80, −0.68, 0.36, −0.40⟩, ⟨0.75, −0.57, 0.25, −0.30⟩⟩	⟨⟨0.51, −0.45, 0.62, −0.57⟩, ⟨0.38, −0.43, 0.44, −0.55⟩⟩	⟨⟨0.32, −0.26, 0.84, −0.77⟩, ⟨0.09, −0.23, 0.89, −0.69⟩⟩	⟨⟨0.42, −0.36, 0.68, −0.71⟩, ⟨0.23, −0.31, 0.65, −0.57⟩⟩	⟨⟨0.63, −0.57, 0.42, −0.47⟩, ⟨0.53, −0.49, 0.32, −0.40⟩⟩
$\mathcal{D}_2$	⟨⟨0.64, −0.59, 0.48, −0.50⟩, ⟨0.52, −0.47, 0.33, −0.40⟩⟩	⟨⟨0.77, −0.66, 0.38, −0.40⟩, ⟨0.64, −0.58, 0.17, −0.27⟩⟩	⟨⟨0.73, −0.57, 0.45, −0.52⟩, ⟨0.51, −0.47, 0.38, −0.41⟩⟩	⟨⟨0.60, −0.45, 0.58, −0.61⟩, ⟨0.32, −0.41, 0.48, −0.55⟩⟩	⟨⟨0.31, −0.26, 0.76, −0.80⟩, ⟨0.07, −0.20, 0.78, −0.66⟩⟩
$\mathcal{D}_3$	⟨⟨0.49, −0.50, 0.61, −0.57⟩, ⟨0.38, −0.44, 0.52, −0.46⟩⟩	⟨⟨0.29, −0.30, 0.73, −0.87⟩, ⟨0.05, −0.16, 0.90, −0.75⟩⟩	⟨⟨0.36, −0.41, 0.64, −0.71⟩, ⟨0.18, −0.25, 0.70, −0.56⟩⟩	⟨⟨0.62, −0.58, 0.45, −0.50⟩, ⟨0.51, −0.47, 0.38, −0.36⟩⟩	⟨⟨0.12, −0.24, 0.86, −0.90⟩, ⟨0.02, −0.10, 0.98, −0.76⟩⟩
$\mathcal{D}_4$	⟨⟨0.95, −0.78, 0.24, −0.10⟩, ⟨0.85, −0.68, 0.07, −0.24⟩⟩	⟨⟨0.79, −0.66, 0.32, −0.40⟩, ⟨0.65, −0.58, 0.19, −0.29⟩⟩	⟨⟨0.52, −0.48, 0.58, −0.64⟩, ⟨0.36, −0.42, 0.51, −0.46⟩⟩	⟨⟨0.40, −0.35, 0.64, −0.70⟩, ⟨0.23, −0.30, 0.66, −0.57⟩⟩	⟨⟨0.33, −0.25, 0.75, −0.88⟩, ⟨0.08, −0.20, 0.80, −0.66⟩⟩
	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
$\mathcal{D}_1$	⟨⟨0.74, −0.66, 0.32, −0.40⟩, ⟨0.68, −0.59, 0.23, −0.35⟩⟩	⟨⟨0.64, −0.57, 0.48, −0.52⟩, ⟨0.51, −0.47, 0.32, −0.41⟩⟩	⟨⟨0.86, −0.69, 0.34, −0.40⟩, ⟨0.65, −0.58, 0.23, −0.30⟩⟩	⟨⟨0.64, −0.58, 0.42, −0.49⟩, ⟨0.50, −0.52, 0.37, −0.38⟩⟩	⟨⟨0.83, −0.68, 0.40, −0.37⟩, ⟨0.68, −0.55, 0.24, −0.35⟩⟩
$\mathcal{D}_2$	⟨⟨0.68, −0.57, 0.42, −0.48⟩, ⟨0.51, −0.45, 0.38, −0.41⟩⟩	⟨⟨0.41, −0.36, 0.70, −0.65⟩, ⟨0.21, −0.34, 0.68, −0.56⟩⟩	⟨⟨0.52, −0.47, 0.60, −0.58⟩, ⟨0.38, −0.40, 0.52, −0.46⟩⟩	⟨⟨0.38, −0.42, 0.68, −0.71⟩, ⟨0.21, −0.32, 0.62, −0.56⟩⟩	⟨⟨0.13, −0.24, 0.87, −0.92⟩, ⟨0, −0.14, 0.98, −0.85⟩⟩
$\mathcal{D}_3$	⟨⟨0.50, −0.46, 0.61, −0.57⟩, ⟨0.38, −0.41, 0.51, −0.46⟩⟩	⟨⟨0.24, −0.31, 0.75, −0.81⟩, ⟨0.07, −0.20, 0.80, −0.68⟩⟩	⟨⟨0.42, −0.36, 0.63, −0.70⟩, ⟨0.22, −0.32, 0.70, −0.59⟩⟩	⟨⟨0.54, −0.45, 0.62, −0.59⟩, ⟨0.38, −0.41, 0.48, −0.51⟩⟩	⟨⟨0.25, −0.30, 0.84, −0.74⟩, ⟨0.08, −0.24, 0.79, −0.68⟩⟩
$\mathcal{D}_4$	⟨⟨0.67, −0.55, 0.49, −0.50⟩, ⟨0.54, −0.47, 0.32, −0.41⟩⟩	⟨⟨0.80, −0.67, 0.33, −0.41⟩, ⟨0.65, −0.56, 0.20, −0.27⟩⟩	⟨⟨0.68, −0.59, 0.42, −0.51⟩, ⟨0.50, −0.47, 0.33, −0.39⟩⟩	⟨⟨0.60, −0.47, 0.58, −0.61⟩, ⟨0.38, −0.40, 0.51, −0.46⟩⟩	⟨⟨0.82, −0.66, 0.30, −0.40⟩, ⟨0.73, −0.57, 0.23, −0.30⟩⟩

Table 6
The initial BLDF decision matrix for expert Ξ_2.

	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$
$\mathcal{D}_1$	⟨⟨0.79, −0.62, 0.45, −0.50⟩, ⟨0.48, −0.54, 0.31, −0.38⟩⟩	⟨⟨0.78, −0.67, 0.32, −0.39⟩, ⟨0.63, −0.58, 0.22, −0.28⟩⟩	⟨⟨0.60, −0.53, 0.59, −0.63⟩, ⟨0.35, −0.44, 0.53, −0.46⟩⟩	⟨⟨0.58, −0.48, 0.60, −0.64⟩, ⟨0.38, −0.40, 0.48, −0.50⟩⟩	⟨⟨0.63, −0.58, 0.50, −0.48⟩, ⟨0.59, −0.45, 0.40, −0.36⟩⟩
$\mathcal{D}_2$	⟨⟨0.82, −0.70, 0.35, −0.40⟩, ⟨0.65, −0.56, 0.20, −0.30⟩⟩	⟨⟨0.65, −0.58, 0.50, −0.48⟩, ⟨0.59, −0.45, 0.39, −0.36⟩⟩	⟨⟨0.59, −0.46, 0.58, −0.57⟩, ⟨0.33, −0.41, 0.60, −0.48⟩⟩	⟨⟨0.38, −0.44, 0.70, −0.68⟩, ⟨0.23, −0.32, 0.66, −0.59⟩⟩	⟨⟨0.50, −0.45, 0.60, −0.59⟩, ⟨0.30, −0.40, 0.50, −0.55⟩⟩
$\mathcal{D}_3$	⟨⟨0.60, −0.50, 0.54, −0.58⟩, ⟨0.39, −0.35, 0.54, −0.48⟩⟩	⟨⟨0.47, −0.32, 0.67, −0.65⟩, ⟨0.27, −0.34, 0.61, −0.59⟩⟩	⟨⟨0.33, −0.41, 0.60, −0.48⟩, ⟨0.59, −0.47, 0.40, −0.37⟩⟩	⟨⟨0.33, −0.25, 0.80, −0.77⟩, ⟨0.09, −0.15, 0.79, −0.67⟩⟩	⟨⟨0.30, −0.40, 0.70, −0.66⟩, ⟨0.15, −0.24, 0.70, −0.58⟩⟩
$\mathcal{D}_4$	⟨⟨0.90, −0.83, 0.26, −0.32⟩, ⟨0.77, −0.60, 0.08, −0.23⟩⟩	⟨⟨0.70, −0.60, 0.49, −0.51⟩, ⟨0.50, −0.45, 0.36, −0.48⟩⟩	⟨⟨0.83, −0.65, 0.32, −0.43⟩, ⟨0.63, −0.59, 0.24, −0.32⟩⟩	⟨⟨0.69, −0.58, 0.48, −0.46⟩, ⟨0.52, −0.40, 0.38, −0.40⟩⟩	⟨⟨0.32, −0.24, 0.80, −0.60⟩, ⟨0.09, −0.15, 0.90, −0.66⟩⟩
	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
$\mathcal{D}_1$	⟨⟨0.98, −0.73, 0.17, −0.30⟩, ⟨0.84, −0.69, 0.10, −0.21⟩⟩	⟨⟨0.79, −0.68, 0.40, −0.36⟩, ⟨0.60, −0.62, 0.14, −0.30⟩⟩	⟨⟨0.82, −0.65, 0.38, −0.42⟩, ⟨0.69, −0.55, 0.30, −0.26⟩⟩	⟨⟨0.87, −0.76, 0.17, −0.34⟩, ⟨0.90, −0.65, 0.10, −0.15⟩⟩	⟨⟨0.86, −0.66, 0.41, −0.39⟩, ⟨0.63, −0.56, 0.29, −0.35⟩⟩
$\mathcal{D}_2$	⟨⟨0.70, −0.55, 0.48, −0.44⟩, ⟨0.40, −0.54, 0.31, −0.37⟩⟩	⟨⟨0.25, −0.34, 0.75, −0.85⟩, ⟨0.05, −0.20, 0.90, −0.75⟩⟩	⟨⟨0.75, −0.67, 0.39, −0.43⟩, ⟨0.68, −0.59, 0.25, −0.34⟩⟩	⟨⟨0.47, −0.36, 0.65, −0.70⟩, ⟨0.10, −0.25, 0.70, −0.65⟩⟩	⟨⟨0.30, −0.27, 0.84, −0.79⟩, ⟨0.06, −0.24, 0.83, −0.68⟩⟩
$\mathcal{D}_3$	⟨⟨0.58, −0.46, 0.61, −0.59⟩, ⟨0.30, −0.40, 0.60, −0.50⟩⟩	⟨⟨0.21, −0.15, 0.89, −0.90⟩, ⟨0.03, −0.10, 0.95, −0.80⟩⟩	⟨⟨0.84, −0.63, 0.40, −0.38⟩, ⟨0.69, −0.58, 0.25, −0.30⟩⟩	⟨⟨0.60, −0.55, 0.50, −0.47⟩, ⟨0.45, −0.50, 0.35, −0.45⟩⟩	⟨⟨0.34, −0.35, 0.65, −0.70⟩, ⟨0.29, −0.34, 0.63, −0.56⟩⟩
$\mathcal{D}_4$	⟨⟨0.74, −0.68, 0.33, −0.40⟩, ⟨0.63, −0.50, 0.30, −0.26⟩⟩	⟨⟨0.72, −0.59, 0.52, −0.48⟩, ⟨0.59, −0.50, 0.40, −0.37⟩⟩	⟨⟨0.85, −0.71, 0.32, −0.30⟩, ⟨0.65, −0.57, 0.26, −0.30⟩⟩	⟨⟨0.70, −0.60, 0.40, −0.36⟩, ⟨0.69, −0.59, 0.19, −0.26⟩⟩	⟨⟨0.93, −0.80, 0.13, −0.32⟩, ⟨0.83, −0.69, 0.07, −0.21⟩⟩

Table 7
The initial BLDF decision matrix for expert Ξ_3.

	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$
$\mathcal{D}_1$	$(\langle 0.70, -0.62, 0.45, -0.50\rangle, \langle 0.48, -0.54, 0.31, -0.38\rangle)$	$(\langle 0.78, -0.67, 0.32, -0.39\rangle, \langle 0.63, -0.58, 0.22, -0.28\rangle)$	$(\langle 0.60, -0.53, 0.59, -0.63\rangle, \langle 0.35, -0.44, 0.53, -0.46\rangle)$	$(\langle 0.58, -0.48, 0.60, -0.64\rangle, \langle 0.38, -0.40, 0.48, -0.50\rangle)$	$(\langle 0.63, -0.58, 0.50, -0.48\rangle, \langle 0.59, -0.45, 0.40, -0.36\rangle)$
$\mathcal{D}_2$	$(\langle 0.82, -0.70, 0.35, -0.40\rangle, \langle 0.65, -0.56, 0.20, -0.30\rangle)$	$(\langle 0.65, -0.58, 0.50, -0.48\rangle, \langle 0.59, -0.45, 0.39, -0.36\rangle)$	$(\langle 0.59, -0.46, 0.58, -0.57\rangle, \langle 0.33, -0.41, 0.60, -0.48\rangle)$	$(\langle 0.38, -0.44, 0.70, -0.68\rangle, \langle 0.23, -0.32, 0.66, -0.59\rangle)$	$(\langle 0.50, -0.45, 0.60, -0.59\rangle, \langle 0.30, -0.40, 0.50, -0.55\rangle)$
$\mathcal{D}_3$	$(\langle 0.60, -0.50, 0.54, -0.58\rangle, \langle 0.39, -0.35, 0.54, -0.48\rangle)$	$(\langle 0.47, -0.32, 0.67, -0.65\rangle, \langle 0.27, -0.34, 0.61, -0.59\rangle)$	$(\langle 0.73, -0.50, 0.48, -0.46\rangle, \langle 0.59, -0.47, 0.40, -0.37\rangle)$	$(\langle 0.33, -0.25, 0.80, -0.77\rangle, \langle 0.09, -0.15, 0.79, -0.67\rangle)$	$(\langle 0.30, -0.40, 0.70, -0.66\rangle, \langle 0.15, -0.24, 0.70, -0.58\rangle)$
$\mathcal{D}_4$	$(\langle 0.90, -0.83, 0.26, -0.32\rangle, \langle 0.77, -0.60, 0.08, -0.23\rangle)$	$(\langle 0.70, -0.60, 0.49, -0.51\rangle, \langle 0.50, -0.45, 0.36, -0.48\rangle)$	$(\langle 0.83, -0.65, 0.32, -0.43\rangle, \langle 0.63, -0.59, 0.24, -0.32\rangle)$	$(\langle 0.69, -0.58, 0.48, -0.46\rangle, \langle 0.52, -0.40, 0.38, -0.40\rangle)$	$(\langle 0.32, -0.24, 0.80, -0.60\rangle, \langle 0.09, -0.15, 0.90, -0.66\rangle)$

	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
$\mathcal{D}_1$	$(\langle 0.98, -0.73, 0.17, -0.30\rangle, \langle 0.84, -0.69, 0.10, -0.21\rangle)$	$(\langle 0.79, -0.68, 0.40, -0.36\rangle, \langle 0.60, -0.62, 0.14, -0.30\rangle)$	$(\langle 0.82, -0.65, 0.38, -0.42\rangle, \langle 0.69, -0.55, 0.30, -0.26\rangle)$	$(\langle 0.87, -0.76, 0.17, -0.3\rangle, \langle 0.90, -0.65, 0.10, -0.15\rangle)$	$(\langle 0.86, -0.66, 0.41, -0.39\rangle, \langle 0.63, -0.56, 0.29, -0.35\rangle)$
$\mathcal{D}_2$	$(\langle 0.70, -0.55, 0.48, -0.44\rangle, \langle 0.40, -0.54, 0.31, -0.37\rangle)$	$(\langle 0.25, -0.34, 0.75, -0.85\rangle, \langle 0.05, -0.20, 0.90, -0.75\rangle)$	$(\langle 0.75, -0.67, 0.39, -0.43\rangle, \langle 0.68, -0.59, 0.25, -0.34\rangle)$	$(\langle 0.47, -0.36, 0.65, -0.70\rangle, \langle 0.10, -0.25, 0.70, -0.65\rangle)$	$(\langle 0.30, -0.27, 0.84, -0.79\rangle, \langle 0.06, -0.24, 0.83, -0.68\rangle)$
$\mathcal{D}_3$	$(\langle 0.58, -0.46, 0.61, -0.59\rangle, \langle 0.30, -0.40, 0.60, -0.50\rangle)$	$(\langle 0.21, -0.15, 0.89, -0.90\rangle, \langle 0.03, -0.10, 0.95, -0.80\rangle)$	$(\langle 0.84, -0.63, 0.40, -0.38\rangle, \langle 0.69, -0.58, 0.25, -0.30\rangle)$	$(\langle 0.60, -0.55, 0.50, -0.47\rangle, \langle 0.45, -0.50, 0.35, -0.45\rangle)$	$(\langle 0.34, -0.35, 0.65, -0.70\rangle, \langle 0.29, -0.34, 0.63, -0.56\rangle)$
$\mathcal{D}_4$	$(\langle 0.74, -0.68, 0.33, -0.40\rangle, \langle 0.63, -0.50, 0.30, -0.26\rangle)$	$(\langle 0.72, -0.59, 0.52, -0.48\rangle, \langle 0.59, -0.50, 0.40, -0.37\rangle)$	$(\langle 0.85, -0.71, 0.32, -0.30\rangle, \langle 0.65, -0.57, 0.26, -0.30\rangle)$	$(\langle 0.70, -0.60, 0.40, -0.36\rangle, \langle 0.69, -0.59, 0.19, -0.26\rangle)$	$(\langle 0.93, -0.80, 0.13, -0.32\rangle, \langle 0.83, -0.69, 0.07, -0.21\rangle)$

Table 8
Aggregated score matrix.

Alternative/Criteria	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
$\mathcal{D}_1$	0.3096	0.1149	−0.3481	−0.1125	0.0644	0.1895	−0.0595	0.3659	0.3644	0.1836
$\mathcal{D}_2$	0.1295	0.1188	−0.1926	−0.1136	−0.3535	0.2039	−0.5950	0.1792	−0.3355	−0.6619
$\mathcal{D}_3$	−0.0726	−0.4237	−0.0441	−0.0618	−0.0590	−0.0321	−0.5749	−0.0440	−0.2456	−0.0792
$\mathcal{D}_4$	0.5292	0.1188	0.1264	−0.1116	−0.4820	0.1069	0.2168	0.4259	0.1208	0.0699

$$F = \begin{pmatrix} 0.5226 & 0.1242 & -0.6582 & 0.7009 & -2.4737 & 0.7595 & 0.1531 & 0.7104 & -0.5839 & 0.5457 \\ 0.2427 & 0.1194 & -0.2528 & 0.7004 & 0.6620 & 0.8137 & -0.7118 & 0.3641 & 0.8507 & -0.7417 \\ -0.0720 & 0.7868 & 0.1344 & 0.7210 & 0.6082 & -0.0746 & -0.6793 & -0.0498 & 0.6664 & 0.1456 \\ 0.8650 & 0.1194 & 0.5790 & 0.7012 & 0.6127 & 0.4486 & 0.5993 & 0.8216 & -0.0846 & 0.3726 \end{pmatrix} \tag{35}$$

Box I.

Table 9
Expert preference for criteria.

Experts/Criteria	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
Ξ_1	4	3	7	10	6	5	9	1	8	2
Ξ_2	2	8	4	9	7	6	10	3	5	1
Ξ_3	4	5	9	10	6	2	8	1	7	3

Proceeding with solving the model in Eq. (14) using LINGO 19 and incorporating Eq. (15), the weights are derived. Finally, utilizing Eq. (16) with ϵ set to 0.5, the combined weights of the criteria obtained are presented in Fig. 4.

In Phase IV, a multistage normalization of the data is applied to the matrix presented in Table 2. By setting α and β values to 0.33, the aggregated matrix is derived using Eq. (20) as Eq. (35) which is given in Box I.

Advancing into Phase V, the development of the utility matrix involves the application of Eqs. (21)–(24), resulting in the matrix presented in Table 11. Subsequently, to establish the sequence of alternatives, the procedures outlined in Phase VI are executed. By setting ρ_j= 0.2, π_j = 0.3 and Υ_j = 0.6, following Eqs. (26)–(28), both the concordance and discordance indices between the alternatives are calculated, and their values are detailed in Tables 12 and 13, respectively. Further, Fig. 5 represents the credibility index between each alternatives as determined using Eq. (30). Finally, the ranking index for each alternative is computed using Eq. (31) and presented in Table 14, with alternative $\mathcal{D}_4$ identified as the optimal choice based on the evaluation.

6. Result validation

In order to assess the effectiveness of the proposed ranking methods and demonstrate the reliability of the results, as well as to identify the key parameters influencing the efficiency of the proposed methodological framework, comparative and sensitivity analyses are conducted, as outlined in the subsequent sections.

6.1. Comparison analysis

We evaluate the robustness of the results in two ways. In the first scenario, the resulting results are compared to previously published HST-based investigations. The second scenario evaluates the suggested method's superiority over other traditional methods.

Case 1: To validate the results obtained from our proposed model for assessing Hydrogen Storage Technologies (HST), we compare them with existing studies conducted by Gumus et al. [60], Sharaf et al. [6], and Acar et al. [64]. While the alternatives and attributes considered in these studies vary slightly across different cases compared to our own, the overall findings align closely with those of our study, validating the reliability of our developed model in handling such scenarios.

Gumus et al. [60] evaluated three storage technologies across five attributes for their applicability in Turkey. However, they did not include factors related to environmental and safety concerns of the technology. Moreover, they relied solely on subjective criteria weighting, neglecting the objectivity of information, which could affect the

Table 10
Estimation of criteria weight.

	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
$\varsigma_{\mathfrak{t}}^{o}$	0.0990	0.1480	0.0982	0.0056	0.1363	0.1312	0.0530	0.1205	0.0687	0.1394
$\varsigma_{\mathfrak{t}}^{s}$	0.1453	0.0877	0.0705	0.0148	0.0574	0.0915	0.0181	0.2286	0.0575	0.2286

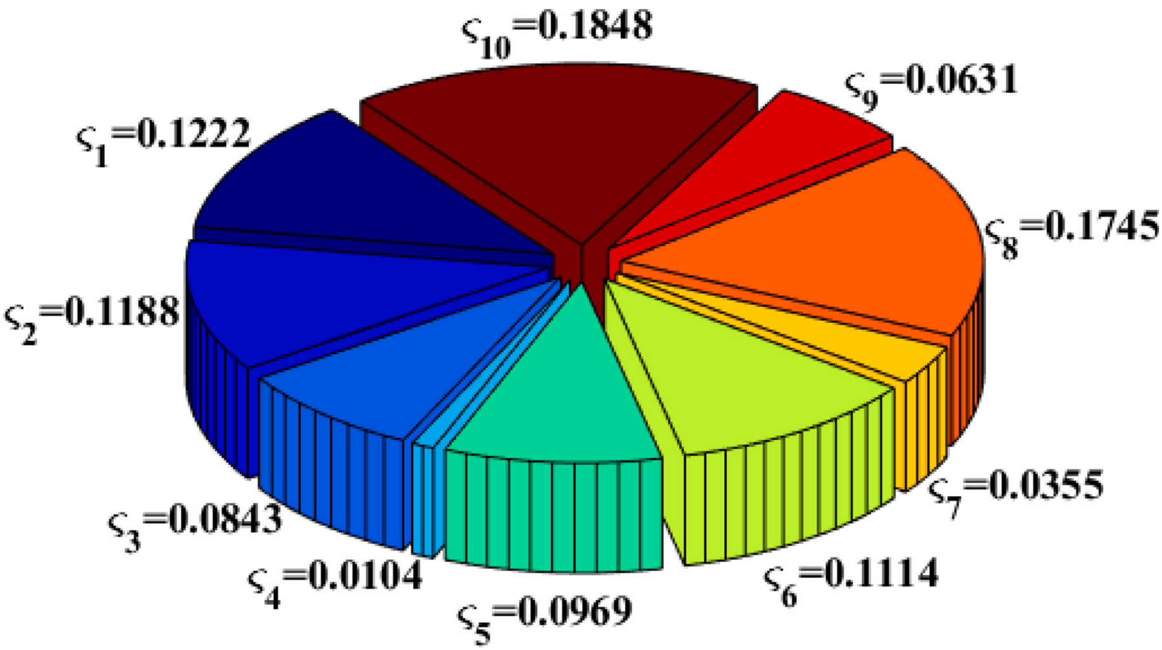
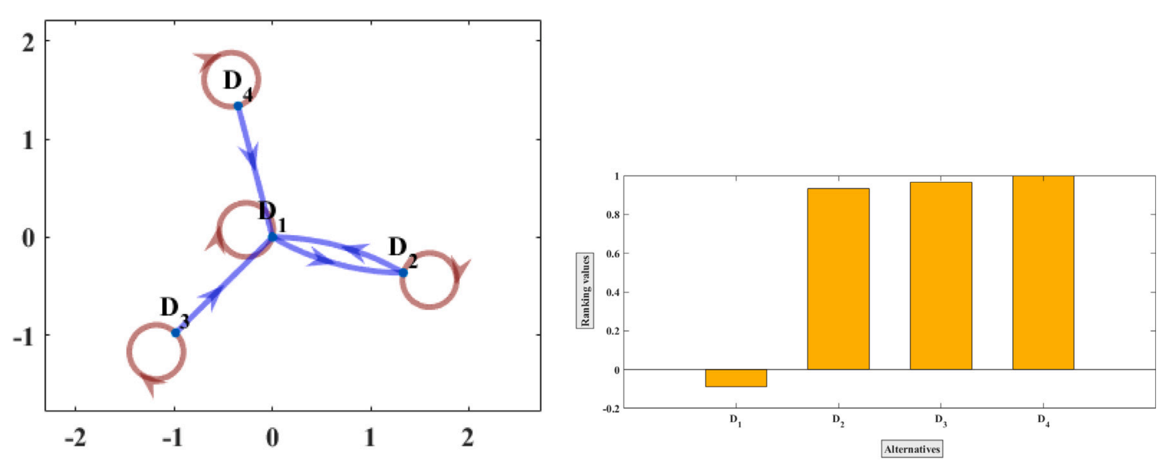


Fig. 4. Relative preference of each attribute.

Table 11
Total utility matrix using MARCOS method.

	$\beth_1$	$\beth_2$	$\beth_3$	$\beth_4$	$\beth_5$	$\beth_6$	$\beth_7$	$\beth_8$	$\beth_9$	$\beth_{10}$
D_1	−0.0889	−0.0204	0.0772	−0.0100	0.3337	−0.1178	−0.0076	−0.1725	0.0513	−0.1398
D_2	−0.0413	−0.0196	0.0297	−0.0099	−0.0893	−0.1262	0.0352	−0.0885	−0.0747	0.1900
D_3	0.0123	−0.1290	−0.0158	−0.0102	−0.0820	0.0116	0.0336	0.0121	−0.0585	−0.0373
D_4	−0.1471	−0.0196	−0.0679	−0.0100	−0.0826	−0.0696	−0.0296	−0.1996	0.0074	−0.0954



(a) Credibility relation between the alternatives (b) Ranking of alternative

Fig. 5. Results using the proposed method.

influence of weight vectors on the problem under consideration. Similarly, Sharaf et al. [6] also solely considered the subjectivity of experts in weighting the attributes. They employed spherical fuzzy-based TOPSIS and VIKOR methods for technology assessment, but the use of these compensatory-based ranking processes could impact the reliability of results.

In contrast, Acar et al. [64] utilized an interval-valued intuitionistic fuzzy-based Analytic Hierarchy Process (AHP) method to evaluate HST

Table 12
Concordance index.

$\mathcal{Y}(\mathcal{D}_i, \mathcal{D}_e)$	$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_3$	$\mathcal{D}_4$
$\mathcal{D}_1$	1	0.8159	0.9999	0.9999
$\mathcal{D}_2$	0.903	1	0.9999	0.9999
$\mathcal{D}_3$	0.903	0.9497	1	0.9999
$\mathcal{D}_4$	0.903	0.842764	0.9795	1

Table 13
Discordance index.

$\mathcal{R}(\mathcal{D}_i, \mathcal{D}_e)$	$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_3$	$\mathcal{D}_4$
$\mathcal{D}_1$	1	0.0183	0	0
$\mathcal{D}_2$	0.0397	1	0	0
$\mathcal{D}_3$	0.0374	0	1	0
$\mathcal{D}_4$	0.0376	0	0	1

Table 14
Preference score using ELECTRE-III method.

Alternative	$\Lambda(\mathcal{D}_i)$	Optimal order
$\mathcal{D}_1$	−0.0886	4
$\mathcal{D}_2$	0.9323	3
$\mathcal{D}_3$	0.9661	2
$\mathcal{D}_4$	1	1

Table 15
Ordering of alternatives using distinct methods.

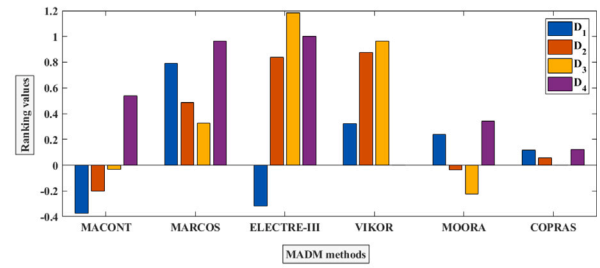
Method	Preference values	Optimal choice
MACONT	−0.3755, −0.2017, −0.0308, 0.5399	$\mathcal{D}_4$
MARCOS	0.7914, 0.4857, 0.3254, 0.9657	$\mathcal{D}_4$
ELECTRE-III	−0.3159, 0.8361, 1.1813, 1	$\mathcal{D}_3$
VIKOR	0.3210, 0.8749, 0.9656, 0	$\mathcal{D}_4$
MOORA	0.2387, −0.0396, −0.2260, 0.3432	$\mathcal{D}_4$
COPRAS	0.1188, 0.0543, −0.0013, 0.1232	$\mathcal{D}_4$

under sustainable parameters, particularly for stationary applications. However, their solution was based on subjective choices, potentially affecting the adaptability of the framework.

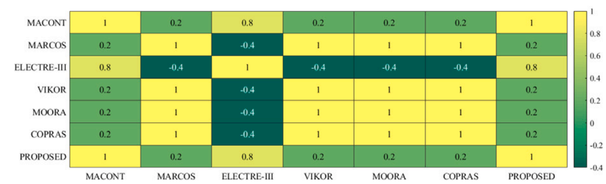
Therefore, our developed methodology not only considers objective parameters but also incorporates subjective inputs, ensuring a comprehensive assessment of the problem. By integrating both compensatory and non-compensatory models for alternative evaluation, we are able to capture a wider range of factors and nuances in the decision-making process. This approach allows us to make more nuanced and informed decisions, accommodating various perspectives and trade-offs leading to the generation of more reliable and effective solutions that better address the intricacies of the problem at hand.

Case 2: To analyze the robustness of the proposed framework and to understand the advantage of implementing integrated frameworks rather than standalone methods for the prioritizing of the alternatives, we compare the obtained results with the individual frameworks of the proposed methodology like MACONT, MAROCS, ELECTRE-III, and other well established techniques like VIKOR, COPRAS and MOORA for assessing the result validity. The Table 15 and Fig. 6 illustrates the incorporated MADM models along with their respective ranking outcomes. Though there is a significant change in ordering of the alternatives however the optimal choices determined by these methods align with the results obtained from the proposed algorithm. This comprehensive comparison allows us to gain insights into the strengths and limitations of each approach and provides valuable validation for the effectiveness of our proposed framework.

Moreover, to delve deeper into assessing the alignment between our proposed method and the considered frameworks, we conducted Spearman rank correlation analysis. The accompanying Fig. 6 illustrates the degree of similarity among different methodologies. Upon evaluating the ordering of alternatives across various methodologies, our proposed method exhibits the highest correlation with the MACONT



(a) Methods and their ranking results



(b) Correlation matirx

Fig. 6. Comparative ranking results.

and ELECTRE-III approaches, while showing less resemblance with the remaining methods. These results underscore the advantage of integrating both compensatory and non-compensatory models within our approach. Through this integration, we are able to generate rankings that closely mirror those of established frameworks like MACONT and ELECTRE-III, highlighting the robustness and efficacy of our integrated methodology in facilitating comprehensive and dependable decision-making outcomes.

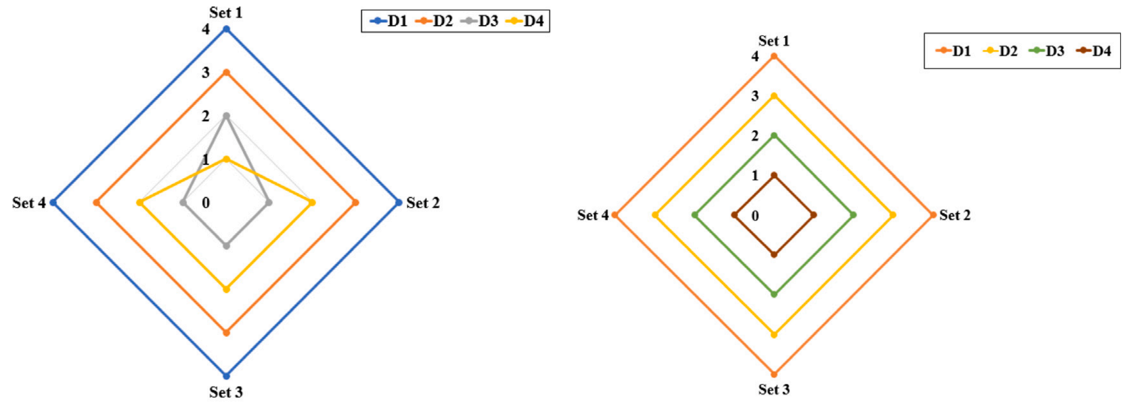
Given these insights, the utilization of an integrated framework emerges as highly dependable. Such a framework offers a well-rounded evaluation, enabling a holistic and efficient approach to addressing trade-offs, accommodating diverse perspectives and criteria, and fostering informed decision-making.

6.2. Sensitivity analysis

A reliability analysis is conducted to examine the key factors influencing the assessment of HST for mobility applications within the country. This analysis is carried out under two distinct scenarios, each with different threshold values: $(0.1, 0.2, 0.5)$ and $(0.05, 0.2, 0.4)$.

Scenario 1: We scrutinize the fluctuations among various parameters on the basis of the benefit and cost attributes. Different proportions for these attributes are explored, ranging from 50%–50%, 70%–30%, 40%–60%, and 20%–80% representing the significance assigned to each attribute grouped under benefit and cost criteria. Notably, adjusting the preference for beneficial parameters and elevating the importance of cost attributes significantly affects the ranking of methods. For instance, as the significance of total system cost increases relative to other attributes, alternative $\mathcal{D}_3$ replaces $\mathcal{D}_4$ as the optimal choice for hydrogen storage. Fig. 7 illustrates the preferences for each option under these settings, emphasizing the importance of developing regulatory policies associated with total system cost to promote sustainable practices.

Scenario 2: We examine changes in aggregation parameter values when determining the integrated weight of attributes. Four values are considered: 0, 0.4, 0.7, and 0.8, reflecting the emphasis placed on weighting algorithms within the equation incorporating values from LOPCOW and OPA methods, respectively. By initially assessing model weights as equally important for both objective and subjective evaluations, we analyze the impact of these evaluations on ranking storage



(a) Scenario 1 (b) Scenario 2

Fig. 7. Sensitive ranking of alternatives.

Table 16
Different set of attribute weights.

Criteria	Set 1	Set 2	Set 3	Set 4
$\beth_1$	0.1453	0.1268	0.1129	0.0990
$\beth_2$	0.0877	0.1118	0.1299	0.1480
$\beth_3$	0.0705	0.0816	0.0899	0.0982
$\beth_4$	0.0148	0.0111	0.0084	0.0056
$\beth_5$	0.0574	0.0890	0.1126	0.1363
$\beth_6$	0.0915	0.1074	0.1193	0.1312
$\beth_7$	0.0181	0.0321	0.0425	0.0530
$\beth_8$	0.2286	0.1854	0.1529	0.1205
$\beth_9$	0.0575	0.0620	0.0653	0.0687
$\beth_{10}$	0.2286	0.1929	0.1662	0.1394

options. Table 16 outlines the various sets of weights allocated to attributes based on different aggregation parameter values, with the resulting order of options depicted in Fig. 7. Although all four cases confirm $\mathcal{D}_4$ as the optimal choice, slight variations in attribute weights are observed compared to initial preferences. This underscores that changes in aggregation parameters have minimal impact on option ranking. However, gradual increases in emphasis on objective data highlight the importance of attributes such as lifetime over environmental feasibility.

The analysis of these scenarios reveals that adjustments in threshold values significantly affect alternative ranking. Moreover, modifications in weights attributed to different factors lead to noticeable shifts in option ranking. Additionally, incorporating weights that combine objective data and decision-makers' subjectivity can influence the analysis of influential parameters for the problem at hand.

7. Discussion

The developed integrated framework has played a pivotal role in evaluating various HSTs based on sustainable parameters. Among the ten attributes analyzed, environmental viability, efficiency, and storage capacity emerge as crucial factors in shaping hydrogen-based storage systems. Particularly in countries like India, where HFCVs face stiff competition from EVs, the proposed study aids policymakers in discerning influential parameters for technology development strategies. By prioritizing environmental sustainability in HST assessments, the study contributes to the transition toward cleaner and more sustainable transportation systems, aligning with India's objectives of reducing greenhouse gas emissions and addressing climate change concerns. Moreover, considering the total cost of the system is imperative, as it impacts the commercial viability of HFCVs, with challenges including infrastructure limitations and energy losses across the value chain. India's advantage in low-cost renewable energy positions it well to produce cost-efficient green hydrogen, competing effectively with conventional fuels. The government's initiative, the Green Hydrogen Mobility Project in Leh, launched in 2022, signifies a significant step forward, with plans for five Fuel Cell Buses to operate in and around Leh. This pioneering project marks the first deployment of FCEVs for public use in India, reflecting positive momentum toward FCEV implementation nationwide.

Among the techniques evaluated under the proposed framework compressed storage emerges as the preferred choice for mobility applications followed by liquid storage. Compressed storage is a matured well established technique and is the mostly preferred choice for vehicular applications due to its technological efficiency, accessibility, and user-friendly attributes, enabling widespread deployment compared to other systems for automobiles. However due to the high pressurize used to store the gaseous hydrogen in these methods requires further analysis regarding leakage and explosion. However when analyzing numerous others factors material based storage options, safety considerations favor material-based storage over liquid storage. In terms of cost and accessibility, compressed and liquid storage outperform other alternatives. As each technology outperforms the other in evaluating either of the factors choosing an ideal choice among them is quite difficult.

Considering the current commercial availability of HFCVs in other countries, it is noteworthy that compressed storage is the sole storage technology available for mobile applications on a commercial scale. This storage method is favored due to its favorable balance across various parameters, including efficiency, storage capacity, ease of use, durability, and cost-effectiveness.

Given these advantages, compressed storage emerges as a sustainable choice for the development of FCEVs in the country. Supported by the nation's Green Hydrogen Mission and government incentives, research and development efforts focused on this technology are expected to yield a promising market size within the FCEV segment. As such, investing in compressed storage technology aligns with the country's objectives for advancing clean energy solutions and fostering a sustainable mobility ecosystem.

Therefore, the proposed fuzzy-based decision analysis proves beneficial in assessing sustainable storage options suitable for the country across ten key parameters. Considering the prevailing uncertainties concerning fluctuating market dynamics in the country, additional parameters can be integrated into the proposed framework to bolster the robustness of the results obtained. By incorporating these supplementary factors, the framework becomes more comprehensive and adept at capturing the complexities of the evolving energy landscape, thus enabling stakeholders to make more informed and resilient decisions regarding HSTs.

7.1. Managerial implications

- With Hydrogen Fuel Cell Vehicles (HFCVs) projected to capture a significant market share in the future, investing in hydrogen refueling stations akin to conventional petrol/diesel stations presents a lucrative opportunity. Hybrid Hydrogen-gasoline fueling stations can be built for efficient use of space. These stations contribute to scalability, efficiency improvement across the value chain, and cost reduction. A government initiative of developing first standalone refueling station fully powered by renewables is expected to be setup in Leh through a stand-alone 1.25 MW solar system.
- Drawing on India's extensive experience with gaseous fuels like LPG and CNG, there is an opportunity to leverage social acceptance and familiarity with gaseous hydrogen for transport. Additionally the government intervention in integrating into public transportation fleets can raise public awareness and acceptance of these vehicles, while also providing a reliable source of demand.
- The seamless integration of hydrogen technology with existing infrastructure simplifies policy restrictions and encourages international investment. Using the proposed decision analysis can help with strategic decision-making by identifying optimal paths for building the country's green hydrogen market, setting it for significant growth by 2025.
- While hydrogen has significant advantages as a fuel, safety considerations about storage, handling, and refueling remain crucial. Setting strict safety standards and conducting public awareness campaigns are critical for addressing these issues and ensuring the safe deployment and environmental feasibility of hydrogen technology in the transportation sector.

8. Conclusion

Creating a cost-effective and environmentally friendly storage and transportation infrastructure is crucial for unlocking the potential of hydrogen in establishing a sustainable energy economy. HFCVs are seen as a long-term solution for decarbonizing the road transport sector. Despite hydrogen's higher efficiency and long-term sustainability compared to conventional fuels, challenges in storing and transporting hydrogen limit the commercial use of these vehicles. Establishing an efficient storage infrastructure is essential to enhance hydrogen's applicability across various sectors, making it a clean and versatile energy carrier that drives innovation, efficiency, and sustainability across industries.

The study conducted explores different HST in the automobile industry. It analyzes the characteristics of these systems, evaluates their performance based on ten key sustainability parameters, and determines the optimal choice among them using a fuzzy enhanced stratified approach. The developed BLDF logic effectively captures the fuzziness and uncertainty in decision scenarios.he proposed BLDF-based MACONT-MARCOS-ELECTRE-III framework suggests that compressed storage for HSTs surpasses other systems concerning efficiency, maturity, energy efficiency, and environmental feasibility. Ongoing technological advancements and infrastructure development are anticipated to enhance the feasibility of compressed storage even further. The combination of multiple frameworks for analysis has resulted in effective solution considering the evaluation problem and comparison analysis justify the robustness of the framework.

The results offer insights into potential sources for hydrogen storage in mobility applications, advancing HFC technology and serving as a valuable resource for policymakers. The study aids in designing strategic initiatives to reduce costs associated with hydrogen storage in the transportation sector, influencing policy decisions for sustainable transportation.

As technological, policy, and societal trends evolve, updating decision-making frameworks with additional assessment criteria and involving a broader decision group becomes essential to align with progressive HST sustainability benchmarks. Incorporating the suggested framework in complex problem assessments enhances practicality, contributing to the development of a robust decision framework.

CRediT authorship contribution statement

Joseph Raj Vikilal Joice Brainy: Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Samayan Narayanamoorthy:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Data curation. **Subramaniam Pragathi:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Data curation. **Soheil Salahshour:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Ali Ahmadian:** Writing – review & editing, Visualization, Software. **Daekook Kang:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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