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Circular Intuitionistic Fuzzy EDAS Approach: A New Paradigm for Decision-Making in the Automotive Industry Sector

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ABSTRACT

The automotive industry has become a robust manufacturing sector in the global manufacturing field, boosting and developing at high speed based on technology updates, environmental protection rules and regulation changes, and customers' new needs and demands. Such dynamics give rise to complex problems like optimizing cost strategy and innovation, operating under high sustainability standards, and navigating the supply chain. These difficulties have led to the need for more structured, logical and effective approaches to decision-making that can handle cross purposes and the world of slow changes and unpredictability. To mitigate these problems, in this context, this study presents the Circular Intuitionistic Fuzzy EDAS (CIF-EDAS) approach to handle decision-making challenges in the automotive industry. Integrating the circular intuitionistic fuzzy sets (CIFSs) with the EDAS approach provides a better assessment of uncertainty and hesitation, enhancing the reliability and strength of multi-criteria decision-making (MCDM) methods. The applicability of the proposed approach is illustrated by a case study in the automotive industry, in which the assessment of different scenarios based on conflicting criteria is effective. Moreover, a comparison analysis has been conducted, demonstrating the proposed approach's superiority and highlighting its efficacy in facilitating robust decision-making. The CIF-EDAS approach is clarified to exemplify its applicability in optimizing decision-making of complicated real-life industrial problems and demonstrating its capability to evolve for the automotive industry's newly emergent restrictive and dynamic demand.

1. Introduction

The automotive sector is one of the driving forces of the global economy and one of the most challenging and changing industries. It develops with technological progress, increasing ecological requirements and consumer demands. Due to their fundamental role in technological development, this industry is under high pressure to produce quality goods at reasonable costs while being

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environmentally responsible. In the rapid industrial digitalization and globalization, competitiveness addresses challenging issues like supply chain management, sustainability, and disruptive technologies. However, these challenges are linked with ambiguity and different criteria; thus, effective decision-making has become more important. For example, supply chain sustainability has become a significant priority in the automotive industry for executing environmental laws and maintaining profitability. It includes the decision to use suppliers committed to environmentally friendly actions, properly utilizing resources, and minimizing risks in the supply chain. There are problems with traditional models of decision-making that are not well equipped for dealing with these problems, including implementing procedural rules for dealing with uncertainty and translating the hesitation that characterizes human judgments. [1]. Moreover, the blending of Industry 4.0 technologies [2] Implementing change has added another dimension to the problem by necessitating complex assessment frameworks. These multifaceted challenges are not limited to supply chains. It also includes risk evaluation, spare part maintenance, and new technologies like hydrogen fuel cells in vehicles that require similar receptions. Various studies address these issues involving the automotive industry, such as risk assessment in automotive parts production [3] and supplier selection for emerging technology, such as hydrogen fuel cell components, and calls for new methodologies to handle fuzzy and uncertain information [4].

Therefore, decision-making in the automotive industry has risen in complexity to the level that the fuzzy framework can handle as a tool for dealing with the levels of uncertainty present in real-life systems. Using a fuzzy framework enables the decision-makers to represent information that is approximate, near, but not equal to some other information to help evaluate the various alternatives and criteria. By integrating fuzzy sets [5] into MCDM models, researchers have developed hybrid methodologies to tackle sustainability and innovation challenges in the automotive sector [6]. Further, this concept was extended into the intuitionistic fuzzy set (IFS) [7] framework, Pythagorean fuzzy set (PyFS) [8], and q-rung fuzzy set (q-ROFS) [9]. All these concepts involve ambiguity to some extent and offer limitations. To define a more comprehensive framework, Atanassov introduced the CIFS [10], which offers more reliability and efficacy in the decision-making evaluation. The Evaluation Based on Distance from Average Solution (EDAS) approach has emerged as a robust and versatile methodology for decision-making, particularly in domains that demand systematic evaluation under uncertainty. The EDAS technique has demonstrated significant efficacy across various applications in the automotive industry. By prioritizing alternatives based on their closeness to an average solution, EDAS provides a balanced framework for assessing alternatives against multiple criteria. For instance, it has been employed to evaluate risk strategies for supply chain sustainability, enabling decision-makers to identify optimal solutions in the face of conflicting environmental and economic objectives [11]. Furthermore, EDAS has proven effective in material selection for hybrid vehicle battery packs, where the comparative evaluation of thermoplastic materials under multiple conflicting attributes is critical [12]. Similarly, the technique has facilitated the selection of electric motor vehicles by integrating diverse performance and sustainability criteria [13]. EDAS offers a comprehensive and adaptable solution for tackling complex decision-making scenarios in the automotive sector. It accommodates uncertainty and complexities through extensions such as fuzzy environments.

The automotive industry involved challenges in decision-making, particularly in managing sustainability, innovation, and risk across complex supply chains and technological advancements. These issues are combined by uncertainty and conflicting criteria, requiring a robust framework for evaluating alternatives effectively. This study aims to address these challenges by introducing the CIF-EDAS approach, leveraging the strengths of CIFS to manage uncertainty and hesitation in decision-making. The proposed framework offers to enhance the evaluation of alternatives in the automotive industry by integrating advanced fuzzy techniques into the EDAS methodology and ensuring reliability and adaptability for sustainability, innovation, and risk management. The proposed approach enhances the capacity to model uncertainty and hesitation in evaluating alternatives by leveraging the CIFS. It offers a robust, data-driven decision-making paradigm for sustainability, digital transformation, and risk management challenges. This comprehensive approach aims to empower stakeholders in the automotive sector to navigate uncertainties and make informed, strategic decisions.

1.1 Existing studies based on the EDAS approach

The EDAS approach has been extensively studied and applied in various fields, demonstrating its versatility and effectiveness in addressing complex decision-making problems. The method's core strength lies in its ability to evaluate alternatives based on distance from an average solution, allowing for balanced and practical decision-making. In recent years, EDAS has been further extended with fuzzy logic and other advanced mathematical frameworks, enhancing its applicability under conditions of uncertainty and ambiguity. Table 1 shows the existing studies highlighting the applications and advancements of the EDAS approach in the automotive industry sector.

Table 1
Existing studies based on the EDAS approach

Study	Domain	Key Focus	Methodology	Findings
Alioğulları et al. [11]	Supply Chain Sustainability	Assessed sustainability strategies by handling uncertainty using a neutrosophic framework.	Interval-valued neutrosophic fuzzy EDAS	Improved decision-making reliability for sustainable supply chain management.
Bulut et al. [12]	Material Selection	Evaluated thermoplastic materials for hybrid vehicle battery packs.	Comparative EDAS with multi-criteria decision-making	Identified optimal materials balancing performance, cost, and sustainability.
Sharma et al. [13]	Electric Vehicle Selection	Evaluated electric motor vehicles across multiple performance and sustainability criteria.	Standard EDAS method	Offered insights for sustainable and performance-based vehicle selection.
Bas [1]	Green Supplier Selection	Focused on selecting environmentally friendly suppliers for the automotive industry.	Integrated EDAS with consensus decision-making	Enhanced supplier selection by considering environmental and economic trade-offs.
Singh et al. [4]	Hydrogen Fuel Cell Supplier Selection	Assessed suppliers under fuzzy and prospect theory frameworks for emerging hydrogen technologies.	Fuzzy-Prospect Theory EDAS	Provided reliable frameworks for emerging green technologies in automotive.

The existing studies reveal their versatility and effectiveness in addressing various decision-making challenges, particularly in the automotive industry. The method has been successfully applied to sustainability, material selection, and supplier evaluation, showcasing its adaptability to complex, multi-criteria environments. Furthermore, integrating the advanced fuzzy framework has significantly enhanced its ability to handle uncertainty and hesitation, making it highly suitable for real-world applications.

1.2 Existing studies based on the Automotive Industry

The automotive industry faces multifaceted challenges such as sustainability, technological innovation, and supply chain optimization. These complexities have provoked researchers to develop advanced decision-making frameworks personalized to the industry's needs. The studies leveraging MCDM approaches, including EDAS, have focused on critical areas like sustainable supply chain management, supplier selection, material evaluation, and risk assessment. These contributions underline the importance of systematic and data-driven decision-making to navigate uncertainties and competing priorities effectively. Table 2 presents the existing studies in the automotive industry, emphasizing their applications and contributions.

Table 2
Existing studies based on the Automotive Industry sector

Study	Domain	Key Focus	Methodology	Findings
Beinabadi et al. [14]	Supply Chain Sustainability	Frameworks for sustainable supply chain management.	Data-driven MCDM	Enhanced environmental and economic trade-off analysis.
Bas [1]	Green Supplier Selection	Environmentally friendly suppliers for automotive production.	Hybrid MCDM integrating consensus and EDAS	Provided effective criteria balancing for green supplier evaluation.
Bulut et al. [12]	Material Selection	Thermoplastic materials for hybrid vehicle battery packs.	EDAS and other MCDM techniques	Identified optimal materials balancing performance, cost, and sustainability.
Kara et al. [6]	Green Supplier Selection	Proposed a hybrid methodology for selecting suppliers with green practices.	Hybrid MCDM	Enabled better decision-making for sustainable supplier networks.

Existing studies in the automotive industry demonstrate the critical role of MCDM methodologies in tackling industry-specific challenges and emphasize the need for innovative and adaptable frameworks to navigate the complexities of modern automotive decision-making, particularly under conditions of uncertainty and conflicting criteria.

1.3 Research Gap

A review of existing studies reveals that while significant advancements have been made in decision-making methodologies for the automotive industry, notable gaps remain. The EDAS approach has been extensively applied across domains such as supply chain sustainability [15] and material selection for hybrid vehicles [16]. However, these studies largely rely on traditional or fuzzy extensions of EDAS, which do not fully address the complexity of human hesitation and uncertainty in decision-making. Similarly, methods applied to supplier selection [17] and risk assessment [18] often overlook the nuanced interplay of conflicting criteria and hesitation in judgments. Furthermore, the automotive industry increasingly requires tools to evaluate complex scenarios involving sustainability, digital transformation, and green energy adoption, such as hydrogen fuel cell technologies. The existing decision-making models lack the sophistication to capture the circular relationships among decision variables fully. This gap highlights the need for a robust decision-making framework to model uncertainty, hesitation, and interdependencies within the automotive sector.

1.4 Problem Statement and Contribution

The automotive industry faces critical decision-making challenges due to increasing complexities in sustainability, supply chain optimization, and technological advancement. The uncertainty and hesitation connected with evaluating conflicting criteria, such as cost, environmental impact, and performance, enhance these challenges. Traditional decision-making approaches often fail to adequately capture the ambiguity and vagueness inherent in human judgments, leading to suboptimal or inconsistent outcomes. However, the MCDM approach, i.e., the EDAS method, has shown potential; the existing studies lack the flexibility to evaluate the hesitation and uncertainty in dynamic industrial contexts comprehensively. This limitation underscores the need for an advanced decision-making framework tailored to the specific requirements of the automotive industry. So, this study aims to fill these gaps by proposing a novel CIF-EDAS approach. The key contributions of this research are the following:

i. By integrating CIFS into the EDAS framework, the proposed method provides a more comprehensive evaluation that deals with uncertainty, hesitation, and interdependencies in decision-making processes.
ii. The study extends the traditional EDAS approach to the CIF framework and offers a better evaluation of alternatives under conditions of vagueness and ambiguity.
iii. The CIF-EDAS approach is demonstrated through case studies on the lifecycle assessment of battery recycling decisions in electric vehicles. However, it can be applied to green supplier selection, material evaluation for hybrid vehicles, and risk management in supply chains, addressing pressing issues in the automotive industry.
iv. The proposed methodology ensures robust, adaptable, and reliable decision-making, empowering stakeholders to navigate the complexities of sustainability, innovation, and risk assessment effectively.
v. These contributions formed the CIF-EDAS approach, a transformative tool for addressing contemporary decision-making challenges in the automotive industry.

1.5 Layout

This paper is organized as follows:

Section 1: Introduction to the automotive industry sector, existing studies, research gap, and contribution.

Section 2: Basic concepts related to CIFS that assist the readers in understanding the basis.

Section 3: Proposed Circular intuitionistic fuzzy EDAS approach (CIF-EDAS).

Section 4: Defines the decision-making framework utilized in evaluating the Battery Recycling Decisions in Electric Vehicles.

Section 5: Presented Conclusion by defining its Limitations and Future Directions.

2. Preliminaries

This section highlights the basic concepts of CIFS, its operational laws, and averaging and geometric operators based on the circular intuitionistic fuzzy (CIF) framework.

Definition 1 [19]: Consider a CIFS $\mathcal{C}_{\mathfrak{z}} = (\varphi_{\mathfrak{z}}, \phi_{\mathfrak{z}}, \psi_{\mathfrak{z}})$ is defined by the degree of triplet, which consists of satisfaction, dissatisfaction, and the radius of the circle, respectively, with the condition; $0 \leq a_{\mathfrak{z}} + \phi_{\mathfrak{z}} \leq 1$ and $\psi_{\mathfrak{z}} \in [0,1]$. For hesitancy degree $\hbar_{\mathcal{C}}$ is determined by $\hbar_{\mathcal{C}} = 1 - \varphi_{\mathfrak{z}} - \phi_{\mathfrak{z}}$. The triplet $(\varphi_{\mathfrak{z}}, \phi_{\mathfrak{z}}, \psi_{\mathfrak{z}})$ is known as a circular intuitionistic fuzzy number (CIFN).

Definition 2 [20]: Consider $\mathcal{C}_{\mathfrak{z}_1} = (\varphi_1, \phi_1, \psi_1)$ and $\mathcal{C}_{\mathfrak{z}_2} = (\varphi_2, \phi_2, \psi_2)$ be the CIFS. Then, the basic operational laws defined by CIFN are;

a) $\mathcal{C}_{\mathfrak{z}_1} \oplus \mathcal{C}_{\mathfrak{z}_2} = \big((\varphi_1 + \varphi_2 - \varphi_1.\varphi_2), (\phi_1.\phi_2), (\psi_1 + \psi_2 - \psi_1.\psi_2)\big)$ (1)

b) $\mathcal{C}_{\mathfrak{z}_1} \otimes \mathcal{C}_{\mathfrak{z}_2} = \big((\varphi_1.\varphi_2), (\phi_1 + \phi_2 - \phi_1.\phi_2), (\psi_1.\psi_2)\big)$ (2)

c) $\sigma\mathcal{C}_{\mathfrak{z}_1} = (1 - (1 - \varphi_1)^{\sigma}, (\phi_1)^{\sigma}, 1 - (1 - \psi_1)^{\sigma})$ (3)

d) $\left(\mathcal{C}_{\mathfrak{z}_1}\right)^{\sigma} = ((\varphi_1)^{\sigma}, 1 - (1 - \phi_1)^{\sigma}, (\psi_1)^{\sigma})$ (4)

Definition 3 [20]: Consider $\mathcal{C}_{\mathfrak{z}_1} = (\varphi_1, \phi_1, \psi_1)$ be the CIFN. The score and accuracy function are defined as follows;

$$\mathcal{S}_{\mathcal{C}_{\mathfrak{z}}} = (\varphi_1 - \phi_1) \times \psi_1 \quad (5)$$

$$\mathcal{S}'_{\mathcal{C}_{\mathfrak{z}}} = (\varphi_1 + \phi_1) \times \psi_1 \quad (6)$$

If the $\mathcal{S}_{\mathcal{C}_{\mathfrak{z}_i}} = \mathcal{S}_{\mathcal{C}_{\mathfrak{z}_j}}$, then to find the ranking, utilize the accuracy function. If $\mathcal{S}'_{\mathcal{C}_{\mathfrak{z}_i}} = \mathcal{S}'_{\mathcal{C}_{\mathfrak{z}_j}}$, then $\mathcal{C}_{\mathfrak{z}_i} = \mathcal{C}_{\mathfrak{z}_j}$.

Definition 4 [21]**:** Consider $\mathcal{C}_{\mathfrak{z}_i} = (\varphi_i, \phi_i, \psi_i)$ be the CIFNs, the circular intuitionistic fuzzy weighted averaging (CIFWA) operator is defined as;

$$\mathrm{CIFWA}\left(\mathcal{C}_{\mathfrak{z}_1}, \mathcal{C}_{\mathfrak{z}_2}, \dots, \mathcal{C}_{\mathfrak{z}_i}\right) = \sum_i w_i \mathcal{C}_{\mathfrak{z}_i} \quad (7)$$

Such that $w_i = (w_1, w_2, \dots, w_n)$ be the weight vector with condition $\sum_i w_i = 1$.

Theorem 1 [21]: The aggregated value obtained by using CIFWA is again CIFN.

$$\mathrm{CIFWA}\left(\mathcal{C}_{\mathfrak{z}_1}, \mathcal{C}_{\mathfrak{z}_2}, \dots, \mathcal{C}_{\mathfrak{z}_i}\right) = \left(1 - \prod_i (1 - \varphi_i)^{w_i}, 1 - \prod_i (\phi_i)^{w_i}, 1 - \prod_i (1 - \psi_i)^{w_i}\right) \quad (8)$$

Here, $w_i = (w_1, w_2, \dots, w_n)$ be the weight vector.

Definition 5 [21]: Consider $\mathcal{C}_{\mathfrak{z}_i} = (\varphi_i, \phi_i, \psi_i)$ be the CIFNs; the circular intuitionistic fuzzy geometric (CIFWG) operator is defined as;

$$\mathrm{CIFWG}\left(\mathcal{C}_{\mathfrak{z}_1}, \mathcal{C}_{\mathfrak{z}_2}, \dots, \mathcal{C}_{\mathfrak{z}_i}\right) = \prod_i w_i \mathcal{C}_{\mathfrak{z}_i} \quad (9)$$

Such that $w_i = (w_1, w_2, \dots, w_n)$ be the weight vector with condition $\sum_i w_i = 1$.

Theorem 2 [21]**:** The aggregated value obtained by using CIFWG is again CIFN.

$$\mathrm{CIFWG}\left(\mathcal{C}_{\mathfrak{z}_1}, \mathcal{C}_{\mathfrak{z}_2}, \dots, \mathcal{C}_{\mathfrak{z}_i}\right) = \left(1 - \prod_i (\varphi_i)^{w_i}, 1 - \prod_i (1 - \phi_i)^{w_i}, 1 - \prod_i (\psi_i)^{w_i}\right) \quad (10)$$

Here, $w_i = (w_1, w_2, \dots, w_n)$ be the weight vector 1.

3. Circular Intuitionistic Fuzzy EDAS Approach

In multi-attribute group decision-making (MAGDM) problems, mainly when there exist conflicting attributes, the traditional EDAS approach offers an efficient and reliable approach that calculates the Positive Distance from Average (PDA), which represents its closeness to the ideal and the Negative Distance from Average (NDA) which measures the distance of an alternative to the ideal. The most preferable choice is the alternative of higher PDA and lower NDA. The main goal is to find the average solution (AV) that acts as a standard for assessing the relative merits of all alternatives.

To facilitate the applicability of the EDAS approach, in this section, the EDAS approach within the CIF framework has been defined to encompass uncertainty and vagueness in decision-making. In the proposed framework, decision data are expressed within CIFNs, which provide a more refined representation of imprecise information. For a decision-making model, consider a collection of alternatives A_i, collection of attributes C_j, the weight values $w_j = (w_1, w_2, \dots, w_n)$ of each attribute that shows the importance of each attribute, assigned by the opinion of decision-makers (hypothetically) with condition $\sum_i w_i = 1$.

So, the computing steps of the proposed approach are outlined below.

i. Formation of decision-matrix $D = \left[\mathcal{C}_{\mathfrak{z}_{ij}}\right]_{m\times n}; i = 1,2, \dots m; j = 1,2, \dots, n$, which highlights the opinion of each decision-maker E_{ij}, can be defined as;

$$D_i = \left[\mathcal{C}_{\mathfrak{z}_{ij}}\right]_{m\times n} = \begin{array}{c} \\ A_1 \\ \vdots \\ A_i \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \dots & C_j \end{array} \\ \begin{bmatrix} \mathcal{C}_{\mathfrak{z}_{11}} & \cdots & \mathcal{C}_{\mathfrak{z}_{1n}} \\ \vdots & \ddots & \vdots \\ \mathcal{C}_{\mathfrak{z}_{m1}} & \cdots & \mathcal{C}_{\mathfrak{z}_{mn}} \end{bmatrix} \end{array}$$

Here, each term $\mathcal{C}_{\mathfrak{z}_{ij}}$ represents the CIFN that depicts the information of each alternative to each attribute.

ii. In the decision matrix, if the information consists of two types i.e. benefit-type and cost-type, then data normalization N is required to obtain the ideal solution and is obtained by;

$$N = \left[\mathcal{C}'_{\mathfrak{z}_{ij}}\right]_{m\times n} = \left[(\varphi_{\mathfrak{z}}, \phi_{\mathfrak{z}}, \psi_{\mathfrak{z}})'\right]_{m\times n} = \left[\phi_{\mathfrak{z}}, \varphi_{\mathfrak{z}}, \psi_{\mathfrak{z}}\right]_{m\times n} \tag{11}$$

For cost type, utilized Eq. (11).

iii. Accumulate the decision information obtained from the multiple decision-makers by considering the significance of each decision-maker, represented by a weight vector w_j, by utilizing the CIFWA and CIFWG operators.

iv. Compute the average solution (AS) of all attributive information C_j by;

$$AS = \left[AS_j\right]_{1\times n} = \left[\frac{\sum \mathcal{C}_{\mathfrak{z}_{ij}}}{m}\right]_{1\times n}$$

Such that $\sum_i \mathcal{C}_{\mathfrak{z}_{ij}} = \left(1 - \prod_i (1-\varphi_i)^{w_i}, 1 - \prod_i (\phi_i)^{w_i}, 1 - \prod_i (1-\psi_i)^{w_i}\right)$ and $AS = \left[AS_j\right]_{1\times n} = \left(\left(1 - \prod_i (1-\varphi_i)^{w_i}\right)^{\frac{1}{m}}, \left(1 - \prod_i (\phi_i)^{w_i}\right)^{\frac{1}{m}}, \left(1 - \prod_i (1-\psi_i)^{w_i}\right)^{1/m}\right)$.

v. Compute the positive and negative distance from the average solution (AS) and is represented as PDAS and NDAS, respectively, and is obtained as;

$$PDAS = \left[PDAS_{ij}\right]_{m\times n} = \frac{1}{\mathcal{S}_{AS_j}} \max\left(0, \left(\mathcal{S}_{\mathcal{C}_{\mathfrak{z}_{ij}}} - \mathcal{S}_{AS_j}\right)\right) \tag{12}$$

$$NDAS = \left[NDAS_{ij}\right]_{m\times n} = \frac{1}{\mathcal{S}_{AS_j}} \max\left(\left(\mathcal{S}_{\mathcal{C}_{\mathfrak{z}_{ij}}} - \mathcal{S}_{AS_j}\right), 0\right) \tag{13}$$

vi. Evaluate the weighted sum (WS) of PDAS and NDAS, which is computed by;

$$WSPDAS_i = \sum_i w_i PDAS_{ij}; WSNDAS_i = \sum_i w_i NDAS_{ij} \tag{14}$$

vii. Normalized N the values WSPDAS and WSNDAS, and then compute the appraisal score of each alternative by;

$$N(WSPDAS)_i = \frac{WSPDAS_i}{\max WSPDAS_i}; N(WSNDAS)_i = 1 - \frac{WSNDAS_i}{\max WSNDAS_i}$$

The appraisal score $App(\mathcal{S})$of each alternative is computed by;

$$App(\mathcal{S})_i = \frac{1}{2}\left(N(WSPDAS)_i + N(WSNDAS)_i\right)$$

viii. Rank the alternative based on their appraisal score value.

The graphical representation of the Algorithm is depicted in Figure 1.

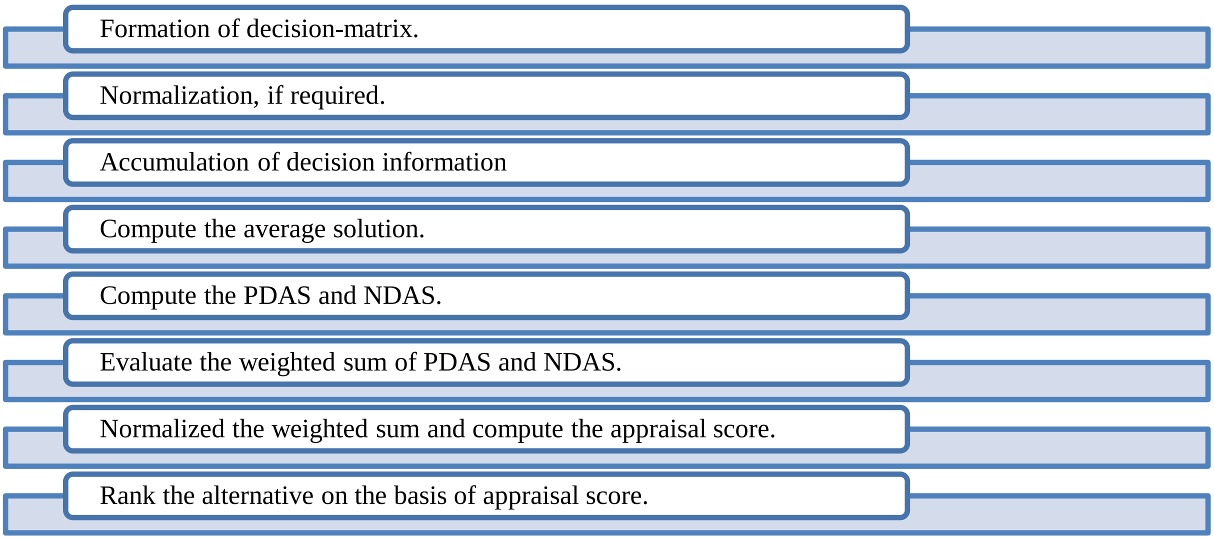

Fig. 1. Algorithm

4. Decision-making in the Automotive Industry

The automotive industry is essential to global economies and a booster of modern mobility. However, it faces significant challenges that require a robust decision-making framework to ensure sustainability and efficiency. The rapidly evolving consumer demands, rigorous environmental regulations, fluctuating raw material costs, and technological advancements create a complex landscape for manufacturers. These challenges demand systematic approaches to navigate risks and grab opportunities effectively. Environmental sustainability remains a pressing concern, as the automotive sector is a major contributor to global carbon emissions. The transition to electric vehicles (EVs) provides a pathway to reduce emissions but introduces new complexities, such as the environmental impact of battery production and recycling. Moreover, the supply chain's weakness to global interruptions ranging from pandemics to trade disputes complicates the decision-making process and leads to delays, cost escalations, and production inefficiencies. Another significant challenge lies in managing the multi-criteria nature of decisions, such as balancing cost, performance, sustainability, and regulatory compliance. The uncertainty surrounding market trends, government policies, and technological breakthroughs further complicates the process. With growing pressure from stakeholders and a devastating volume of data from production lines and market analyses, automotive manufacturers must adopt advanced analytical tools to derive actionable insights. Poor decision-making can result in severe consequences, including financial losses, damaged reputations, and adverse environmental impacts. For example, ignoring supply chain vulnerabilities can disrupt production, while neglecting sustainability concerns may lead to regulatory penalties and diminished consumer trust. So, addressing these issues requires integrating innovative decision-making frameworks that account for complexity and uncertainty.

Industry must embrace advanced methodologies such as CIF-EDAS and lifecycle assessment (LCA) models to tackle these challenges. These approaches allow manufacturers to evaluate multi-criteria scenarios effectively and prioritize sustainability. A data-driven decision-making approach enhances the ability to predict risks and adapt to changes. Engaging stakeholders and incorporating scenario planning further strengthen decision-making, ensuring alignment with environmental, social, and economic goals. So, the decision-making in the automotive industry is a multifaceted challenge with profound implications for society and the environment. By adopting innovative frameworks and prioritizing sustainability, the industry can address these challenges effectively. The following case study demonstrates the application of a decision-making framework to evaluate battery recycling options and highlights the potential for impactful and sustainable decisions.

4.1 Case study: Lifecycle Assessment of Battery Recycling Decisions in Electric Vehicles

The rapid adoption of electric vehicles (EVs) has introduced a pressing challenge, including managing end-of-life batteries in an environmentally sustainable manner. EV batteries are rich in valuable materials such as lithium, cobalt, and nickel, posing significant environmental risks if improperly disposed of. The problem is identifying an optimal recycling method that minimizes ecological impact, conserves resources, and aligns with economic feasibility. Without effective recycling strategies, the accumulation of battery waste could undermine the environmental benefits of transitioning to EVs. Several challenges complicate this decision-making process. Recycling methods vary widely in their environmental impact, efficiency, and cost-effectiveness. For instance, high-temperature methods like pyrometallurgical recycling release significant emissions, while chemical-based approaches such as hydrometallurgical recycling require careful handling of toxic chemicals. Furthermore, direct recycling and second-life applications face scalability and market adoption hurdles. Moreover, the regulatory pressures, public sustainability expectations, and the inherent uncertainties in lifecycle data further complicate the decision.

To address this complex decision-making problem, the CIF-EDAS approach is utilized, which manages the uncertainties in expert evaluations and ranks recycling methods based on their distance from ideal and anti-ideal solutions. By systematically evaluating each recycling alternative against multiple criteria, including environmental impact, economic feasibility, material recovery efficiency, and social acceptance, the CIF-EDAS approach ensures a comprehensive and robust analysis. The criteria for evaluating sustainable battery recycling options were identified through a comprehensive review of previous research and by consulting experts in automotive sustainability and management. Existing literature, such as studies on sustainable supply chain management and recycling frameworks [22], provided a foundation for including environmental impact, economic feasibility, recycling efficiency, and social acceptance criteria. This proposed framework helps in identifying the most sustainable recycling method and provides actionable insights for stakeholders, promoting a circular economy in the automotive industry.

The following attributes and alternatives are considered.

Alternatives (Battery Recycling Methods)

	Alternatives	*Interpretation*
i.	Pyrometallurgical Recycling	High-temperature process that extracts valuable metals like cobalt and nickel but consumes significant energy and emits greenhouse gases.
ii.	Hydrometallurgical Recycling	A chemical-based method that recovers metals through leaching, providing a higher yield of reusable materials with lower emissions.
iii.	Direct Recycling	A mechanical method that refurbishes and reuses battery components without breaking them down into base materials, reducing energy use significantly.
iv.	Second-Life Applications	Reusing EV batteries for stationary energy storage, such as powering homes or renewable energy grids, extends the battery lifecycle.

v. Landfill Disposal — The least sustainable option is where end-of-life batteries are discarded in landfills, leading to environmental contamination.

Attributes for Evaluation:

Attributes	*Interpretation*
i. Environmental Impact	Measures the recycling method's carbon footprint, energy consumption, and ecological damage.
ii. Economic Feasibility	Considers the cost-effectiveness of the process, including operational expenses and revenue from recovered materials.
iii. Material Recovery Efficiency	Evaluate the method's ability to recover high-value materials like lithium, cobalt, and nickel.
iv. Regulatory and Social Acceptance	Assesses how well the method complies with environmental regulations and aligns with public sustainability expectations.

4.2 Numerical Evaluation

For accessing the battery recycling decisions in electric vehicles as a decision-making model, consider a collection of alternatives $A_i: (i = 1,2, \dots ,5)$, and attributes $C_j: (j = 1,2, \dots ,4)$ such that the weight values $w_j = (0.25,0.18,0.35,0.22)$ of each attribute that shows the importance of each attribute, assigned by the opinion of decision-makers (hypothetically) with condition $\sum_i w_i = 1$. So, the computing steps of the proposed methodology are as follows.

i. Formation of decision matrices which highlight the opinion of each decision-maker E_i, displayed in Table 3-5.

Table 3
Opinion of Decision-Maker E_1

	C_1			C_2			C_3			C_4		
	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$
A_1	0.25	0.44	0.35	0.42	0.15	0.29	0.47	0.33	0.40	0.51	0.34	0.43
A_2	0.43	0.25	0.34	0.50	0.28	0.39	0.54	0.29	0.42	0.64	0.17	0.41
A_3	0.55	0.32	0.44	0.58	0.12	0.35	0.62	0.11	0.37	0.80	0.15	0.48
A_4	0.38	0.22	0.30	0.61	0.13	0.37	0.55	0.27	0.41	0.67	0.26	0.47
A_5	0.50	0.15	0.33	0.65	0.10	0.38	0.76	0.25	0.38	0.47	0.35	0.41

Table 4
Opinion of Decision-Maker E_2

	C_1			C_2			C_3			C_4		
	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$	$\varphi_ƺ$	$\phi_ƺ$	$\psi_ƺ$
A_1	0.44	0.35	0.40	0.33	0.27	0.30	0.61	0.28	0.45	0.80	0.15	0.48
A_2	0.53	0.27	0.40	0.64	0.17	0.41	0.43	0.37	0.40	0.23	0.22	0.23
A_3	0.60	0.25	0.43	0.44	0.21	0.33	0.18	0.15	0.17	0.34	0.17	0.26
A_4	0.41	0.28	0.35	0.25	0.32	0.29	0.29	0.32	0.31	0.29	0.34	0.32
A_5	0.14	0.04	0.09	0.27	0.28	0.28	0.55	0.27	0.41	0.28	0.14	0.21

Table 5
Opinion of Decision-Maker E_3

	C_1			C_2			C_3			C_4		
	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ
A_1	0.21	0.22	0.22	0.18	0.12	0.15	0.50	0.25	0.38	0.19	0.15	0.17
A_2	0.69	0.08	0.39	0.59	0.21	0.40	0.22	0.37	0.30	0.26	0.09	0.18
A_3	0.27	0.21	0.24	0.24	0.15	0.20	0.23	0.14	0.19	0.55	0.27	0.41
A_4	0.42	0.25	0.34	0.37	0.19	0.28	0.57	0.26	0.42	0.18	0.35	0.27
A_5	0.45	0.11	0.28	0.47	0.33	0.40	0.24	0.17	0.21	0.28	0.17	0.23

Here, each term $\mathcal{C}_{\delta_{ij}}$ represents the CIFN that depicts the information of each alternative to each attribute.

ii. As in the decision matrix, the information is only one type, then no data normalization N is required.

iii. Accumulate the decision information obtained from the multiple decision-makers E_i by considering the significance of each decision-maker, represented by a weight vector $w_j = (0.35,0.20,0.45)$, by utilizing the CIFWA operator (Eq. 8), shown in Table 6.

Table 6
Accumulation of decision information from Decision-Makers E_i

	C_1			C_2			C_3			C_4		
	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ
A_1	0.28	0.69	0.30	0.30	0.85	0.23	0.51	0.72	0.40	0.49	0.80	0.33
A_2	0.58	0.85	0.37	0.57	0.78	0.40	0.39	0.66	0.36	0.42	0.87	0.27
A_3	0.45	0.75	0.35	0.42	0.85	0.28	0.39	0.87	0.25	0.63	0.80	0.41
A_4	0.40	0.76	0.33	0.45	0.82	0.31	0.52	0.73	0.39	0.42	0.69	0.35
A_5	0.42	0.90	0.26	0.51	0.79	0.37	0.54	0.79	0.37	0.35	0.79	0.29

iv. Compute the average solution (AS) of all attributive information C_j (defined in algorithm step iv) and the results obtained are shown in Table 7.

Table 7
Average Solution (AS) of all C_j

	C_1			C_2			C_3			C_4		
	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ	φ_δ	ϕ_δ	ψ_δ
A_i	0.28	0.69	0.30	0.30	0.85	0.23	0.51	0.72	0.40	0.49	0.80	0.33

v. Compute the positive and negative distance from the average solution (AS), represented as PDAS and NDAS (Eq. 12 and Eq. 13). The results obtained are shown in Table 8.

Table 8
PDAS and NDAS

	PDAS				NDAS			
	C_1	C_2	C_3	C_4	C_1	C_2	C_3	C_4
A_1	0.00	0.00	0.16	0.00	0.11	0.10	0.00	0.00
A_2	0.13	0.29	0.00	0.00	0.00	0.00	0.00	0.16
A_3	0.08	0.00	0.00	0.36	0.00	0.05	0.23	0.00
A_4	0.00	0.00	0.16	0.11	0.01	0.00	0.00	0.00
A_5	0.00	0.11	0.08	0.00	0.12	0.00	0.00	0.22

vi. Evaluate the weighted sum (WS) of PDAS and NDAS (Eq. 14) such that the weight values of each attribute are taken as (hypothetically) $w_j = (0.25,0.18,0.35,0.22)$, and its results are displayed in Table 9.

Table 9
WS of PDAS and NDAS

Alternatives	WSPDAS	WSNDAS
A_1	0.05767	0.04459
A_2	0.08382	0.03621
A_3	0.09929	0.08963
A_4	0.07855	0.00310
A_5	0.04824	0.07840

vii. Normalized N the values WSPDAS and WSNDAS, and then compute the appraisal score $App(\mathcal{S})_i$ of each alternative (by following algorithm step vii), shown in Table 10.

Table 10
Normalization of Weighted Sum and Appraisal Score Value

Alternatives	$N(WSPDAS)_i$	$N(WSNDAS)_i$	$App(\mathcal{S})_i$
A_1	0.05767	0.04459	0.5416
A_2	0.08382	0.03621	0.7201
A_3	0.09929	0.08963	0.5000
A_4	0.07855	0.00310	0.8783
A_5	0.04824	0.07840	0.3056

viii. Rank the alternative based on their appraisal score value, shown in Table 11.

Table 11
Appraisal Score Value and Ranking

Alternatives	$App(\mathcal{S})_i$	Rank
A_1	0.5416	3
A_2	0.7201	2
A_3	0.5000	4
A_4	0.8783	1
A_5	0.3056	5

The pictorial representation of the Appraisal score and ranking of alternatives is depicted in Figure 2.

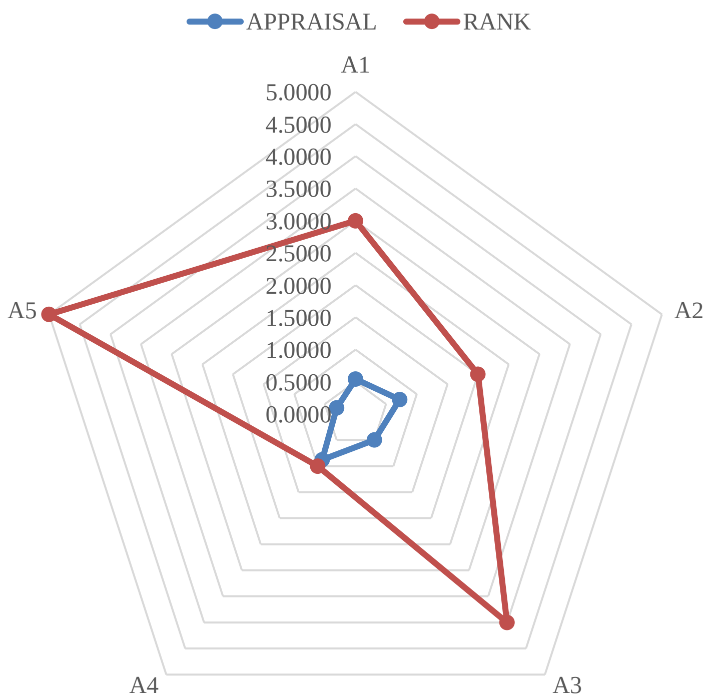

Fig. 2. Appraisal Score Values and Ranking

4.3 Result Discussion and Comparison

Figure 2 reveals that the results of the appraisal score and ranking outcomes which demonstrate critical insights into the prioritization of recycling alternatives for EV batteries and show that the proposed approach offers a more balanced evaluation. The normalized weighted sum and weighted negative distance measures have been effectively utilized to calculate the appraisal scores, leading to a reliable ranking system. So, the result shows that A_4 is the most suitable alternative, having the highest appraisal score value that indicates its superiority and highlights its significant contribution to the sustainable environment, which is then followed by A_2, A_1, A_3 that indicates the decreasing alignment towards the desired outcome and requires significant enhancement. These findings emphasize the importance of utilizing a structured decision-making framework like CIF-EDAS, which captures the inherent complexities and negotiations of such multi-criteria evaluations. Moreover, the results demonstrate the framework's capability to rank alternatives in a manner that aligns with strategic environmental goals for the automotive industry, which not only guides the stakeholders in making informed recycling decisions but also contributes to broader sustainability goals, such as reducing environmental degradation, minimizing resource wastage, and promoting the circular economy.

A comparison analysis was conducted to check the effectiveness and validity of the proposed approach, and the outcome is shown in Table 12. The comparative analysis showed that although all methods provided different rankings of alternatives, the proposed operator pointed to the most desirable solution because it compares alternatives based on a two-dimensional approach incorporating PDAS and NDAS. This reduces bias when ranking the alternatives by providing a chance to weigh the merits and demerits of each available alternative. Furthermore, the proposed approach effectively handles the uncertainty and hesitation in a decision-maker evaluation. It offers a stable, accurate solution even in a challenging scenario, highlighting the proposed approach's superiority in decision-making evaluation.

Table 12
Comparison Analysis

Alternatives	CIFWA	Rank	CIFWG	Rank	Appraisal	Rank
A_1	0.056779	5	−0.10552	1	0.751326	4
A_2	0.089502	3	−0.16956	3	0.908014	2
A_3	0.093377	2	−0.19628	4	0.800728	3
A_4	0.06951	4	−0.12792	2	0.947578	1
A_5	0.109187	1	−0.31861	5	0.082371	5

Figure 3 depicts a pictorial representation of the score values and ranking of alternatives based on the comparison analysis.

The analysis reveals the practical advantages of the proposed approach over traditional methods, such as CIFWA and CIFWG, in evaluating alternatives for battery recycling decisions in electric vehicles. While all methods produced different rankings, the proposed operator demonstrated superior consistency and reliability in identifying the most suitable alternative. The CIFWA approach shows that A_5 as the best alternative due to its aggregation strategy, which emphasizes specific criteria weights. However, this method fails to account for potential geometric interdependencies among the requirements. In contrast, the CIFWG approach, incorporating a geometric aggregation process, placed A_1as the optimal alternative. This divergence between CIFWA and CIFWG underscores their sensitivity to the mathematical formulations and aggregation techniques, which can lead to divergent outcomes under varying conditions. The proposed operator becomes a more holistic and robust evaluation framework and reflects its alignment with the broader objectives of lifecycle assessment in battery recycling. Unlike CIFWA and CIFWG, the proposed operator effectively balances criteria interdependencies while addressing the complexities of decision-making processes.

Fig. 3. Comparison Analysis (Score Values and Ranking)

5. Conclusion

The increasing adoption of electric vehicles (EVs) has brought transformative environmental benefits but has also introduced significant challenges in managing end-of-life battery waste. The need for sustainable and effective recycling strategies has become dominant to mitigate the ecological risks posed by battery disposal and ensure the conservation of critical resources like lithium, cobalt, and nickel. Addressing this multifaceted problem requires a structured and comprehensive decision-making approach that can balance environmental sustainability, economic feasibility, and social acceptance. This study introduced the CIF-EDAS approach as a novel framework for evaluating and prioritizing battery recycling methods. This methodology integrates the fuzzy environment to manage the inherent uncertainties in expert evaluations and the EDAS approach to provide a robust ranking of alternatives by evaluating recycling methods against four critical attributes: environmental impact, economic feasibility, material recovery efficiency, and regulatory and social acceptance. The comparative analysis showed that the proposed operator yields better results and more effective ranking outcomes and offers a comprehensive evaluation reflecting the complexity of such decisions. The resulting outcome of this decision-making framework is not only actionable but also highly adaptable, providing valuable insights for automotive manufacturers, policymakers, and recycling industry stakeholders. Moreover, it also assists decision-makers by providing a flexible and reliable approach to managing the complexities of sustainability-oriented decisions in a rapidly evolving industry.

5.1 Limitation and Future Direction

Despite the efficacy of the CIF-EDAS approach, some limitations exist, including the method's reliance on expert input for the evaluation criteria and their weights, which may produce biases and may vary depending on the expertise and understanding of the stakeholders involved and could lead to inconsistencies in decision-making outcomes when applied to highly dynamic or ambiguous scenarios. Integrating the CIF framework enhances the method's ability to handle uncertainty and vagueness, and it becomes computationally intensive as the number of alternatives and criteria increases, potentially limiting its scalability for larger datasets or complex decision-making environments. Moreover, a deeper exploration of how the method performs across diverse applications and industries is needed. Although the case study validates its effectiveness, the approach has yet to be tested in other domains with unique challenges, such as energy systems, healthcare, or urban planning.

Future research should address these limitations by exploring ways to minimize subjectivity and enhance scalability, developing more automated or semi-automated weight assignment mechanisms, such as those based on machine learning (ML) [23] or data-driven techniques could reduce dependence on expert judgment while improving application consistency. Moreover, it can be extended into the different frameworks of fuzzy systems, including Type 2 fuzzy [24], cubic soft framework [25], Fuzzy switching system [26], complex framework [27], data stabilization [28], hesitant framework [29], TS fuzzy systems [30], interval-valued framework [31], fuzzy fixed point [32], Spherical Fuzzy framework [33], and neutrosophic soft set [34].

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Conflicts of Interest
The authors declare no conflicts of interest.

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