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Comprehensive Analysis of Carbon Footprint Reduction Projects in the Precast Concrete Industry Using Circular Intuitionistic Fuzzy Sets

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Abstract

This study evaluated carbon footprint reduction strategies in the precast concrete industry using a hybrid methodology that combined Circular Intuitionistic Fuzzy Analytic Hierarchy Process (CIF-AHP) and Circular Intuitionistic Fuzzy COmbinative Distance-based Assessment (CIF-CODAS). The research assessed various carbon reduction projects, including energy-efficient technologies, Carbon Capture, Utilization, and Storage (CCUS), and renewable energy integration. The findings showed that CCUS was the most effective strategy, followed by energy-efficient grinding technologies and high-efficiency motors. Waste Heat Recovery (WHR) systems and renewable energy integration ranked lower due to challenges related to large-scale application and cost considerations. The sensitivity analysis demonstrated the robustness of the methodological framework, as it consistently prioritized alternatives across different scenarios. These results emphasized the importance of advanced technologies such as CCUS for achieving substantial reductions in carbon emissions and highlighted the need for ongoing innovation in sustainable concrete production. This study contributed to the literature by offering a systematic approach to decision-making under uncertainty and providing actionable insights for reducing carbon footprints in the precast concrete sector.

Keywords: Carbon footprint reduction, Precast concrete industry, Circular intuitionistic fuzzy analytic hierarchy process, Circular intuitionistic fuzzy combinative distance-based assessment.

1 | Introduction

In today's global landscape, reducing carbon footprints has emerged as a critical imperative for manufacturing companies, driven by a combination of environmental responsibility, regulatory requirements, consumer

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demand, and economic considerations. Manufacturing processes often contribute significantly to carbon emissions, stemming from energy-intensive operations, raw material extraction, transportation, and waste generation. Embracing strategies to reduce carbon footprints aligns with corporate environmental responsibility, aiming to minimize adverse impacts on ecosystems, biodiversity, and climate change. By curbing emissions, companies play a crucial role in preserving natural resources and mitigating global environmental risks. Regulatory frameworks worldwide are increasingly stringent concerning emissions and environmental standards. Compliance with these regulations not only avoids penalties and legal liabilities but also positions manufacturing companies favorably in markets with evolving sustainability norms. Anticipating and exceeding regulatory requirements through proactive emission reduction measures can confer a competitive edge and facilitate market access in regions with stringent environmental policies. While carbon credits are increasingly crucial for leveraging economic opportunities to reduce greenhouse gas emissions, their implementation is fraught with challenges. These include difficulties in accessing finance and the absence of robust, clear policy guidance, even as global climate urgency intensifies [1].

Reducing carbon footprints is synonymous with enhancing operational efficiency. Implementing energy-saving measures, optimizing production processes, and adopting sustainable practices often lead to reduced operational costs. By investing in renewable and energy-efficient technologies and waste-reduction measures, businesses can reduce their environmental footprint while achieving sustained cost savings through lower energy use and more efficient resource management. The long-term economic and environmental advantages of such investments are clear, as demonstrated by studies on sustainable energy systems, which, despite high initial costs, yield significant savings and reduce reliance on fossil fuels [2]. In an era of heightened environmental awareness, consumers, stakeholders, and investors increasingly favor companies demonstrating strong environmental stewardship. Manufacturing companies committed to reducing their carbon footprints cultivate a positive brand image, fostering consumer trust, loyalty, and market differentiation. A reputation for sustainability can attract environmentally conscious consumers and investors, thereby increasing market share and financial resilience. Reducing the carbon footprint in manufacturing involves a multifaceted approach that includes energy efficiency, supply chain optimization, process optimization, and waste management. Implementing energy-efficient technologies, optimizing equipment, and embracing renewable energy sources can significantly lower energy consumption and reduce emissions. This conclusion is supported by macro-level analyses, such as those on the logistics industry, which show that the direct carbon emission coefficient is a primary driver of emissions intensity, highlighting the critical need for clean technology and energy efficiency [3]. Collaborating with suppliers to source materials sustainably, minimizing transportation distances, and adopting circular-economy principles to reduce waste can significantly reduce the overall carbon footprint. Such practices are especially true in closed-loop supply chain models where returned products are recovered, remanufactured, and reintroduced, considerably reducing the carbon emissions associated with new production and raw material extraction [4]. Rethinking manufacturing processes, adopting innovative technologies, and investing in research and development to develop cleaner production methods can lead to substantial reductions in emissions. Implementing efficient waste management practices, recycling initiatives, and circular material flows can mitigate emissions associated with waste disposal. The growing global focus on waste, from electronics to construction materials, underscores the need for systemic frameworks that leverage closed-loop, sustainable supply chains to recover valuable resources and reduce carbon footprints [5].

Olatunji et al. [6] identify key factors influencing carbon efficiency within the manufacturing sector. These include strategic integration into business operations, emphasizing environmental innovation aligned with diverse legislative standards, proactive adoption, life-cycle considerations, supplier-targeted goals, aligning purchasing strategies with environmental innovation objectives, integrating CO_2 emissions into sourcing processes, acknowledging cost as an internal driver, recognizing reputation risk as an external factor, anticipating future pressures on reporting CO_2 emissions across the supply chain, fostering collaborative partnerships with suppliers, and meeting customer expectations regarding environmental responsibility. The prioritization of these factors is crucial, as studies in other sectors, such as healthcare, have shown that economic factors often rank as the most essential criteria for experts when evaluating sustainable supply chain management, followed by managerial and employee factors [7]. In addition to these factors, as an essential key factor, the Carbon Border Adjustment Mechanism (CBAM) entered into force in the transition phase for importers on October 1, 2023.

CBAM stands poised to significantly impact the concrete industry, given its substantial carbon emissions and global market presence. With the concrete sector accounting for a notable share of global carbon dioxide emissions, the CBAM introduces a critical dimension in addressing emissions from energy-intensive industries. For the concrete industry, the CBAM heralds a transformative phase, compelling manufacturers to reevaluate their production practices to comply with stringent carbon-emission standards. This mechanism emphasizes levying tariffs on carbon-intensive imports, fostering a level playing field, and incentivizing emissions reductions in the concrete manufacturing process. Concrete producers face the dual challenge of enhancing efficiency and investing in low-carbon technologies to align with CBAM regulations, ensuring competitiveness while meeting evolving sustainability benchmarks. The CBAM's impact on the concrete industry reflects a pivotal juncture where environmental stewardship converges with economic viability, reshaping strategies and driving innovations toward a more sustainable future. This transition necessitates robust optimization models that can balance economic costs with stringent environmental constraints, a challenge addressed in green supply chain network design [8].

Evaluating projects aimed at reducing carbon footprints requires considering various criteria across economic, environmental, and social dimensions. Key criteria to be defined and identified include direct and indirect greenhouse gas emissions, energy consumption, life-cycle assessments, financial costs related to emissions reductions, social impacts, and the technological feasibility of mitigation strategies. Multi-Criteria Decision Making (MCDM) can help facilitate this evaluation process. Multi-Attribute Decision-Making (MADM) approaches are essential for ranking criteria in sustainable supply chain management, enhancing performance evaluation and structured decision-making in this complex field. [9]. The weight given to these criteria reflects their relative importance in carbon footprint reduction efforts. Measuring and reducing carbon footprints requires comprehensive methodologies that account for the various criteria and trade-offs inherent in environmental decision-making. In this context, MCDM emerges as a valuable approach to assess, prioritize, and address carbon footprints across multiple industries and sectors, and to evaluate and compare various carbon-reduction strategies. These strategies may include energy efficiency improvements, adoption of renewable energy sources, changes in production processes, implementation of Carbon Capture and Storage (CCS) technologies, or changes in supply chain practices. However, the inherent uncertainty in evaluating these strategies—such as (fuzzy) demands, returns, and costs—requires advanced modeling techniques that move beyond traditional fuzzy programming to more accurately capture the hesitancy and complexity of expert judgment in this domain [4], [10].

Despite the proven value of existing MCDM methods, a significant gap remains in their ability to fully capture the profound uncertainty and expert hesitancy inherent in evaluating novel carbon-reduction technologies and strategies within complex industrial systems such as the precast concrete industry. Traditional Fuzzy Sets (FSs) often fall short in representing the precise degree of non-membership and the hesitation margin that domain experts express when assessing innovative, high-stakes projects. This limitation can lead to suboptimal project prioritization and resource misallocation. Therefore, there is a pressing need for a more sophisticated, nuanced decision-making framework that can mathematically model the complex, circular, and hesitant nature of expert opinion to ensure a more robust, reliable, and accurate evaluation of carbon footprint reduction initiatives. Circular Intuitionistic Fuzzy Sets (CIFSs) address this limitation by extending classical intuitionistic FSs by incorporating a radius parameter that captures the dispersion and reliability of expert opinions. This enhanced modeling capability enables a more realistic and robust representation of expert knowledge, making CIFSs particularly suitable for complex industrial decision-making environments, such as the evaluation of carbon-reduction strategies in the concrete industry.

This paper presents a comprehensive analysis of projects and strategies to reduce the concrete industry's carbon footprint. Given the growing concern over environmental sustainability and the significant role the construction sector plays in global carbon emissions, there is a pressing need to explore innovative methods to make the industry greener. To address this, the study utilizes a hybrid decision-making framework that combines the Analytic Hierarchy Process (AHP) and COmbinative Distance-based Assessment (CODAS). The AHP method is employed to derive consistent, transparent criterion weights through hierarchical pairwise comparisons, which is particularly suitable for sustainability problems involving structured criteria systems. CODAS is selected for its strong discrimination capability, as it simultaneously considers Euclidean and Taxicab distances to evaluate alternatives relative to a negative-ideal solution. This characteristic is especially effective for ranking carbon-reduction projects with very similar performance levels, a common challenge in the concrete industry. This hybrid approach is further enhanced by incorporating CIFSs, which provide more precise modeling of ambiguity and imprecision often present in practical decision-making scenarios. In CIFS, uncertainty is represented not only by π but also by the radius (r) parameter, representing a circular area. This representation offers a much more realistic and flexible modeling opportunity, particularly in decision-making processes based on expert opinions. Comparing CIFSs with other extensions of intuitionistic FSs related to this expression is given in *Fig. 1* and *Table 1*. CIFS is preferred for high-uncertainty problems and excels in decision-making, risk analysis, and healthcare. Although CODAS has previously been extended to CIF environments, this study advances the existing literature by integrating Circular Intuitionistic Fuzzy Analytic Hierarchy Process (CIF-AHP) and Circular Intuitionistic Fuzzy COmbinative Distance-based Assessment (CIF-CODAS) within a unified framework explicitly tailored to carbon footprint reduction projects in the concrete industry under CBAM-related regulatory constraints. Furthermore, the proposed approach explicitly incorporates expert reliability through the radius parameter of CIFSs and evaluates methodological robustness through sensitivity analyses.

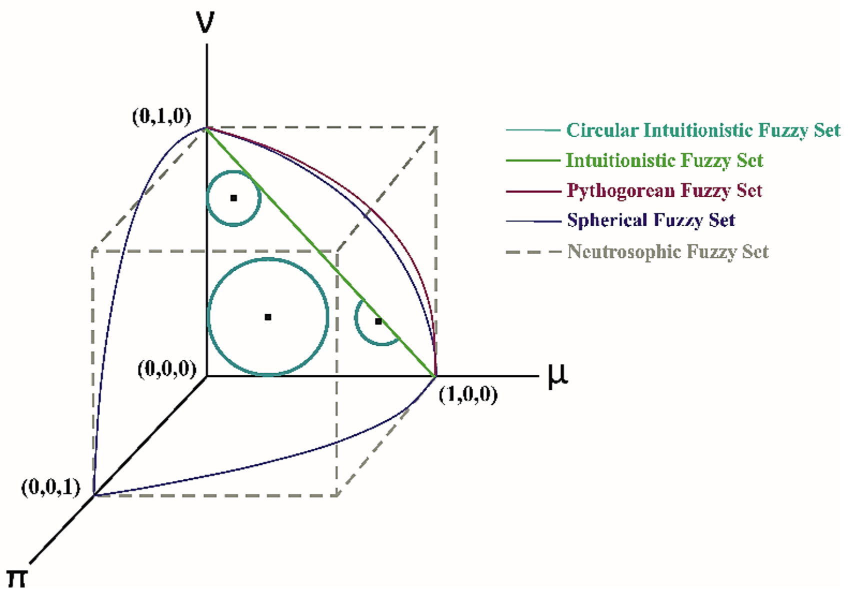


Fig. 1. Geometric representation of some IFSs' extensions [11].

The primary aim of this study is to develop a robust, uncertainty-aware decision-making framework for prioritizing carbon-reduction projects in the concrete industry. This study is motivated by the high carbon intensity of concrete production, the increasing regulatory pressure introduced by CBAM, and the limitations of conventional fuzzy MCDM approaches in adequately capturing expert hesitation and reliability. By integrating CIFSs with a hybrid AHP–CODAS methodology, the proposed framework enables systematic identification and prioritization of practical carbon-reduction projects while providing structured decision support for sustainable practices in the concrete industry.

The structure of this paper is as follows: A review of existing literature on strategies for reducing the carbon footprint in the concrete industry is presented in Section 2. Section 3 elaborates on the research methodology, outlining the integrated CIF AHP and CODAS framework. The results from applying this framework are detailed in Section 4, followed by a discussion of sensitivity analyses in Section 5. The paper concludes in Section 6 with a summary of key insights, study limitations, and directions for future research.

2 | Literature Review

The topic of carbon reduction is highly prevalent in the literature. Over 6,000 articles with the term "carbon reduction" in the abstract and approximately 254 of them with the term "concrete" can be found in the Scopus database. *Fig. 2* shows the distribution of these papers by subject area, gathered from SCOPUS [12].

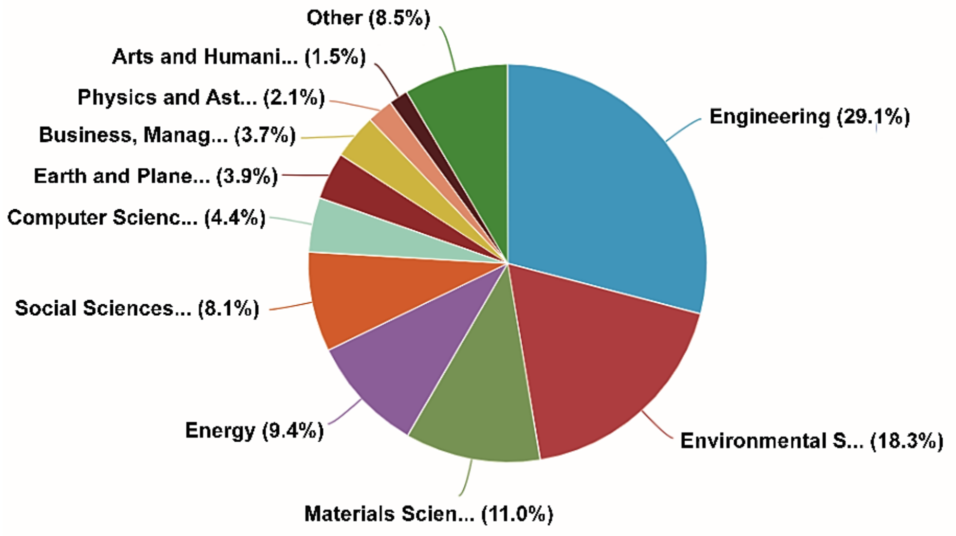


Fig. 2. Documents by subject area.

Upon scrutiny of these papers, a prevailing focus emerges on energy efficiency and carbon reduction within the building sector, particularly through investigations into on-site concrete production methods. Some studies extend their gaze to analyze the overall state of the concrete industry. Villagrán-Zaccardi et al. [13] provided a comprehensive overview of the cement industry's current status in Latin America and the Caribbean. Their work delves into global strategies and opportunities to reduce the carbon footprint of cement and concrete, accounting for regional conditions. Their work also addresses emerging supplementary cementitious materials and examines the roles of industrialization and quality control. Similarly, Chen et al. [14] contributed to the discourse by analyzing trends in material recycling to achieve energy savings and reduce carbon emissions. Their research involves using four renewable slag admixtures in lightweight aggregate concrete. The findings underscore the positive impact of mineral powder materials on the mechanical properties and ultrasonic pulse velocity of lightweight aggregate concrete, highlighting the associated energy savings and carbon-reduction benefits. Xiao et al. [15] delved into the theory and methods of concrete composition, decomposition, and recycling. The majority of the remaining articles focus predominantly on the analysis of concrete material compositions. Tao et al. [16] advanced sustainability in digital fabrication by developing an alkali-activated slag mixture optimized for twin-pipe pumping. Ding et al. [17] compared carbon emissions throughout the life cycle between a steel-ultra-high-performance concrete bridge deck and a conventional steel-concrete bridge deck structure. The results highlight the potential for carbon reduction in ultra-high-performance concrete, contributing significantly to the sustainability of infrastructure development. Xiao et al. [18] channeled their research efforts towards refining low-carbon design methodology, specifically by quantitatively characterizing the dynamic interplay between structure and environment. They introduced a structural sustainability indicator designed to capture both the reliability of the structure and its carbon emission levels simultaneously. Addressing the dual challenges of natural aggregate shortages and the subpar compressive strength of Recycled Coarse Aggregate Concrete (RAC), Wang et al. [19] developed a novel high-performance concrete. Their solution incorporated 50% RAC and a hybrid micropowder of silica fume, slag, and fly ash to enhance its properties. Similarly, to combat resource scarcity and high energy use, Bian et al. [20] created a self-foaming geopolymer lightweight aggregate from waste glass powder, using municipal solid waste incineration bottom ash as a foaming agent

Table 1. Some extensions of IFSs.

	Expression	On MCDM	Vs CIFS
Intuitionistic Fuzzy Set (IFS) [21]	$A_{IFS} = \{x, \mu_A(x), \vartheta_A(x), \|x\epsilon X \rightarrow [0,1]\}$, $\mu_A(x), \vartheta_A(x)$ are degrees of membership and non-membership, respectively, and $\mu_A(x) + \vartheta_A(x) \leq 1$.	More realistic preference modeling than classical fuzzy because it includes both acceptance and rejection levels; methods such as IFS-TOPSIS, IFS-VIKOR, and IFS-AHP are well-established in the literature.	CIFS defines a local uncertainty space around the alternative-criterion evaluation by expanding this point representation of IFS to a circle/disk region; second-level uncertainty can be added to IFS-based MCDM algorithms with minimal modification.
Circular Intuitionistic Fuzzy Set (CIFS) [22]	$C = \{\langle x, \mu_C(x), \vartheta_C(x); r\rangle \| x \in X \rightarrow [0,1]\}$, $\mu_C(x), \vartheta_C(x)$ are degrees of membership and non-membership, respectively. $r: X \rightarrow [0, 1]$ defines the radius of a circle around each point x and $\mu_C(x) + \vartheta_C(x) \leq 1$.	While preserving all the advantages of IFS, it allows for second-level uncertainty and local sensitivity analysis; it creates a natural framework for converging multiple decision makers or scenarios around a single center.	
Pythagorean Fuzzy Set (PFS) [23]	$A_{PFS} = \{x, \mu_A(x), \vartheta_A(x), \|x\epsilon X \rightarrow [0,1]\}$, $\mu_A(x), \vartheta_A(x)$ are degrees of membership and non-membership, respectively, and $\mu_A(x)^2 + \vartheta_A(x)^2 \leq 1$.	It allows the decision maker to express degrees of acceptance and rejection more flexibly; in some cases, it provides better discriminatory power than IFS.	CIFS can work even within the PFS region, but the key difference is that it transforms the 'single viewpoint' into a local uncertainty region by centering the PFS point and defining a circle around it; this provides advantages in robustness and sensitivity analysis.
Spherical Fuzzy Set (SFS) [11]	$A_{SFS} = \{x, \mu_A(x), \vartheta_A(x), \pi_A(x) \|x\epsilon X \rightarrow [0,1]\}$, $\mu_A(x), \vartheta_A(x), \pi_A(x)$ are degrees of membership, Non-membership, and hesitancy, respectively, and $\mu_A(x)^2 + \vartheta_A(x)^2 + \pi_A(x)^2 \leq 1$.	It can model the decision maker's 'partial acceptance-partial rejection-neutral' behavior in fine detail; it has strong expressive power in multi-criteria, multi-determination, high uncertainty problems.	CIFS provides second-level uncertainty without increasing dimensionality (while remaining in the 2D plane of IFS); it offers a practical and balanced alternative in MCDM applications that do not want to build a model as powerful but heavy as SFS.
Neutrosophic Set (NS) [24]	$A_{NS} = \{x, T_A(x), I_A(x), F_A(x) \|x\epsilon X \rightarrow [0,1]\}$, $T_A(x), I_A(x), F_A(x)$ are degrees of truth-membership, indeterminacy-membership, and false-non-membership, respectively, and $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.	Theoretically, any expression can be modeled for decision-making problems involving high uncertainty and conflict. However, explaining the method to the decision maker and standardizing the methods can be challenging.	CIFS operates in a much more constrained and intuitive subspace of this vast neutrosophic space, offering a more manageable and interpretable structure with fewer parameters in terms of MCDM.

It is noteworthy that the precast concrete industry receives limited attention in these articles. The et al. [25] quantified carbon footprint intensities across different cement and concrete production processes in Australia by employing an input-output-based hybrid Life Cycle Assessment (LCA) method. The study aimed to compare traditional process-based LCAs with hybrid approaches, using Australian cement and concrete production as a case study. Luo et al. [26] outlined a pathway for carbon neutrality in the cement industry based on China's conditions. Key findings include the importance of capacity reduction, energy-efficiency improvements, raw-fuel substitution technologies, promoting low-carbon cement, and the essential role of Carbon Capture, Utilization, and Storage (CCUS) technologies. Rangelov et al. [27] assessed various strategies aimed at decreasing the embodied carbon in paving concrete. The study evaluated decarbonization measures, benchmarked concrete paving practices, and identified opportunities for carbon reduction, emphasizing the importance of supplementary cementitious materials and optimized mixture design. Liu et al. [28] focused on the life cycle of precast structures, highlighting the significance of good design, planning, and material choices for carbon reduction and energy conservation in precast concrete plants. Research conducted by Huang and Wang [29] compared the carbon mitigation potential of prefabricated and conventional cast-in-place concrete framing systems. Their investigation identified several influential variables, including the degree of prefabrication (assembly rate), the carbon intensity of materials, key design specifications, and transportation-related considerations, all of which significantly govern total emissions.

On the other hand, CIFS, which offer a much more realistic and flexible modeling approach, especially for decision-making processes based on expert opinions, are preferred for problems with high uncertainty and have become prominent in decision-making areas. For example, by incorporating CIFS into MCDM procedures, more precise results sensitive to the decision maker's attitude (optimistic/pessimistic) have been obtained [30]. Additionally, novel similarity and entropy measures designed explicitly for CIFS have been introduced to better quantify uncertainty and enhance discrimination in decision-making [31]. CIFS is effective in MCDM applications by modeling uncertainty in a multidimensional manner with membership, non-membership, hesitancy, and radius parameters [32]. Moreover, new divergence measures for CIFS have been developed, enabling more refined assessments of information differences between alternatives and contributing to more reliable rankings in practical decision problems [33]. It has been shown that CIFS offers a more flexible and robust decision-making mechanism when used in conjunction with Hamacher operators [34]. Furthermore, an integrated CIF-AHP and CIF-VIKOR methodology was developed and applied to a multi-expert supplier evaluation problem, with results compared to other methods and supported by sensitivity analysis, highlighting the effectiveness of CIFS in handling linguistic assessments and uncertainty [35]. A novel CIFS multi-criteria decision-making method was developed by introducing new formulations for radius calculation and a defuzzification function that incorporates decision-makers' attitudes through optimistic and pessimistic points, and was applied to a supplier selection problem with sensitivity analysis, yielding more precise results than classical IFS-based models [30]. Circular intuitionistic fuzzy Preference Relations (C-IFPRs) have recently been introduced for group decision-making, along with entropy-based schemes for deriving decision-maker weights, algorithms to improve additive consistency and reach group consensus, and a TOPSIS-type selection procedure for ranking alternatives under C-IFSs [36]. Complementing these developments, construction methods for entropy measures of CIFS have been proposed, providing systematic tools for quantifying uncertainty within circular intuitionistic assessments and enhancing the robustness of CIFS-based MCDM frameworks [37]. A CIFS-based CODAS approach was applied to select sustainable oil and gas produced water treatment technologies, prioritizing API gravity separator, MPPE technologies, and adsorption, thereby supporting decision-making processes that address sustainability, resilience, and environmental protection [38]. A novel CIF-CODAS method was proposed and applied for green logistics park location selection, demonstrating superior performance over IF-CODAS, IF-TOPSIS, and IF-EDAS while emphasizing sustainability and environmental considerations [39]. However, the latter two methods, CIFS and CODAS, computed positive and negative distances to the ideal solution by converting them to IFS. In this study, a hybrid MCDM procedure was implemented with both CIF-AHP and CIF-CODAS, and all CIF-CODAS calculations were performed with CIFS.

In summary, these studies collectively provide valuable insights into energy efficiency, carbon reduction, and sustainability in the concrete industry, spanning different stages of the production process and exploring diverse strategies to mitigate environmental impacts. According to Scopus data, there are six studies on 'carbon reduction,' 'MCDM,' and 'concrete' [40]. Aljawhari et al. [41] propose an enhanced life-cycle cost analysis framework for seismic retrofit strategies that incorporates indirect economic losses and environmental sustainability, and introduces a method for optimizing designs to meet specific risk targets. Thomas et al. [42] demonstrated that using fibre-reinforced concrete with Ground Granulated Blast Furnace Slag (GGBS) and RAC for whitetoppings significantly reduces environmental impact and cost, leading to an integrated MCDM framework for ranking these sustainable designs. Caruso et al. [43] showed that integrated retrofitting interventions, particularly exoskeletons, are effectively favored over traditional seismic retrofit solutions by enriching an MCDM approach with additional life-cycle thinking criteria. Indwar et al. [44] compiled the enhanced properties of nanomaterial-doped geopolymer concrete and, through MCDM analysis, identified nano-silica as the most effective nanomaterial for achieving sustainable, high-performance concrete. Revilla Cuesta et al. [45] evaluated self-compacting concrete mixes with industrial by-products and identified optimal combinations of GGBS and recycled aggregates for specific application scenarios to ensure both sustainability and commercial competitiveness, utilizing MCDM analysis. Rashid et al. [46] developed a framework for the sustainable selection of RAC mixes based on achieving target compressive strengths while balancing technical, environmental, and economic parameters through experiments and MCDM techniques. This research aims to fill this gap in the literature, contributing to a deeper understanding of carbon reduction strategies specifically within the context of concrete production.

3 | Concrete Production

In recent years, the concrete production industry has undergone a transformative shift towards more sustainable and environmentally friendly practices. Recognizing the significant carbon footprint of traditional concrete manufacturing, there has been a growing emphasis on implementing carbon-reduction projects within concrete production facilities. Concrete, a fundamental construction material, has long been criticized for its contribution to greenhouse gas emissions, primarily from cement production. In response to these environmental concerns, concrete production facilities worldwide are increasingly adopting innovative strategies to mitigate their carbon impact. One of the primary focuses of carbon-reduction projects is the exploration and integration of alternative binders and low-carbon cements. Supplementary Cementitious Materials like slag, fly ash, and calcined clays are gaining prominence as they replace a portion of traditional cement, reducing both energy consumption and emissions. Portland Limestone Cement and Calcined Clay Cement are emerging as viable alternatives, offering a reduced reliance on clinker and, consequently, a lowered carbon footprint.

Concrete production facilities are also investing in CCU technologies to capture CO_2 emissions generated during manufacturing. These captured emissions can then be stored underground or repurposed for other industrial applications, demonstrating a commitment not only to reducing but also to repurposing carbon emissions. Acknowledging that energy-intensive processes contribute significantly to carbon emissions, concrete production facilities are increasingly turning to renewable energy sources. The integration of solar, wind, and other sustainable energy solutions is significantly mitigating the overall environmental impact of concrete manufacturing.

When applying an MCDM process to select the best project to reduce a concrete production facility's carbon footprint, it's crucial to consider a range of criteria that cover sustainability, feasibility, and effectiveness. The criteria for the analysis have been determined by leveraging insights from the articles reviewed in the literature. Moreover, considering investment value as a main criterion adds an extra layer of significance, given its crucial role in all types of investment decisions. The set of criteria summarized in *Table 2* has been identified and detailed.

Table 2. Decision criteria.

Main Criteria	Sub-Criteria
C1: Operational benefits	C11: Promotion of low-carbon cement
	C12: Benchmarking concrete paving practices
	C13: Capacity reduction
C2: Technological benefits	C21: Technology implementation
	C22: Raw-fuel substitution technology
	C23: Role of CCUS technologies
C3: Investment value	C31: Cost
	C32: Return on investment
	C33: Risk assessment

C1 (operational benefits). In the context of precast concrete manufacturing, operational benefits are strategic initiatives and practices that enhance efficiency, sustainability, and innovation throughout the production process, resulting in positive environmental and economic impacts.

C11 (promotion of low-carbon cement). This sub-criterion highlights the operational benefit of promoting low-carbon cement by recommending a heightened emphasis on innovative product strategies. It aims to increase the proportion of low-carbon cement in total production, aligning with sustainability goals [26].

C12 (benchmarking concrete paving practices). Operational benefits are sought through the assessment of concrete paving practices, accomplished by benchmarking main-lane paving concrete mixtures. This sub-criterion aims to identify best practices and enhance operational efficiency in the concrete industry [27].

C13 (capacity reduction). This sub-criterion highlights the operational benefits of reducing production capacity to achieve carbon-neutrality goals in cement manufacturing [26].

C2 (technological benefits). In the context of precast concrete plant operations, technological benefits refer to the positive outcomes derived from the effective implementation of advanced technologies. This criterion focuses on leveraging technology to improve energy conservation, reduce carbon emissions, and enhance overall operational efficiency.

C21 (technology implementation). This sub-criterion emphasizes the technological benefits of integrating products, materials, equipment, and construction units within precast concrete plants. The aim is to achieve energy conservation and carbon reduction goals through strategic technological implementation [28].

C22 (raw-fuel substitution technology). Focused on technological benefits, this sub-criterion explores the potential of raw-fuel substitution technology. By optimizing alternative raw materials and fuels, it aims to achieve a 10% reduction in CO_2 emissions, contributing to the sustainability and efficiency of precast concrete manufacturing [26].

C23 (Role of CCUS technologies). Highlighting technological benefits, this sub-criterion underscores the significance of CCUS technologies. It discusses pivotal components of CCUS strategies integrated into the cement production process, contributing to the technological advancements in achieving carbon neutrality [26].

C3 (investment value). Investment Value is a criterion that assesses the financial aspects crucial for evaluating the feasibility of precast concrete manufacturing facility projects. It encompasses various financial elements, including startup, operational, and maintenance costs.

C31 (cost). This sub-criterion involves a comprehensive analysis of all financial elements associated with the project, including startup, operational, and maintenance costs. It aims to provide a clear understanding of the overall financial investment required.

C32 (Return on Investment (ROI)). Focused on investment value, this sub-criterion evaluates how quickly the investment is expected to pay off and assesses the profitability of the precast concrete manufacturing facility project. It provides insights into the financial returns over time.

C33 (risk assessment). Within the context of investment value, this sub-criterion involves identifying and evaluating financial and operational risks associated with the precast concrete manufacturing facility project. It aims to ensure a thorough understanding of potential challenges and uncertainties.

Here, C31 and C33 are cost criteria; the others are benefit criteria.

4 | Methodology

Fuzzy MCDM methods are pivotal in addressing decision-making problems characterized by uncertainty and imprecision. These methods extend traditional MCDM techniques by incorporating fuzzy set theory, allowing decision-makers to evaluate multiple conflicting criteria under conditions of vagueness and ambiguity. This approach enhances the robustness and flexibility of decision-making across diverse domains, including engineering, economics, supply chain management, and environmental management. There are between 20 and 30 fuzzy MCDM methods in the literature. Each method integrates fuzzy logic principles to handle the inherent uncertainty in human judgments and preferences, thereby providing a more realistic representation of complex decision environments. The application of fuzzy MCDM methods leads to more informed and reliable decisions, supporting effective strategic planning and resource allocation.

CIF MCDM methods, including CIF-AHP and CIF-CODAS, offer advanced frameworks for addressing decision-making problems characterized by uncertainty and imprecision. These methods leverage intuitionistic FSs and CIF numbers to better model the inherent ambiguity and hesitation in human judgments.

The CIF-AHP method extends the traditional AHP by incorporating CIF logic, enabling a comprehensive evaluation of multiple criteria through pairwise comparisons. This approach captures the degrees of membership, non-membership, and hesitation, providing a more refined prioritization of criteria and alternatives. CIF-AHP is particularly valuable for complex decision-making scenarios where the precision of criteria weights is critical [35].

On the other hand, the CIF-CODAS method combines the strengths of the CODAS framework with the flexibility of CIFSs to assess and rank alternatives based on their distances from the ideal solution. By using both Euclidean and Taxicab distances in a CIF context, CIF-CODAS effectively addresses the vagueness and hesitation inherent in decision data, thereby enhancing the method's discrimination power and robustness [38].

In this section, CIFSs and Circular Intuitionistic Fuzzy Numbers (CIFNs) introduced by Atanassov [22] are briefly explained, and a hybrid CIF-AHP&CODAS procedure is proposed.

4.1 | Preliminaries on CIFSs

The Intuitionistic Fuzzy Sets (IFSs) were introduced in Atanassov [21] as an extension of ordinary FSs of L. Zadeh [47]. In IFSs, the elements of a fixed universe are interpreted as points on the Intuitionistic Fuzzy Interpretation Triangle (IFIT) *Fig. 3.a.* Each element x, evaluated with degrees of membership $\mu_A(x)$ and degrees of non-membership $\vartheta_A(x)$ to a fixed subset A of the universe, is represented as a point with coordinates $\mu_A(x), -0$; where $\mu_A(x), \vartheta_A(x), (\mu_C(x) + \vartheta_A(x))\epsilon[0,1]$ [35]. IFSs not only assign membership and non-membership values to elements but also incorporate a hesitancy degree $\pi = 1 - \mu - \vartheta$, which captures expert uncertainty. This structure allows IFSs to represent incomplete or hesitant judgments more realistically than classical FSs.

In FSs, an element is assigned only a membership value, while in IFSs, an element is assigned both a membership and a non-membership degree. Following Atanassov's proposal of IFSs [21], various extensions of IFSs have been proposed, as seen in *Table 1* and *Fig. 1*. For many of these, various MCDMs have been proposed and implemented as mentioned in Section 2. CIFSs are introduced by Atanassov [22] as a new extension of IFSs.

Definition 1. A CIF set C, applied to a finite set X, is characterized by the structure $C = \{\langle x, \mu_C(x), \vartheta_C(x); r\rangle | x \in X\}$. In this model, the functions $\mu_C(x)$ and $\vartheta_C(x)$ map elements of X to values in the interval [0,1], representing the degrees of membership and non-membership of an element x, respectively. Furthermore, the function $r: X \rightarrow [0,1]$ defines the radius of a circle around each point x. A critical constraint for this model is that the values for every element x in X must satisfy the conditions in *Eq. (1)*:

$$0 \leq \mu_C(x) + \vartheta_C(x) \leq 1 \text{ and } r \in [0,1]. \quad (1)$$

A small radius indicates low uncertainty (precise judgment), while a large radius represents high uncertainty (diffuse judgment). This geometric interpretation allows CIFS to capture multidimensional uncertainty that traditional IFSs or Pythagorean FSs cannot fully represent.

The variable x serves as a third parameter, indicating whether x belongs to CIFS and representing the degree of hesitation associated with it. This is defined as $\pi_C(x) = 1 - \mu_C(x) - \vartheta_C(x)$ where $0 \leq \pi_C(x) \leq 1$. Unlike other IFS, each element (number) in a CIFS cannot be depicted as a triangular shape; instead, it is represented by a circle centered at $\langle \mu_C(x), \vartheta_C(x,)\rangle$ with a radius r. If $r = 0$, the CIFN reduces to an Intuitionistic Fuzzy Number (IFN). A visual example of this is shown in *Fig. 3.b*: the circular shape depicts the uncertainty region, with the center at $\langle \mu_C(x), \vartheta_C(x,)\rangle$ and radius r. If $r = 0$, the CIFN reduces to an IFN. The geometric representations of IFNs and CIFNs are illustrated in *Figs. 3.a* and *3.b*, respectively.

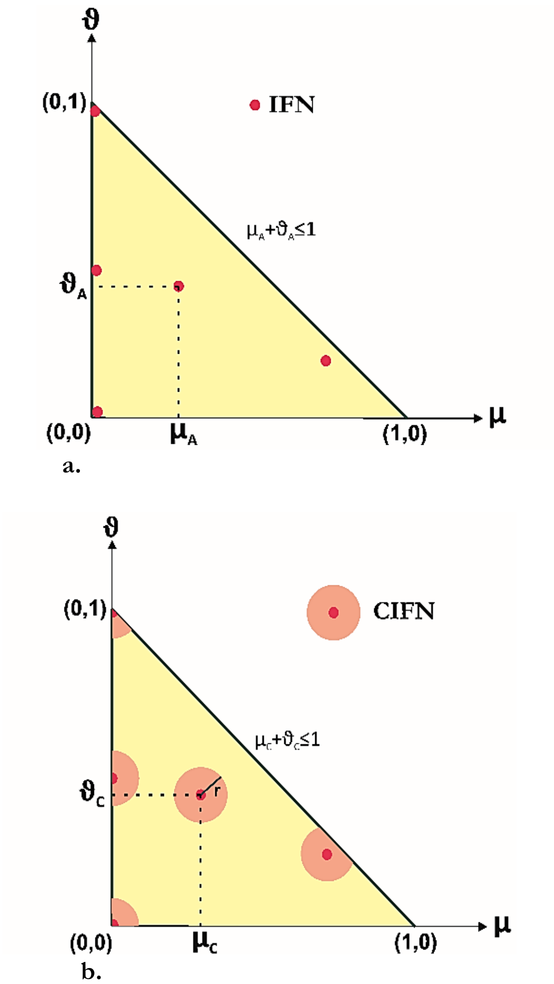


Fig. 3. Geometric representation of: a. IFN; b. CIFN [48].

Definition 2. Let $C_1 = \langle \mu_{C_1}(x), \vartheta_{C_1}(x); r_1\rangle$ and $C_2 = \langle \mu_{C_2}(x), \vartheta_{C_2}(x); r_2\rangle$ represent two CIFNs. Here, the arithmetic operations are performed using the minimum and maximum values of their individual radii. The minimum radius corresponds to the lowest level of uncertainty, while the maximum radius corresponds to the highest level of uncertainty. Consequently, the magnitude of the radius r is inversely related to the certainty of the intuitionistic fuzzy (IF) pair (μ, ϑ). Several fundamental arithmetic operations are defined below:

$$\left.\begin{array}{c}
C_1 \cap_{min} C_2 = \left\{\langle x, \min\left(\mu_{C_1}(x), \mu_{C_2}(x)\right), \max\left(\vartheta_{C_1}(x), \vartheta_{C_2}(x)\right); \min(r_1, r_2)\rangle \,|\, x \in X\right\} \\
C_1 \cap_{max} C_2 = \left\{\langle x, \min\left(\mu_{C_1}(x), \mu_{C_2}(x)\right), \max\left(\vartheta_{C_1}(x), \vartheta_{C_2}(x)\right); \max(r_1, r_2)\rangle \,|\, x \in X\right\} \\
C_1 \cup_{min} C_2 = \left\{\langle x, \max\left(\mu_{C_1}(x), \mu_{C_2}(x)\right), \min\left(\vartheta_{C_1}(x), \vartheta_{C_2}(x)\right); \min(r_1, r_2)\rangle \,|\, x \in X\right\} \\
C_1 \cup_{max} C_2 = \left\{\langle x, \max\left(\mu_{C_1}(x), \mu_{C_2}(x)\right), \min\left(\vartheta_{C_1}(x), \vartheta_{C_2}(x)\right); \max(r_1, r_2)\rangle \,|\, x \in X\right\} \\
C_1 \oplus_{min} C_2 = \{\langle x, \mu_{C_1}(x) + \mu_{C_2}(x) - \mu_{C_1}(x) * \mu_{C_2}(x), \vartheta_{C_1}(x) * \vartheta_{C_2}(x); \min(r_1, r_2)\rangle | x \in X\} \\
C_1 \oplus_{max} C_2 = \{\langle x, \mu_{C_1}(x) + \mu_{C_2}(x) - \mu_{C_1}(x) * \mu_{C_2}(x), \vartheta_{C_1}(x) * \vartheta_{C_2}(x); \max(r_1, r_2)\rangle | x \in X\} \\
C_1 \otimes_{min} C_2 = \{\langle x, \mu_{C_1}(x) * \mu_{C_2}(x), \vartheta_{C_1}(x) + \vartheta_{C_2}(x) - \vartheta_{C_1}(x) * \vartheta_{C_2}(x); \min(r_1, r_2)\rangle | x \in X\} \\
C_1 \otimes_{max} C_2 = \{\langle x, \mu_{C_1}(x) * \mu_{C_2}(x), \vartheta_{C_1}(x) + \vartheta_{C_2}(x) - \vartheta_{C_1}(x) * \vartheta_{C_2}(x); \max(r_1, r_2)\rangle | x \in X\} \\
\lambda * C_1 = \left\{\langle x, 1 - \left(1 - \mu_{C_1}(x)\right)^{\lambda}, \left(\vartheta_{C_1}(x)\right)^{\lambda}; r_1\rangle \,|\, x \in X, \lambda \in R\right\} \\
C_1^{\lambda} = \left\{\langle x, \left(\mu_{C_1}(x)\right)^{\lambda}, 1 - \left(1 - \vartheta_{C_1}(x)\right)^{\lambda};\ r_1 | \, x \in X, \lambda \in R\rangle\right\}
\end{array}\right\}. \quad (2)$$

To illustrate how the membership, non-membership, and radius components behave under the basic CIFS operations defined in *Eq. (2)*, consider two CIFSs $C_1 = (0.70, 0.20; 0.10)$ and $C_2 = (0.50, 0.30; 0.20)$. These values represent the membership degree, non-membership degree, and radius of uncertainty for a given element:

I. Intersection combines the two CIFSs by taking the minimum membership and the maximum non-membership values. The radius (either min or max) reflects whether the aggregation treats uncertainty conservatively or optimistically. Intersection with the minimum radius is computed as $C_1 \cap_{min} C_2 = (0.50, 0.30; 0.10)$ while the intersection with the maximum radius is $C_1 \cap_{max} C_2 = (0.50, 0.30; 0.20)$.

II. Union takes the maximum membership and minimum non-membership values, reflecting a more optimistic combination of the two evaluations. Union with the minimum radius is $C_1 \cup_{min} C_2 = (0.70, 0.20; 0.10)$ and union with the maximum radius is $C_1 \cup_{max} C_2 = (0.70, 0.20; 0.20)$.

III. The addition operator follows the Hamacher-type composition: it increases membership while reducing non-membership, representing the combination of two independent pieces of positive evidence. Addition with the minimum radius yields $C_1 \oplus_{min} C_2 = (0.85, 0.06, 0.10)$ and with the maximum radius yields $C_1 \oplus_{max} C_2 = (0.85, 0.06, 0.20)$.

IV. Multiplication is a more restrictive operation: it lowers membership (both conditions must hold) and increases non-membership. The minimum-radius multiplication results in $C_1 \otimes_{min} C_2 = (0.35, 0.44, 0.10)$ while the maximum-radius case is $C_1 \otimes_{max} C_2 = (0.35, 0.44, 0.20)$

V. Scalar operators adjust the shape of a CIFS according to the parameter λ, allowing the model to represent more optimistic or pessimistic decision-maker attitudes. For example, using $\lambda = 2$ gives $\lambda C_1 = (0.91, 0.04, 0.10)$ while using $\lambda = 0.5$ gives $\lambda C_1 = (0.452, 0.447, 0.10)$. Values $\lambda > 1$ strengthen the evidence, whereas $0 < \lambda < 1$ soften it.

Definition 3. Let a_i=(μ_(C_i,) ϑ_(C_i)) (i=1,...,n) be a set of IF pairs, and they are aggregated using the Intuitionistic Fuzzy Weighted Geometric (IFWG) operator as *Eq. (3)*.

$$IFWG(C_1, \dots, C_n) = \left(\prod_{j=1}^{n} \mu_{C_j}{}^{\omega_j}, \prod_{j=1}^{n} \vartheta_{C_j}{}^{\omega_j}\right), \quad (3)$$

where $\omega = (\omega_1, \dots, \omega_n)^T$ is the weight vector of C_i $(i = 1, \dots, n)$ with $\omega_j \in [0, 1]$ and $\sum_{j=1}^{n} \omega_j = 1$ [30]. If k_i denotes judgements of experts, the radius r_i of the C_i is determined by taking the maximum of the Euclidean distances, according to *Eq. (4)*.

$$r_i = \max_{1\le j\le k_i} \sqrt{\left(\prod_{j=1}^{n} \mu_{C_j}{}^{\omega_j} - \mu_{C_i}\right)^2 + \left(\prod_{j=1}^{n} \vartheta_{C_j}{}^{\omega_j} - \vartheta_{C_i}\right)^2}. \quad (4)$$

The IFWG operator aggregates multiple CIFS numbers while preserving each expert's weighted contribution. The radius r_i is calculated as the maximum Euclidean distance from the aggregated point to the individual expert judgments, providing a geometric interpretation of overall uncertainty. This method ensures that both membership/non-membership and the spatial uncertainty of CIFS are accounted for in the decision-making process.

4.2 | Proposed CIF Analytic Hierarchy Process & CODAS Methodology

ST1 and SF1 are presented for MCDM to demonstrate the flexibility of CIFSs compared to other IFSs.

The proposed CIF-AHP&CODAS methodology is explained below and shown in *Fig. 4*.

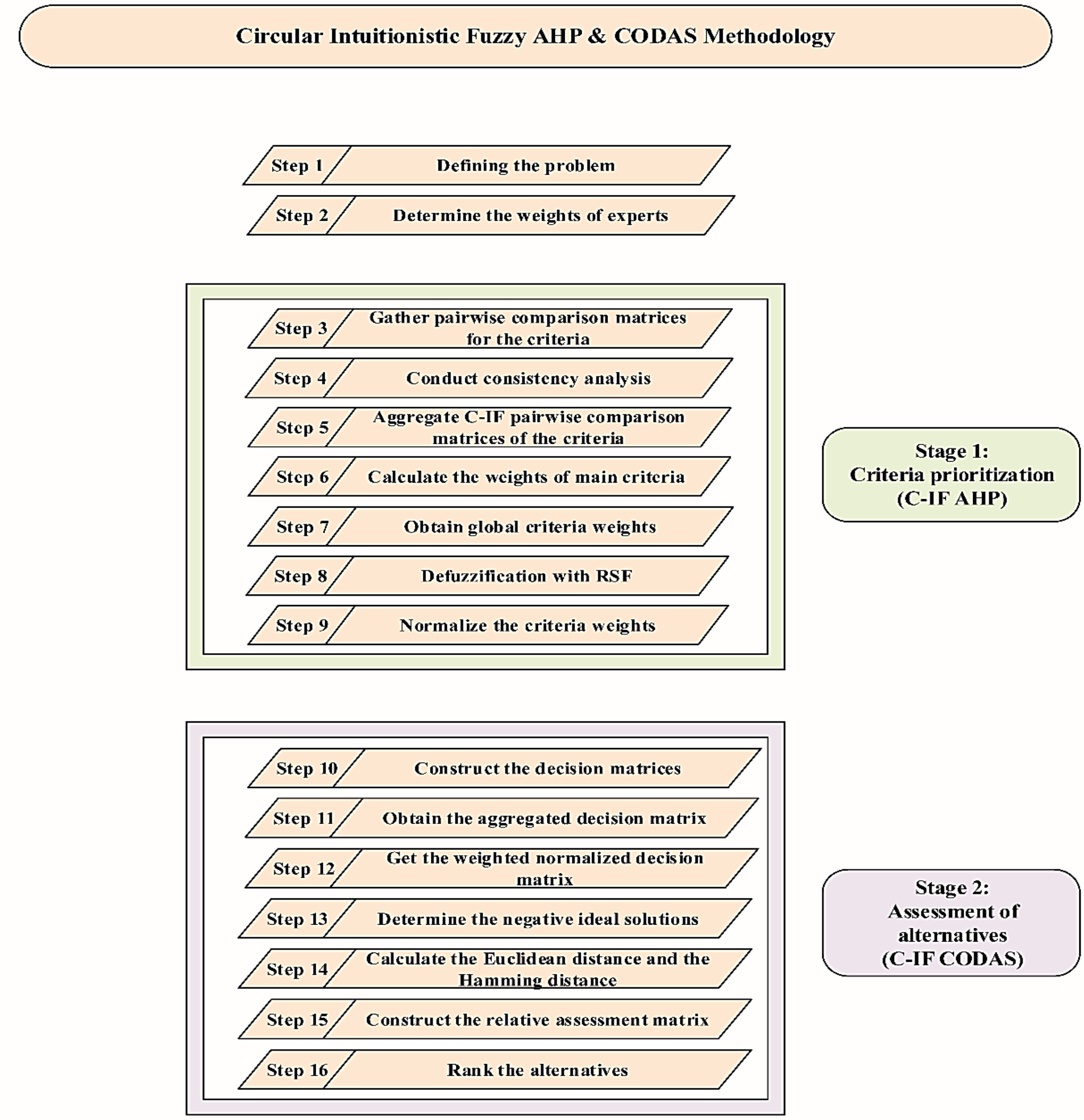


Fig. 4. CIF-AHP&CODAS methodology.

Step 1. A fuzzy MCDM problem is defined by describing a finite set of criteria ($C_j, j = 1, \dots, n$), sub-criteria and alternatives ($A_i, i = 1, \dots, m$).

Step 2. Determine the weights of experts.

Stage 1. Criteria prioritization CIF-AHP [35].

Step 3. Gather pairwise comparison matrices for the criteria.

Within these pairwise comparison matrices, experts provide their assessments by selecting linguistic terms from *Table 3*, each of which corresponds to a predefined IF number. In this study, linguistic terms were used to capture expert judgments, following the well-established practice in fuzzy MCDM. The mapping of linguistic terms to fuzzy numbers is consistent with scales commonly used in the literature [30], [49]. For example, the linguistic expression "exactly equal" is represented by the IF pair (0.50, 0.50). To accommodate uncertainty or indecision, the proposed framework also allows experts to define intermediate values between two adjacent terms, such as between High (H) and Medium High (MH).

Table 3. Linguistic scale using IFNs [30].

Linguistic Terms	(μ, ϑ)	SI
Absolutely Low (AL)	(0.05, 0.85)	0.11
Very Low (VL)	(0.15, 0.75)	0.14
Low (L)	(0.25, 0.65)	0.20
Medium Low (ML)	(0.35, 0.55)	0.33
Almost Equal (AE)	(0.45, 0.45)	1.20
Medium High (MH)	(0.55, 0.35)	3.0
High (H)	(0.65, 0.25)	5.0
Very High (VH)	(0.75, 0.15)	7.0
Absolutely High (AH)	(0.85, 0.05)	9.0

Similar to other fuzzy AHP extensions, the CIF-AHP methodology begins by obtaining IF pairwise comparison matrices for the criteria *Eq. (5)*. The next step involves compiling the intuitionistic fuzzy pairwise comparison matrices for the alternatives with respect to each criterion, based on the evaluations provided by experts.

$$\tilde{X}^k = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_i \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \cdots & C_j & \cdots & C_n \end{array} \\ \begin{bmatrix} 1 & \tilde{x}_{12}^k & \cdots & \tilde{x}_{1j}^k & \cdots & \tilde{x}_{1n}^k \\ \tilde{x}_{21}^k & 1 & \cdots & \tilde{x}_{2j}^k & \cdots & \tilde{x}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{i1}^k & \tilde{x}_{i2}^k & \cdots & \tilde{x}_{ij}^k & \cdots & \tilde{x}_{jn}^k \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ \tilde{x}_{n1}^k & \tilde{x}_{n2}^k & \cdots & \tilde{x}_{nj}^k & \cdots & 1 \end{bmatrix} \end{array}. \tag{5}$$

The aggregated pairwise comparison matrix is obtained with the IFWG operator via *Eq. (3)*.

Step 4. The consistency of the pairwise comparisons is verified by applying Saaty's method [50]. To facilitate this, the linguistic IF evaluations in *Table 2* are first transformed into their crisp Score Index (SI) equivalents via *Eq. (6)*. This conversion yields the definitive SI values listed in *Table 3*.

$$SI = \begin{cases} 1 + 10|\mu(x) * \vartheta(x) - \mu(x) * \vartheta(x) * \pi(x)| & \text{for AE, MH, H, VH, and AH,} \\ \dfrac{1}{1 + 10|\mu(x) * \vartheta(x) - \mu(x) * \vartheta(x) * \pi(x)|} & \text{for ML, L, VL, and AL.} \end{cases} \tag{6}$$

Step 5. Aggregate the evaluations provided by experts in the pairwise comparison matrices by applying *Eq. (3)*, which incorporates the weights assigned to each expert. Next, compute the radii r for the criteria by identifying the maximum Euclidean distance between each expert's evaluation and the aggregated criteria value, as outlined in *Eq. (4)*.

Step 6. The geometric mean of the expert judgments is computed by applying the power and multiplication operations for IFSs, as defined in *Eq. (2)*.

Step 7. A similar procedure is used to calculate the sub-criterion weights. To determine the global criteria weights, the main criteria and sub-criteria weights are multiplied separately for each of the three components of the CIFNs.

Step 8. The computed fuzzy global weights for the criteria are defuzzified by applying the Relative Score Function (RSF). This function, detailed in *Eq. (7)* [30], operates on the principle of vector normalization. In this equation, the parameter represents a small constant, usually set to 0.01.

$$RSF_j = \frac{(1-\vartheta_j)(1+\mu_j)+\mu_j}{3} \times \left(\frac{\frac{1}{r_j}}{\sqrt{\frac{1}{r_1^2}+\frac{1}{r_2^2}+\frac{1}{r_3^2}}}\right)^{\tau}. \quad (7)$$

Step 9. The defuzzified criterion weights are normalized by dividing each weight by the aggregate sum of all weights. The criteria can then be prioritized based on these resulting normalized values.

Stage 2. Assessment of alternatives CIF-CODAS.

Step 10. Construct decision matrices based on the linguistic terms presented in *Table 3*, following consultations with multiple experts.

$$\tilde{D}^k = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11}^k & \tilde{x}_{12}^k & \cdots & \tilde{x}_{1n}^k \\ \tilde{x}_{21}^k & \tilde{x}_{22}^k & \cdots & \tilde{x}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1}^k & \tilde{x}_{m2}^k & \cdots & \tilde{x}_{mn}^k \end{bmatrix} \end{array}, i = 1, \dots, m; j = 1, \dots, n; k = 1, \dots, l. \quad (8)$$

Step 11. Likewise, in *Step 5*, the decision matrices' judgments are aggregated using *Eq. (2)*, and the radius is determined using *Eq. (4)*.

Step 12. The weighted normalized matrix is obtained by multiplying the aggregate decision matrix by the criteria weights.

$$\tilde{R}_{ij} = \tilde{w}_j \otimes \tilde{x}_{ij}, j = 1, \dots, n; i = 1, \dots, m. \quad (9)$$

Step 13. Determine the negative-ideal solutions using *Eq. (10)*.

$$\left.\begin{array}{ll} A^- = Min_i\tilde{x}_{ij} = \langle \min\left(\mu(\tilde{x}_{ij})\right), \max\left(\vartheta(\tilde{x}_{ij})\right); r_{ij}\rangle, & \text{if } C_j \text{ is a benefit criterion} \\ A^- = Max_i\tilde{x}_{ij} = \langle \max\left(\mu(\tilde{x}_{ij})\right), \min\left(\vartheta(\tilde{x}_{ij})\right); r_{ij}\rangle, & \text{if } C_j \text{ is a cost criterion} \end{array}\right\}. \quad (10)$$

Step 14. Calculate the Euclidean distance and the Hamming distance.

The Euclidean distance:

$$E(\tilde{R}_{ij}, A^-) = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[(\mu_{ij}-\mu_j^-)^2 + (\vartheta_{ij}-\vartheta_j^-)^2 + (r_{ij}-r_j^-)^2\right]}. \quad (11)$$

The Hamming distance:

$$H(\tilde{R}_{ij}, A^-) = \frac{1}{2n}\sum_{j=1}^{n}\left(|\mu_{ij}-\mu_j^-| + |\vartheta_{ij}-\vartheta_j^-| + |r_{ij}-r_j^-|\right). \quad (12)$$

Step 15. Construct the relative assessment matrix $\left(RA_{ij} = \{ra_{ij}\}_{m\times n}\right)$ using *Eq. (13)*.

$$ra_{il} = \left([E(\tilde{R}_{ij}, A^-) - E(\tilde{R}_{lj}, A^-)] + \left(\varphi[E(\tilde{R}_{ij}, A^-) - E(\tilde{R}_{lj}, A^-)] * [H(\tilde{R}_{ij}, A^-) - H(\tilde{R}_{lj}, A^-)]\right)\right), l = 1, \dots, m. \quad (13)$$

In this context, φ signifies the threshold function for assessing the equality of the Euclidean distance, ζ refers to the threshold value set by the decision-makers, and $ʐa_{il}$ indicates the priority difference associated with each alternative [51].

$$\varphi\left[E\left(\tilde{R}_{ij}, A^-\right) - E\left(\tilde{R}_{lj}, A^-\right)\right] = \begin{cases} 1, & \text{if} \quad |\zeta| \leq E\left(\tilde{R}_{ij}, A^-\right) - E\left(\tilde{R}_{lj}, A^-\right) \\ 0, & \text{if} \quad \text{others} \end{cases}. \tag{14}$$

Step 16. Rank the alternatives.

The ultimate score for each alternative is computed by applying *Eq. (15)*. Following this calculation, the alternatives are ranked in descending order according to their ultimate score values (δ_i).

$$\delta_i = \sum_{l=1}^{m} ʐa_{il}. \tag{15}$$

5 | Application

The company where the proposed method is applied is a medium-sized cement manufacturing firm located in the Central Anatolia region of Turkey. Due to agreements with the energy management consulting companies that proposed the evaluated projects, the specific details of the projects cannot be disclosed in the article. However, a summary of the projects under consideration is provided below, and the hierarchical structure of the fuzzy MCDM problem is shown in *Fig. 5*.

Alternative 1 (Waste Heat Recovery (WHR) systems). Implementing WHR systems to capture and reuse the heat generated during cement production. Impact: This reduces the need for external energy sources, thereby decreasing CO_2 emissions.

Example 1. A WHR system installed at a cement plant in China reduced energy consumption by 15% and significantly cut carbon emissions.

Alternative 2 (energy-efficient grinding technologies). Project Description: Upgrading to high-efficiency grinding systems, such as Vertical Roller Mills (VRMs) or High-Pressure Grinding Rolls (HPGR). Impact: These technologies consume less energy compared to traditional ball mills. Example: Adoption of VRM in a cement plant in India led to a 25% reduction in energy consumption per ton of cement produced.

Alternative 3 (CCUS: Project description). Implementing CCUS technologies to capture CO_2 emissions from the cement production process and either store them underground or utilize them in other industries. Impact: This directly reduces the amount of CO_2 released into the atmosphere. Example: A pilot project in Norway successfully captured and stored 400,000 tons of CO_2 annually from a cement plant.

Alternative 4 (renewable energy integration: Project description). The incorporation of sustainable power sources, including solar or wind energy, to supply a portion of a facility's total energy consumption. Impact: a significant reduction in dependence on fossil fuels and a consequent decrease in the plant's carbon footprint.

Example 2. A cement plant in Spain installed solar panels, covering 15% of its energy needs and reducing CO_2 emissions by 8%.

Alternative 5 (high-efficiency motors and drives: project description). Upgrading to high-efficiency electric motors and variable frequency drives (VFDs) in cement production machinery. Impact: These upgrades reduce electricity consumption and improve overall energy efficiency.

Example 3. A cement plant in Mexico replaced old motors with high-efficiency motors, resulting in a 10% reduction in electrical energy use.

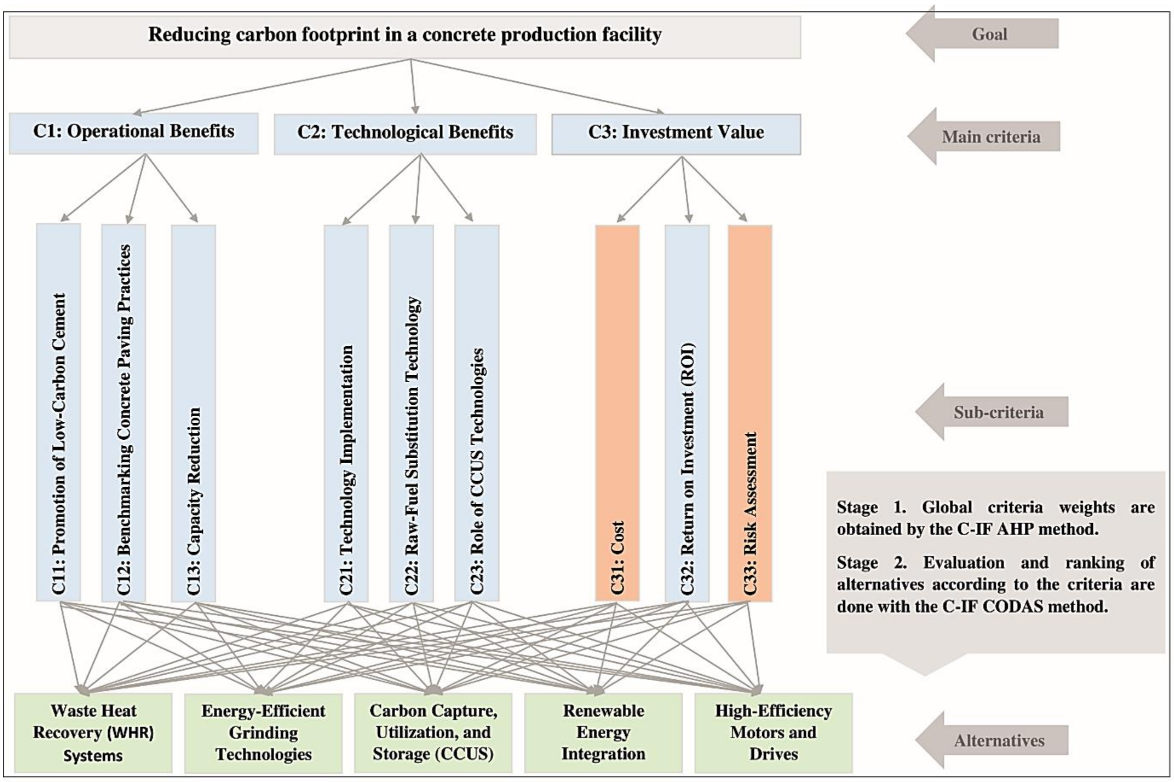


Fig. 5. Hierarchical structure of reducing carbon footprint in a concrete production facility.

Here, the three main criteria and their sub-criteria, as explained in Section 3, are considered and prioritized using the CIF-AHP method. Then, the alternatives listed above are evaluated and ranked according to these criteria using the CIF-CODAS method.

The evaluation of criteria and alternatives is conducted by the finance manager (E1), general manager (E2), and production manager (E3). Their weights, based on their expertise and knowledge in the field, are set at 0.50, 0.30, and 0.20, respectively. Each expert was first asked to determine the importance weights of the criteria through pairwise comparisons, using the linguistic statements provided in *Table 2*. This process involved two main tasks: comparing the main criteria against each other and then comparing the sub-criteria within each main criterion. Pairwise comparison matrices of the criteria, as determined by the experts, are presented in *Table 4*.

Table 4. Pairwise comparison matrices according to experts.

	E1	E2	E3	E1	E2	E3	E1	E2	E3
Criteria	**C1**			**C2**			**C3**		
C1	E	E	E	AH	VH	H	MH	MH	H
C2	AL	VL	L	E	E	E	VH	H	AH
C3	ML	ML	L	VL	L	AL	E	E	E
Sub-Criteria	**C11**			**C12**			**C13**		
C11	E	E	E	AH	VH	H	MH	H	AE
C12	AL	VL	L	E	E	E	MH	ML	AE
C13	ML	L	AE	ML	MH	AE	E	E	E
Sub-Criteria	**C21**			**C22**			**C23**		
C21	E	E	E	VH	MH	VH	ML	MH	MH
C22	VL	ML	ML	E	E	E	H	VH	MH
C23	MH	VL	ML	L	VL	ML	E	E	E
Sub-Criteria	**C31**			**C32**			**C33**		
C31	E	E	E	AE	ML	MH	VL	VL	ML
C32	AE	MH	MH	E	E	E	VH	MH	MH
C33	VH	ML	ML	VL	VH	MH	E	E	E

These judgments are aggregated using *Eq. (3)*, as shown in the fuzzy aggregated pairwise comparison matrix in *Table 5*. The radii in the table are calculated using the Euclidean distance-based formula provided in *Eq. (4)*. The aggregated CIF comparison matrices are presented in *Table 5*. An example calculation was made for $\mathrm{IFWG}(C_{12})$ as: $\mathrm{IFWG}(C_{12}) = \left(\prod_{j=1}^{3} {\mu_{C_j}}^{\omega_j}, \prod_{j=1}^{3} {\vartheta_{C_j}}^{\omega_j}\right) = (0.05^{0.5} * 0.15^{0.3} * 0.25^{0.2}, 0.85^{0.5} * 0.75^{0.3} * 0.65^{0.2}) = (0.096, 0.776)$ and $r_{12} = \max \sqrt{\left(\prod_{j=1}^{3} {\mu_{C_j}}^{\omega_j} - \mu_{C_i}\right)^2 + \left(\prod_{j=1}^{3} {\vartheta_{C_j}}^{\omega_j} - \vartheta_{C_i}\right)^2} = \max\left(\begin{array}{c}\sqrt{(0.05-0.096)^2+(0.85-0.776)^2}; \sqrt{(0.15-0.096)^2+(0.75-0.776)^2}\,; \\ \sqrt{(0.25-0.096)^2+(0.65-0.776)^2}\end{array}\right) = 0.199.$

Table 5. Aggregated CIF pairwise comparison matrices.

	C1			C2			C3		
Criteria	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**
C1	0.5	0.5	0	0.776	0.096	0.199	0.569	0.327	0.112
C2	0.096	0.776	0.199	0.5	0.5	0	0.761	0.140	0.156
C3	0.327	0.569	0.112	0.140	0.737	0.145	0.5	0.5	0
	C11			**C12**			**C13**		
Sub-Criteria	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**
C11	0.5	0.5	0	0.776	0.096	0.199	0.556	0.333	0.158
C12	0.096	0.776	0.199	0.5	0.5	0	0.461	0.421	0.170
C13	0.333	0.556	0.158	0.421	0.461	0.170	0.5	0.5	0
	C21			**C22**			**C23**		
Sub-Criteria	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**
C21	0.5	0.5	0	0.683	0.193	0.206	0.439	0.439	0.142
C22	0.229	0.642	0.152	0.5	0.5	0	0.656	0.229	0.161
C23	0.340	0.482	0.329	0.229	0.656	0.161	0.5	0.5	0
	C31			**C32**			**C33**		
Sub-Criteria	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**
C31	0.5	0.5	0	0.434	0.454	0.156	0.178	0.705	0.232
C32	0.497	0.397	0.071	0.5	0.5	0	0.642	0.229	0.152
C33	0.512	0.287	0.309	0.315	0.397	0.500	0.5	0.5	0

Subsequently, normalization of the defuzzified values is performed. Normalization is achieved by dividing each individual weight by the aggregate sum of all defuzzified weights. The resultant normalized weights for the criteria are calculated as 0.494, 0.277, and 0.229. After calculating the geometric mean and determining the global weights, the normalized CIF weights for the sub-criteria are obtained, as displayed in *Table 6*.

Table 6. The global CIF, defuzzified, and normalized weights of sub-criteria.

Sub-Criteria	μ	ϑ	r	Def.	Norm.	Rank
C11	0.362	0.108	0.040	0.523	0.162	1
C12	0.170	0.196	0.040	0.368	0.114	3
C13	0.249	0.166	0.034	0.428	0.132	2
C21	0.176	0.212	0.041	0.366	0.113	4
C22	0.140	0.262	0.032	0.326	0.101	6
C23	0.113	0.300	0.065	0.294	0.091	8
C31	0.096	0.350	0.034	0.268	0.083	9
C32	0.154	0.237	0.022	0.344	0.106	5
C33	0.123	0.247	0.072	0.318	0.098	7

After obtaining the criteria weights, experts evaluated the alternatives for each sub-criterion. The decision matrices gathered from the three experts are presented in *Table 7*.

Table 7. Decision matrices.

	WHR Systems			Energy-Efficient Grinding			CCUS			Renewable Energy			High-Efficiency Motors		
Experts	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**
C11	H	AH	H	H	H	AH	VH	H	AH	H	VH	H	H	H	VH
C12	ML	H	H	ML	MH	H	ML	H	H	ML	H	H	ML	H	H
C13	ML	H	H	ML	AH	H	ML	H	H	ML	H	H	ML	H	H
C21	MH	H	H	AH	H	H	AH	VH	AH	H	H	VH	H	H	AH
C22	MH	ML	ML	H	H	VH	H	H	H	ML	ML	MH	ML	ML	MH
C23	MH	ML	ML	ML	ML	H	AH	VH	VH	ML	ML	ML	ML	ML	L
C31	AH	H	H	AH	H	H	AH	H	H	AH	H	H	H	MH	VH
C32	H	H	MH	H	MH	H	ML	MH	MH	MH	VH	MH	H	H	MH
C33	MH	MH	H	MH	MH	H	VH	AH	H	AH	AH	MH	ML	MH	L

Following the outlined procedure, the aggregated decision matrix containing CIF numbers is obtained, and then the weighted normalized decision matrix is handled with *Eq. (9)*, as shown in *Table 8*. An example calculation was made for the aggregated decision matrix and weighted normalized decision matrix for the C11 criterion and WHR Systems. $\tilde{x}_{11}^{k} = (0.65^{0.5} * 0.85^{0.3} * 0.65^{0.2}, 0.25^{0.5} * 0.05^{0.3} * 0.25^{0.2}) = (0.704, 0.154)$ and r =179 was also calculated from these values as before. Then, $\widetilde{R}_{11} = (0.362 * 0.704, 0.154 + 0.108 - 0.154 * 0.108, |1 - 0.704 * 0.362 - 0.704 - 0.362 + 0.154 * 0.108|) = (0.225, 0.245, 0.305)$.

Table 8. Weighted normalized decision matrices.

	WHR Systems			Energy-Efficient Grinding			CCUS			Renewable Energy			High-Efficiency Motors		
Criteria	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**	**μ**	**ϑ**	**r**
C11	0.255	0.245	0.305	0.248	0.270	0.277	0.267	0.233	0.351	0.246	0.299	0.263	0.242	0.309	0.249
C12	0.081	0.494	0.345	0.077	0.526	0.380	0.081	0.494	0.345	0.081	0.494	0.345	0.081	0.494	0.345
C13	0.119	0.475	0.217	0.129	0.357	0.143	0.119	0.475	0.217	0.119	0.475	0.217	0.119	0.475	0.217
C21	0.105	0.445	0.183	0.131	0.300	0.027	0.144	0.266	0.124	0.118	0.390	0.085	0.121	0.354	0.055
C22	0.061	0.586	0.475	0.094	0.428	0.157	0.091	0.446	0.184	0.054	0.633	0.555	0.054	0.633	0.555
C23	0.049	0.607	0.531	0.045	0.629	0.588	0.090	0.360	0.025	0.039	0.685	0.663	0.037	0.698	0.694
C31	0.071	0.423	0.128	0.071	0.423	0.128	0.071	0.423	0.128	0.071	0.423	0.128	0.061	0.512	0.294
C32	0.097	0.441	0.184	0.095	0.448	0.198	0.068	0.572	0.443	0.093	0.444	0.213	0.097	0.441	0.184
C33	0.070	0.493	0.319	0.070	0.493	0.319	0.093	0.337	0.057	0.096	0.303	0.021	0.046	0.621	0.579

From *Table 8*, CIF negative ideal solutions are calculated by *Eq. (10)*, and the Euclidean and Hamming distances are obtained via *Eqs. (11)* and *(12)*, respectively. Relevant results are presented in *Tables 9* and *10*. For instance, since C11 was a benefit factor, the negative solution was calculated as $(\min\mu, \max\vartheta) = \left(\min(0.255, 0.248, 0.267, 0.246, 0.242), \max(0.245, 0.270, 0.233, 0.299, 0.309)\right) = (0.242, 0.399)$, and the C31 cost factor was calculated as $(\max\mu, \min\vartheta) = \left(\max(0.071, 0.071, 0.071, 0.071, 0.061), \min(0.423, 0.423, 0.423, 0.423, 0.512)\right) = (0.071, 0.423)$.

Table 9. Negative ideal solutions.

A^-	μ	ϑ	r
C11	0.242	0.309	0.249
C12	0.077	0.526	0.380
C13	0.119	0.475	0.217
C21	0.105	0.445	0.183
C22	0.054	0.633	0.555
C23	0.037	0.698	0.663
C31	0.071	0.423	0.128
C32	0.068	0.572	0.443
C33	0.096	0.303	0.303

Table 10. The Euclidean and Hamming distances.

Alternatives	$E(\tilde{R}_{ij}, A^-)$	$H(\tilde{R}_{ij}, A^-)$
WHR Systems	0.09633	0.06244
Energy-efficient grinding	0.14800	0.11366
CCUS	0.21267	0.13804
Renewable energy	0.09573	0.05979
High-efficiency motors	0.13524	0.09122
WHR systems	0.09633	0.06244

Eqs. (13) and *(14)* construct the relative assessment matrix of alternatives. The results are presented in *Table 11*. It is important to note that the calculations are performed with the threshold value set to 0.05 (ζ = 0.05). Finally, the alternatives are ranked according to the procedure in *Step 16*, using *Eq. (15)*, as shown in *Table 12*.

Table 11. The relative assessment matrix and final rank of the alternatives.

Alternatives	WHR Systems	Energy-Efficient Grinding	CCUS	Renewable Energy	High-Efficiency Motors	δ_i	Rank
WHR systems	0	-0.1029	-0.1919	0.0032	-0.0677	-0.3593	4
Energy-efficient grinding	0.0517	0	-0.08905	0.10614	0.03520	0.1040	2
CCUS	0.1919	0.0890	0	0.1952	0.1242	0.6004	1
Renewable energy	-0.0032	-0.1061	-0.1952	0	-0.0709	-0.3755	5
High-efficiency motors	0.0677	-0.0352	-0.1242	0.0709	0	-0.0208	3

Table 10 shows the rankings, indicating that the third alternative, CCUS, is the best and the fourth alternative (Renewable Energy) is the last in the ranking: $S_3 > S_2 > S_5 > S_1 > S_4$. CCUS ranks highest because it is one of the very few technologies that can directly decarbonize existing critical industries that are otherwise incredibly hard to clean up, such as cement, steel, and chemical production. Even though it's expensive, it is often seen as essential for these sectors to survive in a net-zero world, making its high cost a necessary investment.

Comparative analyses: Two analysis procedures are applied to compare the results. One of these is the Intuitionistic Fuzzy (IF) AHP&CODAS, and the other is the fuzzy (F) AHP&CODAS. In both methods, as in the CIF-AHP&CODAS methodology, the criteria are weighted using the AHP method for the relevant fuzzy number. The alternatives are then ranked using the CODAS method for the relevant fuzzy number. As a result of the comparative analysis, *Table 12* presents the criteria weights and rankings obtained from the AHP methods applied to all three fuzzy number types, and *Table 13* presents the comparison of the alternative rankings obtained from the CODAS methods.

Table 12. The criteria weights and ranks of F, IF, and CIF-AHP.

Criteria	F-AHP	Rank	IF-AHP	Rank	CIF-AHP	Rank
C11	0.439687	1	0.525108	1	0.161553	1
C12	0.095735	4	0.101421	4	0.113676	3
C13	0.126101	3	0.123373	2	0.132394	2
C21	0.12909	2	0.108667	3	0.113074	4
C22	0.075047	5	0.060529	5	0.100811	6
C23	0.039831	7	0.026051	7	0.090926	8
C31	0.014402	9	0.004152	9	0.082792	9
C32	0.050183	6	0.036638	6	0.106388	5
C33	0.029924	8	0.014061	8	0.098385	7

Table 13. The assessment scores and final rankings of F, IF, and CIF-CODAS.

Alternatives	F-CODAS	Rank	IF-CODAS	Rank	CIF-CODAS	Rank
WHR systems	-0.380230407	4	-0.810661962	4	-0.359290188	4
Energy-efficient grinding	0.273251664	2	1.699393434	2	0.103960614	2
CCUS	0.78671931	1	1.880400971	1	0.600426386	1
Renewable energy	-0.459110473	5	-3.137323011	5	-0.375503269	5
High-efficiency motors	-0.083048688	3	0.368190568	3	-0.020816619	3

In *Table 12*, the highest-weighted criterion was C11 across all three methods. The rankings of the other criteria were similar. In *Table 12*, all three methods calculated the alternatives in the same order. The same ranking is obtained with all three methods and is represented in *Fig. 6*.

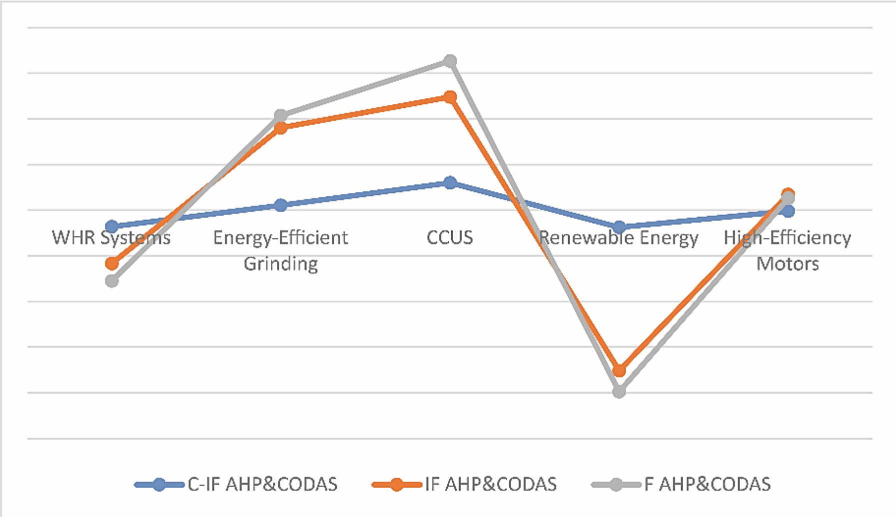
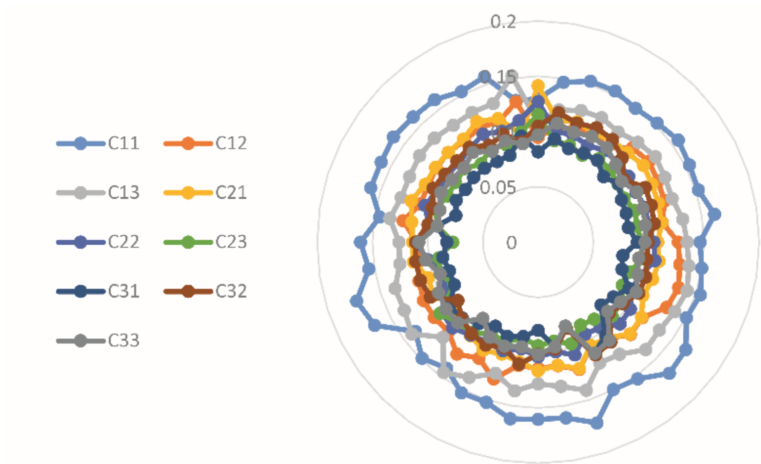
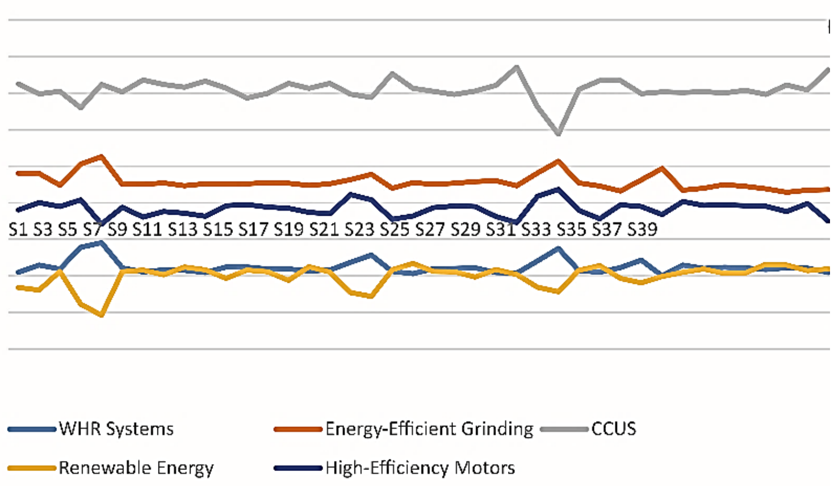


Fig. 6. Assessment scores of comparative analyses.

Sensitivity analyses: To test the reliability of the methodology, sensitivity analyses are conducted across 40 scenarios in which the criteria evaluations are altered. *Figs. 7.a* and *7.b* show the results of the sensitivity analyses on the criteria weights obtained through CIF-AHP and the ranking results for the alternatives, respectively, when using CIF-CODAS.



a.



b.

Fig. 7. Sensitivity analyses; a. CIF-AHP, and b. CIF-CODAS.

Fig. 7 clearly shows that C11 has the highest weight, and CCUS is the best alternative. These findings are consistent with the application results of the proposed method.

6 | Conclusion

This study provided an in-depth evaluation of carbon footprint reduction strategies in the precast concrete industry using the CIF AHP & CODAS methodology. The results revealed that CCUS was the most effective strategy, followed by energy-efficient grinding technologies and high-efficiency motors and drives. The ranking of alternatives highlighted the balance between environmental impact and implementation feasibility, aligning with previous research that emphasized the importance of carbon capture and advanced technologies in mitigating carbon emissions in energy-intensive industries [6], [26].

The robust methodological framework effectively captured the complexities and trade-offs of strategic decision-making, confirming that a transition to low-carbon production requires a combination of transformative technologies such as CCUS and incremental, readily available efficiency improvements.

6.1 | Benefits and Implications

The primary benefit of this study is the structured, nuanced prioritization it offers to industry decision-makers. Identifying CCUS as the top-ranked strategy confirms the growing recognition of its potential within the concrete and cement sectors, a finding supported by [15], [20], who underscore its pivotal role in achieving significant emission reductions. Furthermore, the high ranking of Energy-Efficient Grinding Technologies provides a clear, actionable pathway for companies seeking more cost-effective, immediately feasible solutions to reduce their energy consumption and carbon footprint in the short term. The methodological contribution, demonstrating the practical application of CIF AHP & CODAS, also provides a valuable tool for evaluating complex sustainability criteria under uncertainty, which can be adapted to other environmental challenges.

6.2 | Limitations

Despite its contributions, this study is subject to several limitations. The reliance on expert judgments, while a strength in capturing nuanced trade-offs, may also introduce elements of subjectivity. The generalizability of the findings is somewhat constrained by the limited, specific quantitative project data, which were unavailable due to confidentiality agreements with industry partners. Consequently, the results are more indicative of strategic priorities than definitive quantitative assessments. Finally, while the model is robust, its direct application to other regions or industries might require adjustments to the criterion weights and the use of alternative sets to reflect local conditions and technological availability.

6.3 | Future Research Directions

To build upon this work, future research should pursue several avenues. First, a more detailed quantitative LCA and techno-economic analysis of the top-ranked alternatives, particularly CCUS, would provide crucial data on their long-term financial viability and net environmental benefits. Second, expanding the evaluation framework to include broader sustainability criteria, such as social impact, regulatory compliance complexity, and supply chain resilience, would offer a more holistic decision-making tool. Finally, applying this integrated methodology to other energy-intensive sectors, such as steel or chemicals, would test its transferability and help identify cross-industry insights into carbon-emission reduction strategies.

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The authors declare that they used Artificial Intelligence (AI) tools solely for grammar and language checking. No AI tools were used for content generation, data analysis, result interpretation, or decision-making.

Author Contribution

All authors contributed equally to the conceptualization, methodology, investigation, validation, formal analysis, and writing (original draft, review, and editing).

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Data Availability

All relevant theoretical or literature-based findings are included within the article.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Su, Q. (2024). Addressing the crucial factors affecting the implementation of carbon credit concept using a comprehensive decision making analysis: A case study. *Journal of operational and strategic analytics*, *2*(3). https://doi.org/10.56578/josa020301

[2] Mauludin, M. S., Khairudin, M., Asnawi, R., Prasetyo, S. D., Trisnoaji, T., Rizkita, M. A., … & Rosli, M. A. M. (2025). Sustainable energy solutions in urban management: Carbon emissions and economic assessment of photovoltaic systems at electric vehicle stations in hybrid buildings. *Challenges in Sustainability*, *13*(3), 377–397. https://doi.org/10.56578/cis130305

[3] Sun, Z. T., Zhang, Y. Y., Yu, P. D., Zhang, L. Y., & Pang, J. (2023). Calculation and intensity analysis of logistics industry embodied CO2 emissions in China. *Journal of green economy and low-carbon development*, *2*(1), 27–35. https://doi.org/10.56578/jgelcd020104

[4] Mohajeri, A., Fallah, M., & Hosseinzadeh Lotfi, F. (2014). Carbon based closed loop supply chain design under uncertainty using an interval valued fuzzy stochastic programming approach. *International journal of research in industrial engineering*, *3*(3), 24–48. https://www.riejournal.com/article_48019_664439034a3826683db0aa1cb91e2325.pdf

[5] Malekinejad, P., Mirfakhradini, S. H., Morovati Sharifabadi, A., & Zanjirchi, S. M. (2024). Towards reducing electronic waste in a sustainable closed loop supply chain. *Journal of applied research on industrial engineering*, *11*(4), 497–517. https://doi.org/10.22105/jarie.2023.408887.1555

[6] Olatunji, O. O., Akinlabi, S. A., Ayo, O. O., Madushele, N., Adedeji, P. A., & Fatoba, S. O. (2019). Drivers and barriers to competitive carbon footprint reduction in manufacturing supply chain: A brief review. *Procedia manufacturing*, *35*, 992–1000. https://doi.org/10.1016/j.promfg.2019.06.047

[7] Ebrahim, A. K., Selokolayi, D. D., & Ahmadi, A. (2022). Evaluating supply chain management using the fuzzy analytic hierarchy process technique. *Innovation management and operational strategies*, *3*(1), 1–11. (**In Persian**). https://doi.org/10.22105/imos.2021.293121.1130

[8] Arasteh, A. (2025). Designing an integrated green supply chain model with an emphasis on improving environmental quality and increasing customer satisfaction. *Journal of quality engineering and management*, *15*(1), 31–49. (**In Persian**). https://doi.org/10.48313/jqem.2025.514959.1511

[9] Alem Tabriz, A., & Hemshad, A. S. (2024). Identify and rank the effective criteria and factors for sustainable SCM with MADM approach in the ceramic and tile industry. *Modern research in performance evaluation*, *2*(4), 273–283. (**In Persian**). https://doi.org/10.22105/mrpe.2024.198348

[10] Rezaie Moghadam, S., & Doosti, A. (2022). Designing a multi objective mathematical model for integrated production planning in a reversible supply chain with the uncertainty approach and using the nsgall meta industry. *Journal of decisions and operations research*, *6*(Spec. Issue), 1–24. (**In Persian**). https://doi.org/10.22105/dmor.2021.254802.1245

[11] Kutlu Gündo ugdu, F., & Kahraman, C. (2019). Spherical fuzzy sets and spherical fuzzy TOPSIS method. *Journal of intelligent & fuzzy systems*, *36*(1), 337–352. https://doi.org/10.3233/JIFS-181401

[12] Scopus. (2026). *Search results for title ABS key ("carbon reduction") and title ABS key (concrete)*. https://www.scopus.com

[13] Villagrán Zaccardi, Y., Pareja, R., Rojas, L., Irassar, E. F., Torres Acosta, A., Tobón, J., & John, V. M. (2022). Overview of cement and concrete production in Latin America and the Caribbean with a focus on the goals of reaching carbon neutrality. *RILEM technical letters*, *7*, 30–46. https://doi.org/10.21809/rilemtechlett.2022.155

[14] Chen, T. T., Wang, W. C., & Wang, H. Y. (2020). Mechanical properties and ultrasonic velocity of lightweight aggregate concrete containing mineral powder materials. *Construction and building materials*, *258*, 119550. https://doi.org/10.1016/j.conbuildmat.2020.119550

[15] Xiao, J., Zhang, H., Tang, Y., Lü, Z., Ye, T., Duan, Z., … & Xiao, X. (2023). Principles for waste concrete recycling and basic problems of recycled concrete. *Chinese science bulletin*, *68*(5), 510–523. https://doi.org/10.1360/TB-2022-0521

[16] Tao, Y., Dai, X., De Schutter, G., & Van Tittelboom, K. (2023). Set on demand of alkali activated slag mixture using twin pipe pumping. *Construction and building materials*, *392*, 132003. https://doi.org/10.1016/j.conbuildmat.2023.132003

[17] Ding, C., Jia, Z. J., Wang, Z. H., & Ding, Y. X. (2023). UHPC carbon emission control potential based on life cycle assessment. *Bulletin of the chinese ceramic society*, *42*(4), 1242–1251. https://researching.cn/ArticlePdf/m00115/2023/42/4/2023-04-1242.pdf?utm_source=.com

[18] Xiao, J., Xia, B., Xiao, X., Li, Y., Xue, S., Zhou, Y., … & Xu, B. (2022). Prospects for low carbon design theory of concrete structures. *Chinese science bulletin*, *67*(28–29), 3425–3438. https://doi.org/10.1360/TB-2022-0055

[19] Wang, C., Wang, J., Liu, X., Cai, Y., & Zhang, Y. (2023). Orthogonal experimental design for compressive strength of recycled coarse aggregate concrete with silica fume slag fly ash hybrid micro powders. *Construction and building materials*, *408*, 133669. https://doi.org/10.1016/j.conbuildmat.2023.133669

[20] Bian, Z., Huang, Y., Lu, J. X., Ou, G., Yang, S., & Poon, C. S. (2023). Development of self foaming cold bonded lightweight aggregates from waste glass powder and incineration bottom ash for lightweight concrete. *Journal of cleaner production*, *428*, 139424. https://doi.org/10.1016/j.jclepro.2023.139424

[21] Atanassov, K. T. (1983). Intuitionistic fuzzy sets. *Fuzzy sets and systems*, *20*(1), 87-96. https://doi.org/10.1016/S0165-0114(86)80034-3

[22] Atanassov, K. T. (2020). Circular intuitionistic fuzzy sets. *Journal of intelligent & fuzzy systems*, *39*(5), 5981–5986. https://doi.org/10.3233/JIFS-189072

[23] Yager, R. R. (2013). Pythagorean membership grades in multicriteria decision making. *IEEE transactions on fuzzy systems*, *22*(4), 958–965. IEEE. https://doi.org/10.1109/TFUZZ.2013.2278989

[24] Smarandache, F. (1999). *A unifying field in logics*. American Research Press. https://philpapers.org/rec/SMAAUF?utm_source.com

[25] Teh, S. H., Wiedmann, T., Castel, A., & de Burgh, J. (2017). Hybrid life cycle assessment of greenhouse gas emissions from cement, concrete and geopolymer concrete in Australia. *Journal of cleaner production*, *152*, 312–320. https://doi.org/10.1016/j.jclepro.2017.03.122

[26] Luo, L., Guo, Y., Li, Y. M., Zhang, Z., & Zhu, T. (2022). Research on low carbon development technology path and forecast of cement industry under carbon neutral situation. *The research of environmental sciences*, *35*, 1527–1537. https://dx.doi.org/10.13198/j.issn.1001-6929.2021.12.20

[27] Rangelov, M., Dylla, H., Dobling, B., Gudimettla, J., Sivaneswaran, N., & Praul, M. (2022). Readily implementable strategies for reducing embodied environmental impacts of concrete pavements in the United States. *Transportation research record*, *2676*(9), 436–450. https://doi.org/10.1177/03611981221086934

[28] Liu, P. L., Ho, M. C., & Lin, J. D. (2017). Precast concrete plant import of energy conservation and carbon reduction efficiency research in cement concrete, for example. *Journal of the Chinese institute of civil and hydraulic engineering*, *29*(3). https://doi.org/10.6652/JoCICHE.201709_29(3).0007

[29] Huang, Y., & Wang, A. (2023). Research on carbon emission of prefabricated structure in China. *Buildings*, *13*(5), 1348. https://doi.org/10.3390/buildings13051348

[30] Çakir, E., & Tacs, M. A. (2023). Circular intuitionistic fuzzy decision making and its application. *Expert systems with applications*, *225*, 120076. https://doi.org/10.1016/j.eswa.2023.120076

[31] Alreshidi, N. A., Shah, Z., & Khan, M. J. (2024). Similarity and entropy measures for circular intuitionistic fuzzy sets. *Engineering applications of artificial intelligence*, *131*, 107786. https://doi.org/10.1016/j.engappai.2023.107786

[32] Xu, C., & Wen, Y. (2023). New measure of circular intuitionistic fuzzy sets and its application in decision making. *AIMS math*, *8*(10), 24053–24074. https://doi.org/10.3934/math.20231226

[33] Khan, M. J., Kumam, W., & Alreshidi, N. A. (2022). Divergence measures for circular intuitionistic fuzzy sets and their applications. *Engineering applications of artificial intelligence*, *116*, 105455. https://doi.org/10.1016/j.engappai.2022.105455

[34] Fahmi, A., Khan, A., Maqbool, Z., & Abdeljawad, T. (2025). Circular intuitionistic fuzzy Hamacher aggregation operators for multi attribute decision making. *Scientific reports*, *15*(1), 5618. https://doi.org/10.1038/s41598-025-88845-0

[35] Otay, I., & Kahraman, C. (2022). A novel circular intuitionistic fuzzy AHP &VIKOR methodology: An application to a multi expert supplier evaluation problem. *Pamukkale üniversitesi mühendislik bilimleri dergisi*, *28*(1), 194–207. https://doi.org/10.5505/pajes.2021.90023

[36] Khan, M. J., Ding, W., Jiang, S., & Akram, M. (2025). Group decision making using circular intuitionistic fuzzy preference relations. *Expert systems with applications*, *270*, 126502. https://doi.org/10.1016/j.eswa.2025.126502

[37] Khan, M. J., Jiang, S., Ding, W., & Akram, M. (2025). Construction methods for entropy measures of circular intuitionistic fuzzy sets and their application. *Engineering applications of artificial intelligence*, *160*, 111809. https://doi.org/10.1016/j.engappai.2025.111809

[38] Fetanat, A., & Tayebi, M. (2023). Sustainability and resilience oriented prioritization of oil and gas produced water treatment technologies: A novel decision support system under circular intuitionistic fuzzy set. *Geoenergy science and engineering*, *221*, 211379. https://doi.org/10.1016/j.geoen.2022.211379

[39] Kamber, E., & Baskak, M. (2024). Green logistics park location selection with circular intuitionistic fuzzy CODAS method: The case of Istanbul. *Journal of intelligent & fuzzy systems*, *46*(2), 4173–4189. https://doi.org/10.3233/JIFS-231843

[40] Scopus. (2026). *Document search: "MCDM" AND "Carbon Reduction" AND "Concrete"*. https://www.scopus.com

[41] Aljawhari, K., Gentile, R., & Galasso, C. (2025). Beyond direct economic losses: An integrated approach to seismic retrofit considering sustainability and indirect losses. *Earthquake engineering & structural dynamics*, *54*(6), 1737–1758. https://doi.org/10.1002/eqe.4324

[42] Thomas, T. S., Dhanya, B. S., & Nayar, S. K. (2025). Environmental and economic assessment of whitetoppings made with sustainable concrete mixtures having ground granulated blast furnace slag, recycled concrete aggregates and hybrid fibres. *Road materials and pavement design*, *27*(5), 1–40. https://doi.org/10.1080/14680629.2025.2520552

[43] Caruso, M., Buttazzoni, M., Passoni, C., Labò, S., Marini, A., & Pinho, R. (2024). An updated multi criteria decision making method for the sustainable renovation of buildings including environmental, economic and social life cycle metrics. *Journal of building engineering*, *98*, 110967. https://doi.org/10.1016/j.jobe.2024.110967

[44] Indwar, R., Mishra, U., & Titiksh, A. (2024). Geopolymer concrete containing nanomaterials a step toward sustainable construction. *Environmental science and pollution research*, *32*(42), 1–42. https://doi.org/10.1007/s11356-024-34172-2

[45] Revilla Cuesta, V., Skaf, M., Espinosa, A. B., & Ortega López, V. (2021). Multi criteria feasibility of real use of self compacting concrete with sustainable aggregate, binder and powder. *Journal of cleaner production*, *325*, 129327. https://doi.org/10.1016/j.jclepro.2021.129327

[46] Rashid, K., Rehman, M. U., de Brito, J., & Ghafoor, H. (2020). Multi criteria optimization of recycled aggregate concrete mixes. *Journal of cleaner production*, *276*, 124316. https://doi.org/10.1016/j.jclepro.2020.124316

[47] Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, *8*(3), 338–353. http://dx.doi.org/10.1016/S0019-9958(65)90241-X

[48] Chen, T. Y. (2024). Circular intuitionistic fuzzy median ranking model with a novel scoring mechanism for multiple criteria decision analytics. *Applied artificial intelligence*, *38*(1), 2335416. https://doi.org/10.1080/08839514.2024.2335416

[49] Xu, Z., & Yager, R. R. (2006). Some geometric aggregation operators based on intuitionistic fuzzy sets. *International journal of general systems*, *35*(4), 417–433. https://doi.org/10.1080/03081070600574353

[50] Kahraman, C., & Otay, I. (2021). Extension of vikor method using circular intuitionistic fuzzy sets. *International conference on intelligent and fuzzy systems* (pp. 48–57). Springer. https://doi.org/10.1007/978-3-030-85577-2_6

[51] Wind, Y., & Saaty, T. L. (1980). Marketing applications of the analytic hierarchy process. *Management science*, *26*(7), 641–658. https://doi.org/10.1287/mnsc.26.7.641