

Article

A Novel Integrated Group Decision-Making Framework for Assessing Green Supply Chain Strategies Under Complex Uncertainty

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Abstract

Green supply chain management (GSCM) has become essential for organizations seeking to balance environmental sustainability, regulatory compliance, and economic resilience. However, selecting appropriate green supply chain strategies constitutes a complex multicriteria decision-making (MCDM) problem due to diverse sustainability practices, conflicting objectives, dynamic market conditions, and significant uncertainty in expert evaluations. To address these challenges, this study proposes an intelligent multicriteria group decision-making (MCGDM) framework to assess 15 GSCM strategies across 15 environmental, operational, economic, and regulatory criteria. The framework employs complex fractional orthopair fuzzy sets (C_{FOFS}) to model uncertainty, expert hesitation, and complex-valued judgments. Expert weights are determined using the analytic hierarchy process (AHP), while criteria weights are derived objectively through the entropy method. A modified technique for order preference by similarity to the ideal solution (TOPSIS) is applied to obtain a robust ranking of alternatives. Evaluations from five multidisciplinary experts ensure practical relevance and validity. The results indicate enhanced uncertainty modeling, improved ranking stability, and greater interpretability compared with conventional fuzzy and deterministic approaches. The proposed framework provides a transparent and effective decision support tool for strategic GSCM planning.

Keywords: fractional orthopair fuzzy set; TOPSIS method; entropy method; green supply chain management; sustainable decision-making



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1. Introduction

The growing global emphasis on environmental sustainability, climate change mitigation, and regulatory compliance has elevated the importance of green supply chain management (GSCM) as a strategic approach for sustainable industrial development [1].

GSCM integrates environmentally responsible practices across procurement, manufacturing, transportation, distribution, and end-of-life management to reduce carbon emissions, optimize resource utilization, and enhance operational efficiency [2]. Despite widespread adoption of strategies, such as green procurement, eco-friendly supplier selection, sustainable transportation, reverse logistics, and circular economy initiatives [3], evaluating and prioritizing these diverse strategies remains challenging due to differences in operational mechanisms [4], environmental impacts [5], economic implications [6], regulatory requirements [7], and implementation maturity [8]. Traditional single-factor or isolated managerial assessments are insufficient for such complex decisions [9]; instead, decision-makers must consider multiple environmental [10], operational [11], economic [12], and strategic criteria [13], including resource efficiency [8], energy consumption [14], flexibility [15], scalability [16], risk [17], and cost [18]. Multicriteria group decision-making (MCGDM) frameworks provide a structured and transparent approach for integrating expert judgments across these dimensions [19]. However, evaluations are inherently uncertain, as experts operate under incomplete performance data, dynamic market conditions, evolving regulations, and ambiguous environmental impacts. Variability in supplier behavior, demand, technology readiness, and policy enforcement further complicates the decision environment, making uncertainty, hesitation, and partial knowledge intrinsic to sustainable supply chain decision-making (GSDM).

In practical industrial settings, organizations must prioritize green supply chain strategies under constraints such as limited financial resources, regulatory requirements, and technological readiness [20]. Multiple initiatives ranging from green procurement and eco-friendly supplier collaboration to reverse logistics and circular economy practices offer varying environmental, operational, and economic benefits, as well as differing implementation costs and risks [21]. Evaluating these competing strategies simultaneously across multiple criteria, including environmental performance, operational feasibility, cost efficiency, and regulatory compliance, is inherently complex. Traditional decision-making (DM) approaches often fail to account for the uncertainty, incomplete information, and subjective expert judgments that characterize real-world sustainability assessments. Consequently, advanced MCGDM frameworks capable of integrating expert assessments and modeling uncertainty are essential for providing reliable, transparent, and actionable support in sustainable supply chain strategy selection.

Addressing uncertainty is critical for ensuring reliable, robust, and interpretable outcomes in green supply chain strategy evaluation [22]. Traditional decision models often fail to capture vague assessments, conflicting expert views, and incomplete information, which can lead to misleading rankings or misrepresentation of risk [23]. While fuzzy sets (FSs) [24] and their extensions, such as the intuitionistic fuzzy set (IFS) [25], the Pythagorean fuzzy set (PFS) [26,27], and q -rung orthopair fuzzy sets (q -ROFSs) [28], have improved the representation of uncertainty, these frameworks remain limited in handling complex, multi-dimensional, and fractional uncertainty patterns typical of real-world sustainability decisions. In particular, they struggle to accommodate subtle variations in expert hesitation, conflicting judgments, and complex-valued uncertainty arising in multicriteria green supply chain evaluations. These limitations motivate the need for a more generalized fuzzy framework capable of capturing magnitude, hesitation, and phase-based uncertainty simultaneously, providing a more flexible and accurate foundation for decision support in sustainability-oriented supply chain management.

To address the limitations of traditional fuzzy frameworks in capturing complex, multi-dimensional uncertainty, this study employs complex fractional orthopair fuzzy sets (C_{FOFS}), which enable simultaneous modeling of magnitude, hesitation, and phase-related uncertainty. Such capabilities are particularly relevant for evaluating green supply

chain strategies, where expert judgments are inherently uncertain, multi-dimensional, and often incomplete or ambiguous. Within the proposed framework, expert knowledge from sustainability management, industrial engineering, supply chain analytics, logistics, and environmental policy is incorporated using the AHP, ensuring structured and consistent weighting of interdisciplinary expertise. Complementarily, entropy-based criteria weighting is applied to objectively capture the importance of each criterion, balancing subjective judgments and enhancing evaluation reliability. Finally, TOPSIS is used to rank the candidate strategies based on their relative closeness to the ideal solution, providing clear, interpretable, and robust decision support for complex sustainability-oriented supply chain evaluations. Together, these components create a comprehensive, uncertainty-aware, and expert-driven framework that directly supports informed DM in green supply chain strategy selection.

1.1. Research Gap

Despite growing interest in green supply chain management, existing studies on strategy evaluation remain fragmented and methodologically limited. Many focus on conceptual discussions, isolated sustainability practices, or single case assessments rather than providing a structured, comparative evaluation of heterogeneous strategies. Existing MCDM and MCGDM approaches often rely on deterministic or classical fuzzy frameworks. Such frameworks are insufficient for capturing the high uncertainty, expert hesitation, and ambiguous information inherent in real-world green supply chain decisions, which are characterized by evolving regulations, market volatility, and incomplete performance data. While advanced fuzzy models have improved uncertainty representation, none have applied the most generalized C_{FOFS} framework for green supply chain evaluation. Additionally, prior research rarely combines scientifically grounded expert weighting with objective criteria weighting, and most frameworks lack an integrated architecture that model's uncertainty, fuses expert opinions, optimizes criterion significance, and produces interpretable rankings. This gap highlights the need for a comprehensive, uncertainty-aware, and expert-driven MCGDM framework, which is the focus of the present study, to support robust and actionable sustainability DM.

1.2. Motivation

The increasing emphasis on environmental sustainability, carbon neutrality, and regulatory compliance requires reliable, scientifically grounded tools for strategic DM in green supply chain management. Selecting optimal strategies is complex, involving uncertainty, incomplete data, and diverse expert judgments that are often linguistic or ambiguous. Traditional DM methods are inadequate for capturing such complexity, hesitation, and variability. The proposed C_{FOFS} -based MCGDM framework addresses these challenges by modeling magnitude, hesitation, and phase-related uncertainty, while integrating the AHP for expert weighting, entropy for objective criterion evaluation, and TOPSIS for transparent, robust ranking. This integrated approach provides a comprehensive, uncertainty-aware, and actionable decision support tool, enabling practitioners to identify strategies that balance environmental performance, operational feasibility, regulatory compliance, and long-term sustainability.

1.3. Contributions and Research Objectives

This study proposes a novel C_{FOFS} -based MCGDM framework for evaluating green supply chain strategies, addressing the limitations of existing fuzzy DM methods in handling multi-dimensional uncertainty, expert hesitation, and complex-valued assessments. The main contributions are summarized as follows:

- (1) Development of the C_{FOFS} model: Unlike prior complex fuzzy methods (C_{q-ROFS} [29], $C_{p,q-QOFS}$ [30]), C_{FOFS} integrates the complex fractional orthopair, MF and NMF, enabling simultaneous modeling of magnitude, phase, and subtle fractional hesitation. This allows more precise representation of heterogeneous expert judgments across multiple criteria.
- (2) Comprehensive mathematical framework: This study establishes operational laws, score and accuracy functions, and aggregation mechanisms for C_{FOFS} , supporting reliable fusion of expert evaluations and facilitating accurate comparison of green supply chain alternatives under uncertainty.
- (3) Integrated weighting and ranking mechanism: Expert importance is determined using the AHP, while entropy weights capture objective criterion significance, and TOPSIS ranks alternatives based on proximity to the ideal solution. This unified approach ensures transparent, consistent, and actionable decision support for sustainability-oriented strategy selection.
- (4) Practical novelty and applicability: Compared to existing methods, the proposed framework provides enhanced capability to model fractional uncertainty, complex phase information, and heterogeneous expert assessments, making it particularly suitable for real-world green supply chain DM. As illustrated in Table 1, C_{FOFS} delivers richer, more actionable evaluations than other complex fuzzy approaches, directly supporting informed and robust sustainability decisions.
- (5) Practical implications: From a practical perspective, the proposed framework provides a structured and reliable decision support tool for organizations involved in green supply chain management. It enables decision-makers to prioritize competing sustainability strategies under uncertainty, considering multiple conflicting criteria, such as environmental performance, cost, and regulatory compliance. By accurately modeling expert hesitation and complex uncertainty, the framework supports more realistic and transparent evaluations, reducing the risk of biased or oversimplified decisions. Furthermore, the integration of expert and objective weighting allows organizations to optimize resource allocation, improve sustainability planning, and enhance strategic DM in dynamic and uncertain environments.

Based on these contributions, the main research objectives are:

- To develop an intelligent C_{FOFS} -based MCGDM framework for evaluating green supply chain strategies under multi-dimensional uncertainty.
- To capture fractional and phase-based uncertainty in expert assessments using C_{FOFS} .
- To determine expert weights using the AHP and compute objective criteria weights using the entropy method.
- To apply TOPSIS to generate interpretable and actionable rankings of candidate green supply chain strategies.

Table 1. Comparison of the proposed C_{FOFS} model with existing fuzzy decision-making approaches.

Method	Membership Structure	Ability to Handle Hesitation	Parameter Flexibility	Complex/Phase Information	Applicability to Green Supply Chain Evaluation
C_{IFS} [31]	Complex MF and NMF	Moderate	No	Yes	Introduces phase modeling; partially suitable for sustainability decisions
C_{PFS} [32]	Complex MF and NMF	High	Limited	Yes	Improved uncertainty tolerance with phase info; partially applicable

Table 1. Cont.

Method	Membership Structure	Ability to Handle Hesitation	Parameter Flexibility	Complex/Phase Information	Applicability to Green Supply Chain Evaluation
C_{q-ROFS} [29]	Complex MF and NMF	High	Yes	Yes	Captures multi-dimensional uncertainty, but integer-powered q-rungs limit fine-grained hesitation modeling
$C_{p,q-QOFS}$ [30]	Complex MF and NMF	High	Yes	Yes	Allows flexible orthopair modeling across criteria; still constrained in representing fractional hesitation or subtle uncertainty
Proposed C_{FOFS}	Complex fractional orthopair MF and NMF	High	Yes	Yes	Integrates magnitude, phase, and fractional hesitation, enabling precise, multi-dimensional, and actionable evaluation of green supply chain strategies

The comparison in Table 1 illustrates that while complex fuzzy methods, such as C_{q-ROFS} and $C_{p,q-QOFS}$, improve the modeling of multi-dimensional uncertainty, their integer- or fixed-powered structures limit the ability to capture subtle, fractional variations in expert hesitation. In contrast, the proposed C_{FOFS} framework employs complex fractional orthopair, MF and NMF, providing fine-grained control over both magnitude and phase of uncertainty, and effectively integrating heterogeneous expert judgments across multiple criteria. This enhanced capability allows C_{FOFS} to deliver more accurate, reliable, and actionable evaluations of green supply chain strategies under real-world uncertainty, thus offering distinct practical advantages over closely related methods. Consequently, the framework not only advances methodological rigor but also strengthens the DM support for sustainability-oriented industrial planning.

1.4. Manuscript Structure

The remainder of this paper is organized as follows. Section 1 presents the introduction. Section 2 provides the necessary preliminaries related to the proposed framework. Section 3 outlines the proposed methodology along with all relevant theoretical components. Section 4 introduces the proposed MCGDM problem and elaborates on all procedural steps. Section 5 conducts a comprehensive sensitivity analysis, while Section 6 offers a comparative analysis with existing approaches. Finally, Section 7 concludes this paper and discusses the limitations and future research directions.

2. Preliminaries

In this section, we present the basic concept related to the proposed work.

Definition 1. [28] Let $\mathcal{U}$ be a universal set. IFS A can be defined as

$$A = \{\varepsilon, \Omega_A(\varepsilon), \mathcal{U}_A(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (1)$$

In Equation (1), $\Omega_A(\varepsilon), \mathcal{U}_A(\varepsilon)$ represent MF and NMF, respectively, having the condition $0 \leq \Omega_A(\varepsilon) + \mathcal{U}_A(\varepsilon) \leq 1$.

Definition 2. [31] Consider $\mathcal{U}$ to be a universal set. $C_{IFS} \bar{A}$ can be defined as

$$\bar{A} = \{\varepsilon, \Omega_{\bar{A}}(\varepsilon), \bar{U}_{\bar{A}}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (2)$$

where $\Omega_{\bar{A}}(\varepsilon) = \Omega_{\bar{A}_{IR}} e^{i2\Pi(\Omega_{\bar{A}_{IM}})}$ and $\bar{U}_{\bar{A}}(\varepsilon) = \bar{U}_{\bar{A}_{IR}} e^{i2\Pi(\bar{U}_{\bar{A}_{IM}})}$ represent MF and NMF, respectively, with the condition $0 \leq \Omega_{\bar{A}_{IR}}(\varepsilon) + \bar{U}_{\bar{A}_{IR}}(\varepsilon) \leq 1$ and $0 \leq \Omega_{\bar{A}_{IM}}(\varepsilon) + \bar{U}_{\bar{A}_{IM}}(\varepsilon) \leq 1$. The hesitancy can be expressed as $\pi_{\bar{A}}(\varepsilon) = (1 - \Omega_{\bar{A}_{IR}}(\varepsilon) - \bar{U}_{\bar{A}_{IR}}(\varepsilon)) e^{i2\Pi(1 - \Omega_{\bar{A}_{IM}}(\varepsilon) - \bar{U}_{\bar{A}_{IM}}(\varepsilon))}$.

Definition 3. [26] Let $\mathcal{U}$ be a universal set. PFS B can be expressed as

$$B = \{\varepsilon, \Omega_B(\varepsilon), \bar{U}_B(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (3)$$

In Equation (3), $\Omega_B(\varepsilon), \bar{U}_B(\varepsilon)$ represent MF and NMF, respectively, with the condition $0 \leq (\Omega_B(\varepsilon))^2 + (\bar{U}_B(\varepsilon))^2 \leq 1$.

Definition 4. [32] Let $\mathcal{U}$ be a universal set. $C_{PFS} \bar{B}$ can be defined as

$$\bar{B} = \{\varepsilon, \Omega_{\bar{B}}(\varepsilon), \bar{U}_{\bar{B}}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (4)$$

where $\Omega_{\bar{B}}(\varepsilon) = \Omega_{\bar{B}_{IR}} e^{i2\Pi(\Omega_{\bar{B}_{IM}})}$ and $\bar{U}_{\bar{B}}(\varepsilon) = \bar{U}_{\bar{B}_{IR}} e^{i2\Pi(\bar{U}_{\bar{B}_{IM}})}$ represent MF and NMF, respectively, with the condition $0 \leq (\Omega_{\bar{B}_{IR}}(\varepsilon))^2 + (\bar{U}_{\bar{B}_{IR}}(\varepsilon))^2 \leq 1$ and $0 \leq (\Omega_{\bar{B}_{IM}}(\varepsilon))^2 + (\bar{U}_{\bar{B}_{IM}}(\varepsilon))^2 \leq 1$. The hesitancy can be expressed as $\pi_{\bar{B}}(\varepsilon) = \sqrt{(1 - \Omega_{\bar{B}_{IR}}(\varepsilon) - \bar{U}_{\bar{B}_{IR}}(\varepsilon)) e^{i2\Pi(1 - \Omega_{\bar{B}_{IM}}(\varepsilon) - \bar{U}_{\bar{B}_{IM}}(\varepsilon))}}$.

Definition 5. [28] Consider $\mathcal{U}$ to be a universal set. q -ROFS Γ can be defined as

$$\Gamma = \{\varepsilon, \Omega_{\Gamma}(\varepsilon), \bar{U}_{\Gamma}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (5)$$

In Equation (5), $\Omega_{\Gamma}(\varepsilon), \bar{U}_{\Gamma}(\varepsilon)$ represent MF and NMF, respectively, with the condition $0 \leq (\Omega_{\Gamma}(\varepsilon))^q + (\bar{U}_{\Gamma}(\varepsilon))^q \leq 1$. Where q is the positive integer.

Definition 6. [29] Consider $\mathcal{U}$ be a universal set. $C_{q-ROFS} \bar{\Gamma}$ can be expressed as

$$\bar{\Gamma} = \{\varepsilon, \Omega_{\bar{\Gamma}}(\varepsilon), \bar{U}_{\bar{\Gamma}}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (6)$$

where $\Omega_{\bar{\Gamma}}(\varepsilon) = \Omega_{\bar{\Gamma}_{IR}} e^{i2\Pi(\Omega_{\bar{\Gamma}_{IM}})}$ and $\bar{U}_{\bar{\Gamma}}(\varepsilon) = \bar{U}_{\bar{\Gamma}_{IR}} e^{i2\Pi(\bar{U}_{\bar{\Gamma}_{IM}})}$ represent MF and NMF, respectively, with the condition $0 \leq (\Omega_{\bar{\Gamma}_{IR}}(\varepsilon))^q + (\bar{U}_{\bar{\Gamma}_{IR}}(\varepsilon))^q \leq 1$ and $0 \leq (\Omega_{\bar{\Gamma}_{IM}}(\varepsilon))^q + (\bar{U}_{\bar{\Gamma}_{IM}}(\varepsilon))^q \leq 1$. The hesitancy can be expressed as $\pi_{\bar{\Gamma}}(\varepsilon) = \sqrt[q]{(1 - (\Omega_{\bar{\Gamma}_{IR}}(\varepsilon))^q - (\bar{U}_{\bar{\Gamma}_{IR}}(\varepsilon))^q) e^{i2\Pi(1 - (\Omega_{\bar{\Gamma}_{IM}}(\varepsilon))^q - (\bar{U}_{\bar{\Gamma}_{IM}}(\varepsilon))^q)}}$, where q belongs to the positive integer.

Definition 7. [33] Let $\mathcal{U}$ be a universal set. (p, q) -QOFS Z can be defined as

$$Z = \{\varepsilon, \Omega_Z(\varepsilon), \bar{U}_Z(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (7)$$

In Equation (7), $\Omega_Z(\varepsilon), \bar{U}_Z(\varepsilon)$ represents MF and NMF, respectively, with the condition $0 \leq (\Omega_Z(\varepsilon))^p + (\bar{U}_Z(\varepsilon))^q \leq 1$, and the hesitancy function can be defined as $\pi_Z(\varepsilon) = \sqrt[r]{(1 - (\Omega_Z(\varepsilon))^p - (\bar{U}_Z(\varepsilon))^q)}$, where p, q are positive and $r = LCM(p, q)$.

Definition 8. [30] Consider $\mathcal{U}$ to be a universal set. $C_{(p,q)-QOFS} \bar{Z}$ can be defined as

$$\bar{Z} = \{\varepsilon, \Omega_{\bar{Z}}(\varepsilon), \mathcal{U}_{\bar{Z}}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (8)$$

In Equation (8), $\Omega_{\bar{Z}}(\varepsilon) = \Omega_{\bar{Z}_{IR}} e^{i2\Pi(\Omega_{\bar{Z}_{IM}})}$ and $\mathcal{U}_{\bar{Z}}(\varepsilon) = \mathcal{U}_{\bar{Z}_{IR}} e^{i2\Pi(\mathcal{U}_{\bar{Z}_{IM}})}$ represent MF and NMF, respectively, with the condition $0 \leq \left(\Omega_{\bar{Z}_{IR}}(\varepsilon)\right)^p + \left(\mathcal{U}_{\bar{Z}_{IR}}(\varepsilon)\right)^q \leq 1$ and $0 \leq \left(\Omega_{\bar{Z}_{IM}}(\varepsilon)\right)^p + \left(\mathcal{U}_{\bar{Z}_{IM}}(\varepsilon)\right)^q \leq 1$. The hesitancy can be expressed as $\pi_{\bar{Z}}(\varepsilon) = \sqrt[r]{1 - \left(\Omega_{\bar{Z}_{IR}}(\varepsilon)\right)^p - \left(\mathcal{U}_{\bar{Z}_{IR}}(\varepsilon)\right)^q} e^{i2\Pi(1 - (\Omega_{\bar{Z}_{IM}}(\varepsilon))^p - (\mathcal{U}_{\bar{Z}_{IM}}(\varepsilon))^q)}$, where p, q are the positive integers, while $r = LCM(p, q)$.

Definition 9. [34] Let $\mathcal{U}$ be a universal set. FOFS $\mathcal{F}$ can be defined as

$$\mathcal{F} = \{\varepsilon, \Omega_{\mathcal{F}}(\varepsilon), \mathcal{U}_{\mathcal{F}}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (9)$$

where $\Omega_{\mathcal{F}}(\varepsilon), \mathcal{U}_{\mathcal{F}}(\varepsilon)$ represent MF and NMF, respectively, having the condition $0 \leq (\Omega_{\mathcal{F}}(\varepsilon))^{p/q} + (\mathcal{U}_{\mathcal{F}}(\varepsilon))^{p/q} \leq 1$, and the hesitancy function can be defined as $\pi_{\mathcal{F}}(\varepsilon) = \left(1 - (\Omega_{\mathcal{F}}(\varepsilon))^{p/q} - (\mathcal{U}_{\mathcal{F}}(\varepsilon))^{p/q}\right)^{q/p}$, where p, q are positive integers such that $p \geq q$. For simplicity, the FOFS can be written as $\mathcal{F}_i = (\Omega_i, \mathcal{U}_i)$.

Definition 10. [34] Let $\mathcal{F}_1 = (\Omega_1, \mathcal{U}_1)$ and $\mathcal{F}_2 = (\Omega_2, \mathcal{U}_2)$ be any two FOFNs and $\lambda > 0$; then,

$$\begin{aligned} (1) \quad \mathcal{F}_1 \oplus \mathcal{F}_2 &= \left(\left(\Omega_1^{p/q} + \Omega_2^{p/q} - \Omega_1^{p/q} \Omega_2^{p/q} \right)^{q/p}, \mathcal{U}_1 \mathcal{U}_2 \right), \\ (2) \quad \mathcal{F}_1 \otimes \mathcal{F}_2 &= \left(\Omega_1 \Omega_2, \left(\mathcal{U}_1^{p/q} + \mathcal{U}_2^{p/q} - \mathcal{U}_1^{p/q} \mathcal{U}_2^{p/q} \right)^{q/p} \right), \\ (3) \quad \lambda \mathcal{F}_1 &= \left(\left(1 - \left(1 - \Omega_1^{p/q} \right)^\lambda \right)^{q/p}, \mathcal{U}_1^\lambda \right), \\ (4) \quad \mathcal{F}_1^\lambda &= \left(\Omega_1^\lambda, \left(1 - \left(1 - \mathcal{U}_1^{p/q} \right)^\lambda \right)^{q/p} \right). \end{aligned}$$

Definition 11. [34] Consider two FOFNs such that $\mathcal{F}_1 = (\Omega_1, \mathcal{U}_1)$ and $\mathcal{F}_2 = (\Omega_2, \mathcal{U}_2)$, and λ_1, λ_2 and λ_3 are positive real numbers, and then the following properties are satisfied:

$$\begin{aligned} (1) \quad \mathcal{F}_1 \oplus \mathcal{F}_2 &= \mathcal{F}_2 \oplus \mathcal{F}_1, \\ (2) \quad \lambda_1(\mathcal{F}_1 \otimes \mathcal{F}_2) &= \lambda_1 \mathcal{F}_2 \otimes \lambda_1 \mathcal{F}_1, \\ (3) \quad \mathcal{F}_1(\lambda_1 \oplus \lambda_2) &= \lambda_1 \mathcal{F}_1 \oplus \lambda_2 \mathcal{F}_1, \\ (4) \quad (\mathcal{F}_1 \otimes \mathcal{F}_2)^{\lambda_1} &= \mathcal{F}_1^{\lambda_1} \otimes \mathcal{F}_2^{\lambda_1}, \\ (5) \quad \mathcal{F}_1^{\lambda_1 + \lambda_2} &= \mathcal{F}_1^{\lambda_1} \otimes \mathcal{F}_2^{\lambda_1}. \end{aligned}$$

Definition 12. If we take $\mathcal{F} = (\Omega, \mathcal{U})$ as the FOFN, then the score function $S_c(\mathcal{F})$ of $\mathcal{F}$ can be defined as

$$S_c(\mathcal{F}) = \frac{1 + \Omega^{p/q} - \mathcal{U}^{p/q}}{2}. \quad (10)$$

3. Proposed Work

In this section, we introduce the foundational concepts underlying the proposed framework, including the fundamental operations, as well as the score and accuracy functions. Furthermore, we develop a set of aggregation operators designed to effectively integrate the information within the C_{FOFS} .

Definition 13. Let $\mathcal{U}$ be a universal set. $C_{FOFS} \bar{\mathcal{F}}$ can be expressed as

$$\bar{\mathcal{F}} = \{\varepsilon, \Omega_{\bar{\mathcal{F}}}(\varepsilon), \mathcal{U}_{\bar{\mathcal{F}}}(\varepsilon) | \varepsilon \in \mathcal{U}\} \quad (11)$$

In Equation (11), $\Omega_{\bar{\mathcal{F}}}(\varepsilon) = \Omega_{\bar{\mathcal{F}}_{IR}} e^{i2\Pi(\Omega_{\bar{\mathcal{F}}_{IM}})}$ and $\mathcal{U}_{\bar{\mathcal{F}}}(\varepsilon) = \mathcal{U}_{\bar{\mathcal{F}}_{IR}} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM}})}$ represent MF and NMF, respectively, having the condition $0 \leq \left(\Omega_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} \leq 1$ and $0 \leq \left(\Omega_{\bar{\mathcal{F}}_{IM}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM}}(\varepsilon)\right)^{p/q} \leq 1$. The hesitancy can be expressed as $\pi_{\bar{\mathcal{F}}}(\varepsilon) = \left(1 - \left(\Omega_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} - \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q}\right)^{q/p} e^{i2\Pi(1 - (\Omega_{\bar{\mathcal{F}}_{IM}}(\varepsilon))^{p/q} - (\mathcal{U}_{\bar{\mathcal{F}}_{IM}}(\varepsilon))^{p/q})}$, where p and q are positive integers such that $p \geq q$. For simplicity, the FOFS can be written as $\bar{\mathcal{F}}_i = \left(\Omega_{IR_i} e^{i2\Pi(\Omega_{IM_i})}, \mathcal{U}_{IR_i} e^{i2\Pi(\mathcal{U}_{IM_i})}\right)$. The parameters p and q control the flexibility of the orthopair space and generalize several existing fuzzy models.

Remark 1. Suppose that we want to determine the minimum values of p and q for some specific structure $\left(\Omega_{\bar{\mathcal{F}}_{IR}} e^{i2\Pi(\Omega_{\bar{\mathcal{F}}_{IM}})}, \mathcal{U}_{\bar{\mathcal{F}}_{IR}} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM}})}\right)$, such that $0 \leq \left(\Omega_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} \leq 1$ and $0 \leq \left(\Omega_{\bar{\mathcal{F}}_{IM}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM}}(\varepsilon)\right)^{p/q} \leq 1$. Even though there might not be a closed-form solution for specific problems, iterative computation methods can always provide a unique response. The lowest values of p and q that satisfy these requirements are defined as $0 \leq \left(\Omega_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR}}(\varepsilon)\right)^{p/q} \leq 1$ and $0 \leq \left(\Omega_{\bar{\mathcal{F}}_{IM}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM}}(\varepsilon)\right)^{p/q} \leq 1$.

The parameters p and q in the C_{FOFS} framework act as control factors that regulate the influence of MF, NMF, and the hesitation degrees in the DM process. These parameters provide flexibility in modeling uncertainty and allow the decision system to adapt to different evaluation environments. The selection of p and q can be determined based on expert knowledge, empirical data analysis, or optimization techniques, depending on the nature of the decision problem. Generally, a higher value of p increases the influence of the membership information and highlights the effectiveness of alternatives, whereas a higher value of q strengthens the role of non-membership information and emphasizes risk mitigation. Therefore, the parameters p and q can be adjusted dynamically in practical applications to reflect different DM preferences and uncertainty levels, which enhances the flexibility and applicability of the proposed C_{FOFS} model.

Example 1. Let us consider two C_{FOFS} s, $\bar{\mathcal{F}}_1 = (0.60e^{i2\Pi(0.20)}, 0.30e^{i2\Pi(0.25)})$, $\bar{\mathcal{F}}_2 = (0.55e^{i2\Pi(0.18)}, 0.35e^{i2\Pi(0.22)})$, take $p = 2$ and $q = 1$, and then we have $(0.60)^2 + (0.30)^2 = 0.36 + 0.09 = 0.45 \leq 1$, which confirms the validity of the C_{FOFS} representation.

Definition 14. Consider $\bar{\mathcal{F}}_1 = (\Omega_{IR_1} e^{i2\Pi(\Omega_{IM_1})}, \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_1})})$ and $\bar{\mathcal{F}}_2 = (\Omega_{IR_2} e^{i2\Pi(\Omega_{IM_2})}, \mathcal{U}_{IR_2} e^{i2\Pi(\mathcal{U}_{IM_2})})$ to be two FOFSs and $\xi > 0$ to be any positive real number; then,

$$\begin{aligned} (1) \quad \bar{\mathcal{F}}_1 \oplus \bar{\mathcal{F}}_2 &= \left(\left(\Omega_{IR_1}^{p/q} + \Omega_{IR_2}^{p/q} - \Omega_{IR_1}^{p/q} \Omega_{IR_2}^{p/q} \right)^{q/p} e^{i2\Pi \left(\left(\Omega_{IM_1}^{p/q} + \Omega_{IM_2}^{p/q} - \Omega_{IM_1}^{p/q} \Omega_{IM_2}^{p/q} \right)^{q/p} \right)}, \mathcal{U}_{IR_1} \mathcal{U}_{IR_2} e^{i2\Pi(\mathcal{U}_{IM_1} \mathcal{U}_{IM_2})} \right), \\ (2) \quad \bar{\mathcal{F}}_1 \otimes \bar{\mathcal{F}}_2 &= \left(\Omega_{IR_1} \Omega_{IR_2} e^{i2\Pi(\Omega_{IM_1} \Omega_{IM_2})}, \left(\mathcal{U}_{IR_1}^{p/q} + \mathcal{U}_{IR_2}^{p/q} - \mathcal{U}_{IR_1}^{p/q} \mathcal{U}_{IR_2}^{p/q} \right)^{q/p} e^{i2\Pi \left(\left(\mathcal{U}_{IM_1}^{p/q} + \mathcal{U}_{IM_2}^{p/q} - \mathcal{U}_{IM_1}^{p/q} \mathcal{U}_{IM_2}^{p/q} \right)^{q/p} \right)} \right), \end{aligned}$$

$$\begin{aligned}
 (3) \quad \xi \bar{\mathcal{F}}_1 &= \left(\left(1 - \left(1 - \Omega_{IR_1}^{p/q} \right)^\xi \right)^{q/p} e^{i2\Pi \left(1 - \left(1 - \Omega_{IM_1}^{p/q} \right)^\xi \right)^{q/p}}, \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_1})} \right), \\
 (4) \quad \bar{\mathcal{F}}_1^\xi &= \left(\Omega_{IR_1} e^{i2\Pi(\Omega_{IM_1})}, \left(1 - \left(1 - \mathcal{U}_{IR_1}^{p/q} \right)^\xi \right)^{q/p} e^{i2\Pi \left(1 - \left(1 - \mathcal{U}_{IM_1}^{p/q} \right)^\xi \right)^{q/p}} \right), \\
 (5) \quad \bar{\mathcal{F}}_1 \cup \bar{\mathcal{F}}_2 &= \left(\max(\Omega_{1IR}, \Omega_{2IR}) e^{i2\Pi(\max(\Omega_{1IM}, \Omega_{2IM}))}, \min(\mathcal{U}_{1IR}, \mathcal{U}_{2IR}) e^{i2\Pi(\min(\mathcal{U}_{1IM}, \mathcal{U}_{2IM}))} \right), \\
 (6) \quad \bar{\mathcal{F}}_1 \cap \bar{\mathcal{F}}_2 &= \left(\min(\Omega_{1IR}, \Omega_{2IR}) e^{i2\Pi(\min(\Omega_{1IM}, \Omega_{2IM}))}, \max(\mathcal{U}_{1IR}, \mathcal{U}_{2IR}) e^{i2\Pi(\max(\mathcal{U}_{1IM}, \mathcal{U}_{2IM}))} \right), \\
 (7) \quad \bar{\mathcal{F}}_1^c &= \left((\mathcal{U}_{IR_1}, \Omega_{IR_1}) e^{i2\Pi(\mathcal{U}_{IM_1}, \Omega_{IM_1})} \right).
 \end{aligned}$$

Definition 15. Let $\bar{\mathcal{F}}_1 = (\Omega_{IR_1} e^{i2\Pi(\Omega_{IM_1})}, \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_1})})$ be an FOFN; then, the $\mathcal{S}_C(\bar{\mathcal{F}})$ can be defined as

$$\mathcal{S}_C(\bar{\mathcal{F}}) = \frac{1 + \Omega_{IR}^{p/q} + \Omega_{IM}^{p/q} - \mathcal{U}_{IR}^{p/q} - \mathcal{U}_{IM}^{p/q}}{2} \quad (12)$$

where $0 \leq \mathcal{S}_C(\bar{\mathcal{F}}) \leq 1$.

Definition 16. Assume $\bar{\mathcal{F}}_1 = (\Omega_{IR_1} e^{i2\Pi(\Omega_{IM_1})}, \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_1})})$ to be an FOFN; then, the $\mathcal{A}_C(\bar{\mathcal{F}})$ can be defined as

$$\mathcal{A}_C(\bar{\mathcal{F}}) = \frac{\Omega_{IR}^{p/q} + \Omega_{IM}^{p/q} + \mathcal{U}_{IR}^{p/q} + \mathcal{U}_{IM}^{p/q}}{2} \quad (13)$$

where $0 \leq \mathcal{A}_C(\bar{\mathcal{F}}) \leq 1$.

Definition 17. Consider any two FOFNs, $\bar{\mathcal{F}}_1$ and $\bar{\mathcal{F}}_2$. Based on the defined score and accuracy functions, the following properties are satisfied:

- (1) If $\mathcal{A}_C(\bar{\mathcal{F}}_1) < \mathcal{A}_C(\bar{\mathcal{F}}_2) \Rightarrow \bar{\mathcal{F}}_1 < \bar{\mathcal{F}}_2$,
- (2) If $\mathcal{A}_C(\bar{\mathcal{F}}_1) > \mathcal{A}_C(\bar{\mathcal{F}}_2) \Rightarrow \bar{\mathcal{F}}_1 > \bar{\mathcal{F}}_2$,
- (3) If $\mathcal{A}_C(\bar{\mathcal{F}}_1) = \mathcal{A}_C(\bar{\mathcal{F}}_2) \Rightarrow \bar{\mathcal{F}}_1 = \bar{\mathcal{F}}_2$,
- (4) If $\mathcal{S}_C(\bar{\mathcal{F}}_1) < \mathcal{S}_C(\bar{\mathcal{F}}_2) \Rightarrow \bar{\mathcal{F}}_1 < \bar{\mathcal{F}}_2$,
- (5) If $\mathcal{S}_C(\bar{\mathcal{F}}_1) > \mathcal{S}_C(\bar{\mathcal{F}}_2) \Rightarrow \bar{\mathcal{F}}_1 > \bar{\mathcal{F}}_2$,
- (6) $\mathcal{S}_C(\bar{\mathcal{F}}_1) = \mathcal{S}_C(\bar{\mathcal{F}}_2) \Rightarrow \bar{\mathcal{F}}_1 = \bar{\mathcal{F}}_2$.

Theorem 1. Let $\bar{\mathcal{F}}_1 = (\Omega_{IR_1} e^{i2\Pi(\Omega_{IM_1})}, \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_1})})$ and $\bar{\mathcal{F}}_2 = (\Omega_{IR_2} e^{i2\Pi(\Omega_{IM_2})}, \mathcal{U}_{IR_2} e^{i2\Pi(\mathcal{U}_{IM_2})})$ be two FOFNs and ξ_1, ξ_2 and ξ_3 be any positive real number; then,

- (1) $\bar{\mathcal{F}}_1 \oplus \bar{\mathcal{F}}_2 = \bar{\mathcal{F}}_2 \oplus \bar{\mathcal{F}}_1$,
- (2) $\bar{\mathcal{F}}_1 \otimes \bar{\mathcal{F}}_2 = \bar{\mathcal{F}}_2 \otimes \bar{\mathcal{F}}_1$,
- (3) $\xi_1(\bar{\mathcal{F}}_1 \oplus \bar{\mathcal{F}}_2) = \xi_1 \bar{\mathcal{F}}_2 \oplus \xi_1 \bar{\mathcal{F}}_1$,
- (4) $\bar{\mathcal{F}}_1(\xi_1 \oplus \xi_2) = \xi_1 \bar{\mathcal{F}}_1 \oplus \xi_2 \bar{\mathcal{F}}_1$,
- (5) $(\bar{\mathcal{F}}_1 \otimes \bar{\mathcal{F}}_2)^{\xi_1} = \bar{\mathcal{F}}_1^{\xi_1} \otimes \bar{\mathcal{F}}_2^{\xi_1}$,
- (6) $\bar{\mathcal{F}}_1^{\xi_1} \otimes \bar{\mathcal{F}}_1^{\xi_1} = \bar{\mathcal{F}}_1^{\xi_1 + \xi_1}$.

Proof. By utilizing definition 14 to proof theorem 1, we obtain $\bar{\mathcal{F}}_1 = (\Omega_{IR_1} e^{i2\Pi(\Omega_{IM_1})}, \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_1})})$ and $\bar{\mathcal{F}}_2 = (\Omega_{IR_2} e^{i2\Pi(\Omega_{IM_2})}, \mathcal{U}_{IR_2} e^{i2\Pi(\mathcal{U}_{IM_2})})$,

$$\begin{aligned}\bar{\mathcal{F}}_1 \oplus \bar{\mathcal{F}}_2 &= \left(\left(\Omega_{IR_1}^{p/q} + \Omega_{IR_2}^{p/q} - \Omega_{IR_1}^{p/q} \Omega_{IR_2}^{p/q} \right)^{q/p} e^{i2\Pi \left(\left(\Omega_{IM_1}^{p/q} + \Omega_{IM_2}^{p/q} - \Omega_{IM_1}^{p/q} \Omega_{IM_2}^{p/q} \right)^{q/p} \right)}, \mathcal{U}_{IR_1} \mathcal{U}_{IR_2} e^{i2\Pi(\mathcal{U}_{IM_1} \mathcal{U}_{IM_2})} \right), \\ &= \left(\left(\Omega_{IR_2}^{p/q} + \Omega_{IR_1}^{p/q} - \Omega_{IR_2}^{p/q} \Omega_{IR_1}^{p/q} \right)^{q/p} e^{i2\Pi \left(\left(\Omega_{IM_2}^{p/q} + \Omega_{IM_1}^{p/q} - \Omega_{IM_2}^{p/q} \Omega_{IM_1}^{p/q} \right)^{q/p} \right)}, \mathcal{U}_{IR_2} \mathcal{U}_{IR_1} e^{i2\Pi(\mathcal{U}_{IM_2} \mathcal{U}_{IM_1})} \right), \\ &= \bar{\mathcal{F}}_2 \oplus \bar{\mathcal{F}}_1.\end{aligned}$$

In the same way,

$$\begin{aligned}\bar{\mathcal{F}}_1 \otimes \bar{\mathcal{F}}_2 &= \left(\Omega_{IR_1} \Omega_{IR_2} e^{i2\Pi(\Omega_{IM_1} \Omega_{IM_2})}, \left(\mathcal{U}_{IR_1}^{p/q} + \mathcal{U}_{IR_2}^{p/q} - \mathcal{U}_{IR_1}^{p/q} \mathcal{U}_{IR_2}^{p/q} \right)^{q/p} e^{i2\Pi \left(\mathcal{U}_{IM_1}^{p/q} + \mathcal{U}_{IM_2}^{p/q} - \mathcal{U}_{IM_1}^{p/q} \mathcal{U}_{IM_2}^{p/q} \right)^{q/p}} \right), \\ &= \left(\Omega_{IR_2} \Omega_{IR_1} e^{i2\Pi(\Omega_{IM_2} \Omega_{IM_1})}, \left(\mathcal{U}_{IR_2}^{p/q} + \mathcal{U}_{IR_1}^{p/q} - \mathcal{U}_{IR_2}^{p/q} \mathcal{U}_{IR_1}^{p/q} \right)^{q/p} e^{i2\Pi \left(\mathcal{U}_{IM_2}^{p/q} + \mathcal{U}_{IM_1}^{p/q} - \mathcal{U}_{IM_2}^{p/q} \mathcal{U}_{IM_1}^{p/q} \right)^{q/p}} \right), \\ &= \bar{\mathcal{F}}_2 \otimes \bar{\mathcal{F}}_1.\end{aligned}$$

□

In the same way, we can prove the remaining part of the theorem.

3.1. Aggregation Operators in the C_{FOFS} Framework

In this section, we present a set of aggregation operators (AOs) specifically developed for the C_{FOFS} framework. These operators extend existing FOFS operators into the complex domain, introducing new theoretical properties that allow for more effective modeling of uncertainty. They are designed to combine and process information represented by complex FOFSs while preserving the essential characteristics of MF, NMF, and hesitancy. Moreover, the proposed operators integrate score and accuracy functions to ensure robust and reliable decision-making in a fuzzy environment.

Definition 18. Let $\bar{\mathcal{F}}_i = \left(\Omega_{IR_i} e^{i2\Pi(\Omega_{IM_i})}, \mathcal{U}_{IR_i} e^{i2\Pi(\mathcal{U}_{IM_i})} \right)$, for $(i = 1, 2, \dots, n)$, represent a collection of n C_{FOFS} . Then, the n C_{FOF} –WA operator can be defined as follows:

$$C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) = \oplus_{i=1}^n \omega_i \bar{\mathcal{F}}_i \quad (14)$$

In Equation (14), ω_i represents the weight of ω^{th} of the C_{FOFS} . Here, $\omega_i \in [0, 1]$ and $\sum_{i=1}^n \omega_i = 1$.

Theorem 2. The result obtained from the C_{FOF} –WA operator is itself a C_{FOF} –WA and can be expressed as follows:

$$\begin{aligned}C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) &= \\ &\left(\left(1 - \prod_{i=1}^n \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q} \right)^{\omega_i} \right)^{q/p} e^{i2\Pi \left(1 - \prod_{i=1}^n \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q} \right)^{\omega_i} \right)^{q/p}}, \prod_{i=1}^n \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i} \right)} \right),\end{aligned}$$

Proof. To prove the theorem, we employ the method of mathematical induction.

Step 1. For $i = 2$,

Step 1. For $\alpha = 2$, the result implies that $C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2) = \oplus_{i=1}^2 \omega_i \bar{\mathcal{F}}_i = \omega_1 \bar{\mathcal{F}}_1 \oplus \omega_2 \bar{\mathcal{F}}_2$,

$$\begin{aligned}
 &= \left(\left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_1}}^{p/q} \right)^{\omega_1} \right)^{q/p} e^{i2\Pi \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_1}}^{p/q} \right)^{\omega_1} \right)^{q/p}}, \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_2}}^{p/q} \right)^{\omega_2} \right)^{q/p} e^{i2\Pi \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_2}}^{p/q} \right)^{\omega_2} \right)^{q/p}} \right) \\
 &\quad \oplus \left(\left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_1}}^{p/q} \right)^{\omega_1} \right)^{q/p} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_1}}^{\omega_1} \right)}, \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_2}}^{p/q} \right)^{\omega_2} \right)^{q/p} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_2}}^{\omega_2} \right)} \right) \\
 &= \left(\left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_1}}^{p/q} - \Omega_{\bar{\mathcal{F}}_{IR_2}}^{p/q} \right)^{\omega_1} \right)^{q/p} e^{i2\Pi \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_1}}^{p/q} - \Omega_{\bar{\mathcal{F}}_{IM_2}}^{p/q} \right)^{\omega_1} \right)^{q/p}}, \mathcal{U}_{\bar{\mathcal{F}}_{IR_1}}^{\omega_1} \mathcal{U}_{\bar{\mathcal{F}}_{IR_2}}^{\omega_2} e^{i2\Pi \left(\left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_1}}^{\omega_1} \right) \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_2}}^{\omega_2} \right) \right)} \right) \\
 &= \left(\left(1 - \prod_{x=1}^2 \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_x}}^{p/q} \right)^{\omega_i} \right)^{q/p} e^{i2\Pi \left(1 - \prod_{x=1}^2 \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_x}}^{p/q} \right)^{\omega_i} \right)^{q/p}}, \mathcal{U}_{\bar{\mathcal{F}}_{IR_1}}^{\omega_1} \mathcal{U}_{\bar{\mathcal{F}}_{IR_2}}^{\omega_2} e^{i2\Pi \left(\left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_1}}^{\omega_1} \right) \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_2}}^{\omega_2} \right) \right)} \right)
 \end{aligned}$$

Hence the result is true for $n = 2$.

Step 2. Let the results be true for $n = \zeta$; then, we have

$$C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_\zeta) = \left(\left(1 - \prod_{i=1}^\zeta \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q} \right)^{\omega_i} \right)^{q/p} e^{i2\Pi \left(1 - \prod_{i=1}^\zeta \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q} \right)^{\omega_i} \right)^{q/p}}, \prod_{i=1}^\zeta \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i} \right)} \right)$$

Step 3. For $i = \zeta + 1$, $C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2) = \oplus_{i=1}^\zeta \omega_i \bar{\mathcal{F}}_i \oplus \omega_{\zeta+1} \bar{\mathcal{F}}_{\zeta+1}$

$$\begin{aligned}
 &= \left(\left(\left(1 - \prod_{i=1}^\zeta \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q} \right)^{\omega_i} \right)^{q/p} e^{i2\Pi \left(1 - \prod_{i=1}^\zeta \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q} \right)^{\omega_i} \right)^{q/p}} \right), \prod_{i=1}^\zeta \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i} \right)} \right) \\
 &\quad \oplus \left(\left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_{\zeta+1}}}^{p/q} \right)^{\omega_{\zeta+1}} \right)^{q/p} e^{i2\Pi \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_{\zeta+1}}}^{p/q} \right)^{\omega_{\zeta+1}} \right)^{q/p}}, \mathcal{U}_{\bar{\mathcal{F}}_{IR_{\zeta+1}}}^{\omega_{\zeta+1}} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_{\zeta+1}}}^{\omega_{\zeta+1}} \right)} \right) \\
 &= \left(\left(1 - \prod_{i=1}^{\zeta+1} \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q} \right)^{\omega_i} \right)^{q/p} e^{i2\Pi \left(1 - \prod_{i=1}^{\zeta+1} \left(1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q} \right)^{\omega_i} \right)^{q/p}}, \prod_{i=1}^{\zeta+1} \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi \left(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i} \right)} \right)
 \end{aligned}$$

Therefore, we conclude that the result holds for $n = \zeta + 1$. By the principle of mathematical induction, it is consequently valid for all natural numbers. $\square$

Theorem 3. Let $\bar{\mathcal{F}}_i = \left(\Omega_{IR_i} e^{i2\Pi(\Omega_{IM_i})}, \mathcal{U}_{IR_i} e^{i2\Pi(\mathcal{U}_{IM_i})} \right)$, for $(i = 1, 2, \dots, n)$, represent a collection of n C_{FOFS} . Consider $\bar{\mathcal{F}}^- = \min(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n)$ and $\bar{\mathcal{F}}^+ = \max(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n)$; then, $\bar{\mathcal{F}}^- \leq C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) \leq \bar{\mathcal{F}}^+$.

Proof. The proof is straightforward. $\square$

Definition 19. Let $\bar{\mathcal{F}}_i = \left(\Omega_{IR_i} e^{i2\Pi(\Omega_{IM_i})}, \mathcal{U}_{IR_i} e^{i2\Pi(\mathcal{U}_{IM_i})} \right)$, for $(i = 1, 2, \dots, n)$, represent a collection of n C_{FOFNS} . Then, the n $C_{FOF} - OWA$ operator can be defined as follows:

$$C_{FOF} - OWA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) = \oplus_{i=1}^n \bar{\mathcal{F}}_i^{\omega_i} \quad (15)$$

In Equation (15), ω_i represents the weight of ω^{th} of the C_{FOFS} . Here, $\omega_i \in [0, 1]$ and $\sum_{i=1}^n \omega_i = 1$.

Theorem 4. For C_{FOFNs} , the results produced by the C_{FOF} –WG operator can be expressed as follows:

$$C_{FOF} - OWA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) = \left(\prod_{i=1}^n \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i})}, \left(1 - \prod_{i=1}^n \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q}\right)^{\omega_i}\right)^{q/p} e^{i2\Pi(1 - \prod_{i=1}^n (1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q})^{\omega_i})^{q/p}} \right) \quad (16)$$

Proof. We proved the theorem by using mathematical induction methods.

Step 1. For $i = 2$, the result implies that $C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2) = \otimes_{i=1}^2 \bar{\mathcal{F}}_1^{\omega_1} \otimes \bar{\mathcal{F}}_2^{\omega_2}$,

$$\begin{aligned} &= \left(\left(\mathcal{U}_{\bar{\mathcal{F}}_{IR_1}}^{\omega_1} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_1}}^{\omega_1})}, \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_1}}^{p/q}\right)^{\omega_1}\right)^{q/p} e^{i2\Pi(1 - (1 - \Omega_{\bar{\mathcal{F}}_{IM_1}}^{p/q})^{\omega_1})^{q/p}} \right) \otimes \right. \\ &\quad \left. \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR_2}}^{\omega_2} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_2}}^{\omega_2})}, \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_2}}^{p/q}\right)^{\omega_2}\right)^{q/p} e^{i2\Pi(1 - (1 - \Omega_{\bar{\mathcal{F}}_{IM_2}}^{p/q})^{\omega_2})^{q/p}} \right) \right), \\ &= \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR_1}}^{\omega_1} \mathcal{U}_{\bar{\mathcal{F}}_{IR_2}}^{\omega_2} e^{i2\Pi((\mathcal{U}_{\bar{\mathcal{F}}_{IM_1}}^{\omega_1})(\mathcal{U}_{\bar{\mathcal{F}}_{IM_2}}^{\omega_2}))}, \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_1}}^{p/q}\right)^{\omega_1} \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_2}}^{p/q}\right)^{\omega_2}\right)^{q/p} \right)^{q/p} e^{i2\Pi(1 - (1 - \Omega_{\bar{\mathcal{F}}_{IM_1}}^{p/q})^{\omega_1} (1 - (1 - \Omega_{\bar{\mathcal{F}}_{IM_2}}^{p/q})^{\omega_2})^{q/p})^{q/p}} \right), \\ &= \left(\prod_{i=1}^2 \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i})}, \left(1 - \prod_{i=1}^2 \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q}\right)^{\omega_i}\right)^{q/p} e^{i2\Pi(1 - \prod_{i=1}^2 (1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q})^{\omega_i})^{q/p}} \right), \end{aligned}$$

The result is true for $n = 2$.

Step 2. Let the results be true for $n = \zeta$; then, we have

$$C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_\zeta) = \left(\prod_{i=1}^\zeta \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i})}, \left(1 - \prod_{i=1}^\zeta \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q}\right)^{\omega_i}\right)^{q/p} e^{i2\Pi(1 - \prod_{i=1}^\zeta (1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q})^{\omega_i})^{q/p}} \right),$$

Step 3. For $i = \zeta + 1$, $C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2) = \otimes_{i=1}^\zeta \omega_i \bar{\mathcal{F}}_i \otimes \omega_{\zeta+1} \bar{\mathcal{F}}_{\zeta+1}$

$$\begin{aligned} &= \left(\left(\prod_{i=1}^\zeta \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i})}, \left(1 - \prod_{i=1}^\zeta \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q}\right)^{\omega_i}\right)^{q/p} e^{i2\Pi(1 - \prod_{i=1}^\zeta (1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q})^{\omega_i})^{q/p}} \right) \right. \\ &\quad \left. \otimes \left(\mathcal{U}_{\bar{\mathcal{F}}_{IR_{\zeta+1}}}^{\omega_{\zeta+1}} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_{\zeta+1}}}^{\omega_{\zeta+1}})}, \left(1 - \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_{\zeta+1}}}^{p/q}\right)^{\omega_{\zeta+1}}\right)^{q/p} e^{i2\Pi(1 - (1 - \Omega_{\bar{\mathcal{F}}_{IM_{\zeta+1}}}^{p/q})^{\omega_{\zeta+1}})^{q/p}} \right) \right), \\ &= \left(\prod_{i=1}^{\zeta+1} \mathcal{U}_{\bar{\mathcal{F}}_{IR_i}}^{\omega_i} e^{i2\Pi(\mathcal{U}_{\bar{\mathcal{F}}_{IM_i}}^{\omega_i})}, \left(1 - \prod_{i=1}^{\zeta+1} \left(1 - \Omega_{\bar{\mathcal{F}}_{IR_i}}^{p/q}\right)^{\omega_i}\right)^{q/p} e^{i2\Pi(1 - \prod_{i=1}^{\zeta+1} (1 - \Omega_{\bar{\mathcal{F}}_{IM_i}}^{p/q})^{\omega_i})^{q/p}} \right), \end{aligned}$$

Therefore, we conclude that the result holds for $n = \zeta + 1$. By the principle of mathematical induction, it is consequently valid for all-natural numbers. $\square$

Theorem 5. Let $\bar{\mathcal{F}}_i = \left(\Omega_{IR_{\bar{\mathcal{F}}_i}} e^{i2\Pi\left(\Omega_{IM_{\bar{\mathcal{F}}_i}}\right)}, \mathcal{U}_{IR_{\bar{\mathcal{F}}_i}} e^{i2\Pi\left(\mathcal{U}_{IM_{\bar{\mathcal{F}}_i}}\right)} \right)$, and $\tilde{\mathcal{F}}_i = \left(\Omega_{IR_{\tilde{\mathcal{F}}_i}} e^{i2\Pi\left(\Omega_{IM_{\tilde{\mathcal{F}}_i}}\right)}, \mathcal{U}_{IR_{\tilde{\mathcal{F}}_i}} e^{i2\Pi\left(\mathcal{U}_{IM_{\tilde{\mathcal{F}}_i}}\right)} \right)$ be two C_{FOFNs} . If $\bar{\mathcal{F}}_i \leq \tilde{\mathcal{F}}_i$ for all values of i , then $C_{FOF} - WA(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) \leq C_{FOF} - WA(\tilde{\mathcal{F}}_1, \tilde{\mathcal{F}}_2, \dots, \tilde{\mathcal{F}}_n)$ and $C_{FOF} - WG(\bar{\mathcal{F}}_1, \bar{\mathcal{F}}_2, \dots, \bar{\mathcal{F}}_n) \leq C_{FOF} - WG(\tilde{\mathcal{F}}_1, \tilde{\mathcal{F}}_2, \dots, \tilde{\mathcal{F}}_n)$.

Proof. The proof is straightforward. $\square$

3.2. Proposed MCGDM Approach for the C_{FOF} Framework

The overall decision-making process of the proposed framework follows a structured MCGDM procedure integrating the AHP, entropy weighting, and TOPSIS within the C_{FOFS} environment. The framework is designed to evaluate multiple green supply chain strategies under uncertainty while incorporating both expert judgments and objective data characteristics. Initially, the relevant decision criteria and candidate strategies are identified based on the literature review and expert consultation. Subsequently, expert weights are determined using the AHP method through pairwise comparisons, ensuring the reliability and consistency of expert influence in the group decision-making process. After determining expert weights, the entropy weighting method is employed to calculate objective importance values for the evaluation criteria by analyzing the dispersion of information in the decision matrix. This step helps reduce subjective bias in the weighting process. Next, the C_{FOFS} -based decision matrix is constructed using the evaluations provided by the expert panel. Finally, the TOPSIS method is applied to determine the relative closeness of each alternative to the PIS and NIS. Based on these closeness coefficients, the green supply chain strategies are ranked to identify the most suitable strategy for sustainable supply chain implementation. The details of the proposed algorithm are provided below.

The methodology consists of two phases: Phase 1: The weights of the experts are determined using the AHP method, while the criterion weights are computed through the entropy measure. Phase 2: The alternatives are ranked using the TOPSIS approach based on the optimized weights obtained in Phase 1. The AHP supports systematic and consistent expert weight extraction, whereas the entropy method offers an objective mechanism for evaluating attribute significance. The integration of TOPSIS provides a practical and efficient strategy for identifying the most suitable alternative in real-world DM scenarios. A schematic representation of the proposed framework is shown in Figure 1, and its procedural steps are detailed thereafter.

MCGDM is a complex analytical process involving the evaluation of multiple alternatives against several, often conflicting, criteria with input from multiple experts or decision-makers. In real-world applications, such as resource allocation, investment analysis, and policy planning, decisions typically incorporate opinions from various stakeholders possessing diverse judgments and preferences. In this study, we consider an MCGDM scenario comprising m alternatives $\{Q_1, Q_2, \dots, Q_m\}$, evaluated under n criteria $\{\mathcal{R}_1, \mathcal{R}_2, \dots, \mathcal{R}_n\}$, with assessments provided by γ experts $\{E_1, E_2, \dots, E_\tau\}$. Each expert assigns evaluations to the alternatives based on the defined criteria, resulting in a corresponding decision matrix. The main aim is to develop a unified DM framework capable of aggregating expert judgments, addressing trade-offs between conflicting attributes, and determining the

most appropriate alternatives. The structural form of the decision matrices is presented in Equation (17).

$$B^{(l)} = \begin{pmatrix} \beta_{11}^{(\tau)} & \beta_{12}^{(\tau)} & \cdots & \beta_{1n}^{(\tau)} \\ \beta_{21}^{(\tau)} & \beta_{22}^{(\tau)} & \cdots & \beta_{2n}^{(\tau)} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{m1}^{(\tau)} & \beta_{m2}^{(\tau)} & \cdots & \beta_{mn}^{(\tau)} \end{pmatrix} \quad (17)$$

In Equation (17), $B_{ij}^{(\tau)} = (\Omega_{IR_{\mathcal{F}_i}} e^{i2\Pi(\Omega_{IM_{\mathcal{F}_i}})}, \mathcal{U}_{IR_{\mathcal{F}_i}} e^{i2\Pi(\mathcal{U}_{IM_{\mathcal{F}_i}})})$, $(i = 1, 2, \dots, m; j = 1, 2, \dots, n; \tau = 1, 2, \dots, \gamma)$.

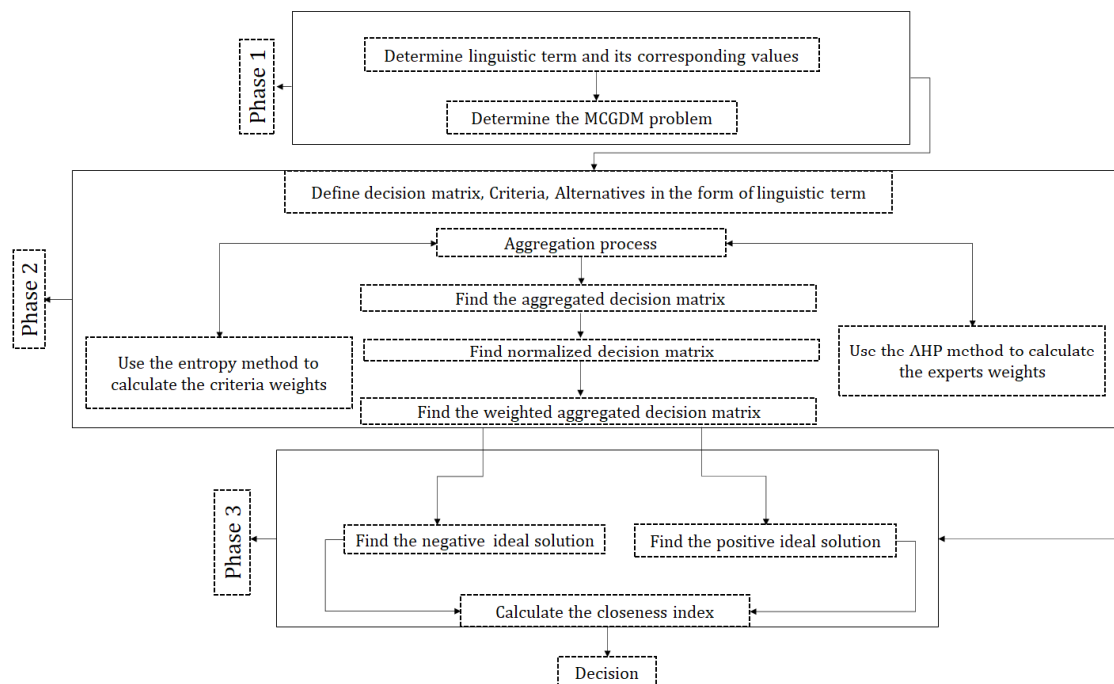


Figure 1. Flowchart of the proposed MCGDM problem.

Step 1. *Determination of Expert Weights:* Assigning appropriate weights to experts is a crucial part of the MCGDM process, as it ensures that the influence of each decision-maker is properly reflected during aggregation. The general procedure for computing expert weights is outlined below:

- (1) **Identification of Evaluation Criteria:** Select relevant attributes to assess the experts' credibility. Commonly adopted criteria include: professional experience, domain knowledge, research or project contributions, reputation, reliability, and decision-making competence
- (2) **Expert Scoring:** Each expert is evaluated with respect to the selected criteria using a predefined scoring scale (1–5 or 1–9, depending on decision-making preference).
- (3) **Score Aggregation:** The individual criterion scores are summed to obtain the total score for each expert.
- (4) **Normalization to Derive Expert Weights:** The aggregated scores are normalized so that their sum equals 1. The normalization formula is given by:

$$\omega_{\gamma} = \frac{\text{Total score of experts } \gamma}{\sum_{j=1}^{\gamma} \text{Total score of experts } j} \quad (18)$$

- (5) **Application of Weights:** The normalized weights are then incorporated into the collective DM process to ensure balanced and proportional consideration of all expert judgments.

Step 2. *Construction of the aggregated decision matrix:* In this step, the individual assessments provided by each expert are unified to form a collective decision matrix. The aggregation is performed using the proposed $C_{FOF} - WA$ or $C_{FOF} - WG$ operator, depending on the nature of the evaluation. The computed criteria weights are incorporated simultaneously to ensure that attributes with higher significance exert greater influence on the final aggregated values.

Step 3. *Normalization of the aggregated decision matrix:* In the considered MCGDM framework, the evaluation criteria are classified into two categories: Benefit criteria (BC): criteria where higher values are desirable. Cost criteria (CC): criteria for which lower values are preferred. To ensure comparability across criteria with different scales, units, and directional preferences, the aggregated decision matrix must be normalized. For benefit-type criteria, the MD component is retained as given, whereas for cost-type criteria, the MD and NMD values are transformed inversely to reflect minimization preference. This transformation produces a standardized decision matrix in which all criteria move in a consistent positive direction, enabling fair alternative evaluation. The normalized decision is constructed by using the following Equation (19):

$$N = \begin{cases} \left(\Omega_{IR\bar{F}_{ij}} e^{i2\Pi\left(\Omega_{IM\bar{F}_{ij}}\right)}, \mathcal{U}_{IR\bar{F}_{ij}} e^{i2\Pi\left(\mathcal{U}_{IM\bar{F}_{ij}}\right)} \right) & \text{for } j \in \Delta \\ \left(\mathcal{U}_{IR\bar{F}_{ij}} e^{i2\Pi\left(\mathcal{U}_{IM\bar{F}_{ij}}\right)}, \Omega_{IR\bar{F}_{ij}} e^{i2\Pi\left(\Omega_{IM\bar{F}_{ij}}\right)} \right) & \text{for } j \in \nabla \end{cases} \quad (19)$$

Step 4. Select the values of the parameters p and q , such that $0 \leq \left(\Omega_{\bar{F}_{IR}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{F}_{IR}}(\varepsilon)\right)^{p/q} \leq 1$ and $0 \leq \left(\Omega_{\bar{F}_{IM}}(\varepsilon)\right)^{p/q} + \left(\mathcal{U}_{\bar{F}_{IM}}(\varepsilon)\right)^{p/q} \leq 1$.

Step 5. We will utilize the entropy method [35], presented in 1948 by Shannon, to find the criteria weighted in the FOFS framework. To find the criteria weights, we will use the following Equation (20):

$$\bar{\omega}_i = \frac{1 + \frac{1}{m} \sum_{j=1}^m \left(\Omega_{\bar{F}_{ijIR}} \ln(\Omega_{\bar{F}_{ijIR}}) + \Omega_{\bar{F}_{ijIM}} \ln(\Omega_{\bar{F}_{ijIM}}) + \mathcal{U}_{\bar{F}_{ijIR}} \ln(\mathcal{U}_{\bar{F}_{ijIR}}) + \mathcal{U}_{\bar{F}_{ijIM}} \ln(\mathcal{U}_{\bar{F}_{ijIM}}) \right)}{\sum_{i=1}^n \left(1 + \frac{1}{m} \sum_{j=1}^m \left(\Omega_{\bar{F}_{ijIR}} \ln(\Omega_{\bar{F}_{ijIR}}) + \Omega_{\bar{F}_{ijIM}} \ln(\Omega_{\bar{F}_{ijIM}}) + \mathcal{U}_{\bar{F}_{ijIR}} \ln(\mathcal{U}_{\bar{F}_{ijIR}}) + \mathcal{U}_{\bar{F}_{ijIM}} \ln(\mathcal{U}_{\bar{F}_{ijIM}}) \right) \right)} \quad (20)$$

Step 6. Find the weighted aggregated decision matrix by using the proposed $C_{FOF} - WA$ or $C_{FOF} - WG$ operators.

Step 7. Determine the positive ideal solution (PIS) $\mathcal{P}^+$ and negative ideal solution (NIS) $\mathcal{P}^-$, which can be expressed as

$$\mathcal{P}^+ = \left(\min(\Omega_{\bar{F}_{ijIR}}, \Omega_{\bar{F}_{ijIR}}) e^{i2\Pi\left(\min(\Omega_{\bar{F}_{ijIM}}, \Omega_{\bar{F}_{ijIM}})\right)}, \max(\mathcal{U}_{\bar{F}_{ijIR}}, \mathcal{U}_{\bar{F}_{ijIR}}) e^{i2\Pi\left(\max(\mathcal{U}_{\bar{F}_{ijIM}}, \mathcal{U}_{\bar{F}_{ijIM}})\right)} \right) \quad (21)$$

$$\mathcal{P}^- = \left(\max(\Omega_{\bar{F}_{ijIR}}, \Omega_{\bar{F}_{ijIR}}) e^{i2\Pi\left(\max(\Omega_{\bar{F}_{ijIM}}, \Omega_{\bar{F}_{ijIM}})\right)}, \min(\mathcal{U}_{\bar{F}_{ijIR}}, \mathcal{U}_{\bar{F}_{ijIR}}) e^{i2\Pi\left(\min(\mathcal{U}_{\bar{F}_{ijIM}}, \mathcal{U}_{\bar{F}_{ijIM}})\right)} \right) \quad (22)$$

where $i = 1, 2, \dots, m; j = 1, 2, \dots, n$.

Step 8. We calculate the distance between each alternative $Q_j = \{Q_1, Q_2, \dots, Q_m\}$ and the P^+ and P^- , which are given by:

$$\mathcal{D}(Q_j, P^+) = \frac{1}{2} \sum_{j=1}^n \left(\left| \Omega_{\mathcal{F}_{ijIR}}^{p/q} - \left(\Omega_{\mathcal{F}_{ijIR}}^+ \right)^{p/q} \right| + \left| \mathcal{V}_{\mathcal{F}_{ijIR}}^{p/q} - \left(\mathcal{V}_{\mathcal{F}_{ijIR}}^+ \right)^{p/q} \right| + \left| \Omega_{\mathcal{F}_{ijIM}}^{p/q} - \left(\Omega_{\mathcal{F}_{ijIM}}^+ \right)^{p/q} \right| + \left| \mathcal{V}_{\mathcal{F}_{ijIM}}^{p/q} - \left(\mathcal{V}_{\mathcal{F}_{ijIM}}^+ \right)^{p/q} \right| \right). \quad (23)$$

$$\mathcal{D}(Q_j, P^-) = \frac{1}{2} \sum_{j=1}^n \left(\left| \Omega_{\mathcal{F}_{ijIR}}^{p/q} - \left(\Omega_{\mathcal{F}_{ijIR}}^- \right)^{p/q} \right| + \left| \mathcal{V}_{\mathcal{F}_{ijIR}}^{p/q} - \left(\mathcal{V}_{\mathcal{F}_{ijIR}}^- \right)^{p/q} \right| + \left| \Omega_{\mathcal{F}_{ijIM}}^{p/q} - \left(\Omega_{\mathcal{F}_{ijIM}}^- \right)^{p/q} \right| + \left| \mathcal{V}_{\mathcal{F}_{ijIM}}^{p/q} - \left(\mathcal{V}_{\mathcal{F}_{ijIM}}^- \right)^{p/q} \right| \right). \quad (24)$$

The parameters used in Equations (22) and (23) are flexible and can be changed according to the requirement in the DM process. In general, the optimal option is higher $\mathcal{D}(Q_j, P^-)$, while the $\mathcal{D}(Q_j, P^+)$ value represents a more desirable alternative. $\mathcal{D}_{\min}(Q_j, P^+) = \min(\mathcal{D}(Q_j, P^+))$, $\mathcal{D}_{\max}(Q_j, P^+) = \max(\mathcal{D}(Q_j, P^+))$ ($j = 1, 2, \dots, m$).

Step 9. Find the closeness index ($\mathcal{G}_i$) for each alternative by the following Equation (25):

$$\mathcal{G}_i = \frac{\mathcal{D}(Q_j, P^-)}{\mathcal{D}_{\max}(Q_j, P^-)} - \frac{\mathcal{D}(Q_j, P^+)}{\mathcal{D}_{\min}(Q_j, P^+)}. \quad (25)$$

The alternative, $Q_j = (j = 1, 2, \dots, m)$, is examined to determine the closeness to the P^+ and the distance from the P^- using the $\mathcal{G}_i$. The optimal choice is indicated by a higher closeness index and vice versa. The flowchart of the proposed MCGDM is presented in Figure 1.

3.3. Differences Between the Classical TOPSIS Method and the Proposed C_{FOFS} TOPSIS Method

The classical TOPSIS method is typically applied to crisp numerical data or simple fuzzy representations. In contrast, the proposed approach extends TOPSIS to operate within the C_{FOFS} environment. In this framework, the decision matrix elements are expressed as C_{FOFS} numbers with complex-valued MF and NMF under fractional orthopair constraints. Accordingly, the aggregation process, score computation, and distance measures are adapted to accommodate the real and imaginary components of C_{FOFS} values. While these modifications enhance the modeling of multi-dimensional uncertainty, the fundamental TOPSIS principle of ranking alternatives based on their closeness to the PIS and NIS remains unchanged. The comparison of the classical TOPSIS method and the proposed C_{FOFS} TOPSIS approach is presented in Table 2.

Table 2. Comparison between the classical TOPSIS method and the proposed C_{FOFS} TOPSIS approach.

Aspect	Classical TOPSIS	Proposed C_{FOFS} TOPSIS
Data Representation	Crisp numerical values	C_{FOFS} numbers
Uncertainty Modeling	Limited	Complex fractional orthopair structure
Membership Representation	Not applicable	Complex-valued MF and NMF
Hesitancy Handling	Not explicitly modeled	Explicitly represented
Distance Calculation	Euclidean distance	Distance based on C_{FOFS} score values
Decision Environment	Deterministic	Uncertain and multi-dimensional

3.4. Linguistic Terms

In the proposed MCGDM problem, linguistic terms are employed to capture expert opinions and express their assessments qualitatively. This is crucial when evaluating complex systems, such as space mining technologies for asteroid and lunar resource extraction, where exact numerical evaluations may not fully reflect expert judgment. To address this challenge, the framework adopts 15 carefully defined linguistic terms such as, Minimal, Marginal, Subdued, Moderate Low, Balanced, Refined, Enhanced, Prominent, Superior, Exceptional, Optimal, Advanced, Distinguished, Pioneering, and Ultimate. Each term is expressed as a C_{FOFN} , capturing both magnitude and phase to model expert uncertainty, hesitation, and perception rigorously. By transforming linguistic terms into C_{FOFN} s, the framework preserves real-world ambiguity while enabling the creation of a coherent C_{FOFN} -based decision matrix. This approach ensures even subtle differences in expert judgment are accurately captured, providing a robust link between qualitative opinions and quantitative analysis. The linguistic terms and its key features are shown in Table 3.

Table 3. Linguistic terms and their key features.

Linguistic Variable	Notation	Intensity Level	C_{FOFN}	Fuzzy Interpretation	Application Relevance
Minimal	M_N	Extremely weak MF; very strong NMF	$\left(0.05e^{i2\pi(0.03)}, 0.95e^{i2\pi(0.07)}\right)$	Extremely weak MF; very strong NMF	Represents highly undesirable or severely underperforming technologies
Marginal	M_G	Very low agreement; high dissatisfaction	$\left(0.15e^{i2\pi(0.04)}, 0.90e^{i2\pi(0.09)}\right)$	Very low MF; high NMF	Used when a technology barely meets the basic requirement
Subdued	S_D	Low MF, moderately high NMF	$\left(0.25e^{i2\pi(0.06)}, 0.80e^{i2\pi(0.12)}\right)$	Low MF; moderately high NMF	Applied to technologies demonstrating below-average performance
Moderate Low	M_L	Slightly weak MF; noticeable hesitation	$\left(0.35e^{i2\pi(0.08)}, 0.70e^{i2\pi(0.10)}\right)$	Weak MF; noticeable hesitation	Represents alternatives approaching but still below standard
Balanced	B_L	MF $\cong$ NMF; high neutrality	$\left(0.50e^{i2\pi(0.02)}, 0.50e^{i2\pi(0.11)}\right)$	MF approximately equal to NMF	Appropriate when performance is average or ambiguous
Refined	R_F	Slightly dominant MF over NMF	$\left(0.60e^{i2\pi(0.05)}, 0.35e^{i2\pi(0.13)}\right)$	Slight MF > NMF	Used for alternatives with modest but clear positive tendencies
Enhanced	E_N	Good agreement; reduced hesitation	$\left(0.70e^{i2\pi(0.09)}, 0.25e^{i2\pi(0.06)}\right)$	Strong MF; reduced hesitation	Indicates reliably positive performance across technical criteria
Prominent	P_R	Strong MF; low NMF	$\left(0.80e^{i2\pi(0.07)}, 0.20e^{i2\pi(0.14)}\right)$	Strong MF; low NMF	Reflects strong and consistent performance
Superior	S_P	Very strong MF; minimal disagreement	$\left(0.88e^{i2\pi(0.10)}, 0.12e^{i2\pi(0.04)}\right)$	Very strong MF; minimal NMF	Applied to high-performing, efficient technologies
Exceptional	E_X	Near-maximum MF; very weak NMF	$\left(0.92e^{i2\pi(0.11)}, 0.08e^{i2\pi(0.03)}\right)$	Near-maximum MF; very weak NMF	Represents standout breakthroughs or highly innovative technologies
Optimal	O_P	Almost perfect MF; negligible NMF	$\left(0.95e^{i2\pi(0.12)}, 0.06e^{i2\pi(0.09)}\right)$	Very high MF; negligible NMF	Reserved for the best possible technology under all criteria
Advanced	A_D	Highly reliable MF; minimal NMF	$\left(0.96e^{i2\pi(0.13)}, 0.05e^{i2\pi(0.02)}\right)$	Highly reliable MF; minimal NMF	Applied to technologies with advanced capabilities

Table 3. Cont.

Linguistic Variable	Notation	Intensity Level	C_{FOFN}	Fuzzy Interpretation	Application Relevance
Distinguished	D_G	Strong MF; very low disagreement	$\left(0.97e^{i2\pi(0.14)}, 0.04e^{i2\pi(0.08)}\right)$	Strong MF; very low NMF	Represents technologies with exceptional distinction
Pioneering	P_N	Near-ideal MF; negligible NMF	$\left(0.98e^{i2\pi(0.09)}, 0.03e^{i2\pi(0.02)}\right)$	Near-ideal MF; negligible NMF	Indicates technologies introducing novel and pioneering approaches
Ultimate	U_T	Almost perfect MF; nearly no NMF	$\left(0.99e^{i2\pi(0.06)}, 0.01e^{i2\pi(0.10)}\right)$	Almost perfect MF; nearly no NMF	Reserved for the most superior, state-of-the-art technology

4. An Intelligent MCGDM Framework for the Evaluation of Green Supply Chain Strategies

The management and optimization of green supply chain strategies have become critical for organizations seeking sustainable operations, carbon neutrality, and regulatory compliance. Selecting the most appropriate green supply chain strategy is a complex decision-making problem, requiring careful consideration of multiple environmental, operational, and regulatory factors under high uncertainty. To address this challenge, we propose an intelligent MCGDM framework for the evaluation of green supply chain strategies, which systematically assesses 15 candidate strategies: green procurement, eco-friendly supplier selection, sustainable transportation, reverse logistics, carbon footprint monitoring, energy efficient manufacturing, waste minimization programs, closed loop supply chain, green packaging, supplier environmental auditing, renewable energy integration, lifecycle assessment adoption, green inventory management, digitalized sustainable logistics, and circular economy implementation. These strategies are evaluated across 15 criteria encompassing environmental efficiency, resource utilization, energy efficiency, operational flexibility, scalability, environmental risk, regulatory compliance, implementation cost, strategy effectiveness, supply chain transparency, technological readiness, stakeholder engagement, process complexity, lifecycle impact, and economic feasibility. Expert judgment is incorporated from a panel of five domain specialists: a sustainability management expert, an industrial engineer, a supply chain analytics expert, a logistics and operations specialist, and an environmental policy expert. The proposed framework enables structured, intelligent, and transparent MCGDM to identify the most suitable strategies for effective, sustainable, and resilient green supply chain management.

4.1. Expert Contribution and Decision Influence Structure for Green Supply Chain Strategy Evaluation

To ensure scientific rigor and practical relevance in the proposed C_{FOF} -based MCGDM framework, evaluations were conducted by five experts with complementary expertise in sustainability management, industrial engineering, supply chain analytics, logistics operations, and environmental policy. Their collective knowledge enabled a comprehensive assessment of 15 GSCM strategies across environmental, operational, economic, and regulatory criteria. The experts evaluated aspects such as environmental performance, resource utilization, energy efficiency, operational feasibility, implementation cost, regulatory compliance, and overall effectiveness of the strategies. Expert weights were determined using the AHP, and the normalized weights were incorporated into the C_{FOF} aggregation process to ensure a balanced, transparent, and consensus-based group decision-making framework.

4.2. Methodology of the Analytic Hierarchy Process for Expert Weights

In the proposed C_{FOF} -based MCGDM framework for evaluating GSCM strategies, the five experts possess different levels of expertise and relevance to the decision problem. Signifying equal importance to all experts may not accurately reflect their contributions; therefore, the AHP [36] is employed to determine appropriate and transparent expert weights. This approach ensures that the influence of each expert is determined systematically according to their knowledge and experience in sustainability management, supply chain operations, and environmental policy. Let the expert set be defined as:

$$E_i = \{E_1, E_2, E_3, E_4, E_5\}$$

In the AHP, the relative importance of expert E_i compared with expert E_j is expressed using Saaty's 1 – 9 scale, forming the pairwise comparison matrix: $E_i = (e_{ij})_{5 \times 5}$, here $e_{ij} > 0$, $e_{ji} = 1/e_{ij}$ and $e_{ij} = 1$. Thus, the general form of the pairwise comparison can be expressed as

$$E_{ij} = \begin{pmatrix} 1 & e_{12} & e_{13} & e_{14} & e_{15} \\ 1/e_{12} & 1 & e_{23} & e_{24} & e_{25} \\ 1/e_{13} & 1/e_{23} & 1 & e_{34} & e_{35} \\ 1/e_{14} & 1/e_{24} & 1/e_{34} & 1 & e_{45} \\ 1/e_{15} & 1/e_{25} & 1/e_{35} & 1/e_{45} & 1 \end{pmatrix}$$

AHP-based Calculation of Experts: Based on Saaty's methodology, the pairwise comparison matrix for the five experts can be expressed as

$$E_i = \begin{bmatrix} 1.0 & 3.0 & 3.0 & 2.0 & 2.0 \\ 0.5 & 1.0 & 1.0 & 3.0 & 3.0 \\ 0.5 & 1.0 & 1.0 & 3.0 & 3.0 \\ 0.2 & 0.5 & 0.5 & 1.0 & 1.0 \\ 0.2 & 0.5 & 0.5 & 1.0 & 1.0 \end{bmatrix}$$

Each column of the pairwise comparison matrix is normalized, and the priority vector is obtained by averaging the normalized values. The resulting weight vector is given as $\omega = [0.109, 0.205, 0.208, 0.110, 0.369]$. These weights satisfy the condition $\sum_{i=1}^5 \omega_i = 1$ and represent the relative influence of each expert based on their domain expertise in GSCM strategy evaluation. Table 4 summarizes the professional background and domain expertise of the participating experts, thereby demonstrating the suitability of the expert panel for the present green supply chain evaluation problem.

Table 4. Experts and their influence in the GSCM MCGDM framework.

Expert	Designation/Role	Primary Specialization	Relevant Contribution to GSCM Strategy Evaluation	Experience (Years)	Assigned Weight
E ₁	Senior Sustainability Manager	Environmental Sustainability and Green Operations	Environmental Sustainability and Green Operations	14	0.109
E ₂	Industrial Engineering Specialist	Industrial Engineering Specialist	Industrial Engineering Specialist	12	0.205
E ₃	Supply Chain Analytics Expert	Supply Chain Analytics Expert	Supply Chain Analytics Expert	18	0.208
E ₄	Logistics and Operations Manager	Logistics and Operations Manager	Logistics and Operations Manager	10	0.110
E ₅	Environmental Policy and Regulatory Advisor	Environmental Policy and Regulatory Advisor	Environmental Policy and Regulatory Advisor	11	0.369

4.3. Multicriteria Evaluation Parameters for Green Supply Chain Strategy Assessment

The proposed GSCM MCGDM framework evaluates 15 strategies using a comprehensive set of criteria identified through expert consultation and the literature on sustainable supply chain practices. These criteria encompass key environmental, operational, economic, and regulatory factors that determine the overall sustainability, efficiency, and feasibility of GSCM strategies. To ensure transparent and robust assessment, criteria are classified as benefit criteria (BC), where higher values indicate superior performance, and cost criteria (CC), where lower values are preferable. Each criterion is evaluated using the C_{FOF} -linguistic scale to model expert uncertainty and hesitation. The 15 criteria include: resource efficiency, waste reduction, energy consumption, system complexity, reliability, automation level, scalability, environmental impact resilience, process complexity, throughput, maintenance requirements, technology maturity, product quality, regulatory compliance, and overall implementation cost. This selection provides a balanced framework for evaluating and comparing GSCM strategies. Table 3 presents the formal definitions, codes, descriptions, relevance, measurement domains, evaluation scales, and types for all criteria used to assess the performance alternatives. Let the set of alternatives be $Q_i = \{Q_1, Q_2, \dots, Q_m\}$ and evaluated under n criteria $\mathcal{R}_i = \{\mathcal{R}_1, \mathcal{R}_2, \dots, \mathcal{R}_n\}$.

The selection of the 15 evaluation criteria was carried out through a three-stage process. First, a comprehensive review of the relevant literature on GSCM, sustainability assessment, and fuzzy MCGDM was conducted to identify the most frequently used and theoretically significant evaluation dimensions. This review provided the preliminary pool of candidate criteria. Second, these criteria were examined through expert consultation involving specialists in sustainability management, industrial engineering, supply chain analytics, logistics and operations, and environmental policy. Their role was to verify the relevance, clarity, and applicability of each criterion to the evaluation of green supply chain strategies. Third, the final set of 15 criteria were retained based on their practical suitability for real-world green supply chain decision environments, ensuring that the framework reflects not only prior academic work but also industrial and managerial practice. The comprehensive evaluation criteria are presented in Table 5.

Table 5. Comprehensive evaluation criteria for green supply chain strategies.

Criterion Code	Criterion Name	Description	Reason for Inclusion	Measurement Domain	Type
$\mathcal{R}_1$	Resource Efficiency	Measures how effectively resources are used in supply chain operations	Indicates operational productivity and sustainability	Operational/Resource	BC
$\mathcal{R}_2$	Waste Reduction	Volume of waste minimized during supply chain activities	Enhances environmental performance and sustainability	Environmental	BC
$\mathcal{R}_3$	Energy Consumption	Total energy used across supply chain processes	Lower consumption reduces environmental impact and cost	Engineering/Energy	CC
$\mathcal{R}_4$	System Complexity	Number and difficulty of processes or operations	High complexity increases risk, inefficiency, and maintenance difficulty	Operations	CC
$\mathcal{R}_5$	Reliability	Ability to maintain continuous operation without failure	Ensures supply chain continuity and reduces operational risks	Operations	BC
$\mathcal{R}_6$	Automation Level	Degree of automation in processes	Reduces human error, increases efficiency	Technology/AI	BC
$\mathcal{R}_7$	Scalability	Potential to expand operations sustainably	Supports growth without increasing environmental footprint	Strategic Planning	BC

Table 5. Cont.

Criterion Code	Criterion Name	Description	Reason for Inclusion	Measurement Domain	Type
$\mathcal{R}_8$	Environmental Impact Resilience	Ability to perform under variable environmental conditions	Ensures adaptability and sustainability under external pressures	Environmental	BC
$\mathcal{R}_9$	Process Complexity	Operational steps and technical difficulty	Simpler processes reduce errors and energy consumption	Operations	CC
$\mathcal{R}_{10}$	Throughput	Volume of products or materials processed per unit of time	Higher throughput increases efficiency	Operational/Logistics	BC
$\mathcal{R}_{11}$	Maintenance Requirements	Frequency and difficulty of upkeep	Minimizing maintenance reduces downtime and resource usage	Operations	CC
$\mathcal{R}_{12}$	Technology Maturity	Readiness and maturity of technology applied	Ensures feasibility and smooth implementation	Technology	BC
$\mathcal{R}_{13}$	Product Quality	Quality of products delivered	Impacts customer satisfaction and regulatory compliance	Operational/Quality	BC
$\mathcal{R}_{14}$	Regulatory Compliance	Adherence to environmental and industry regulations	Avoids legal risks and ensures sustainability	Legal/Regulatory	CC
$\mathcal{R}_{15}$	Implementation Cost	Total cost of implementing the supply chain strategy	Affects economic feasibility and decision-making	Economic	CC

4.4. Comprehensive Overview of Green Supply Chain Strategy Alternatives in the Proposed MCGDM Framework

In alignment with the objectives of establishing a scientifically robust and operationally relevant decision support system for sustainable supply chains, this study evaluates 15 diverse green supply chain strategies as decision alternatives. These alternatives represent different sustainability paradigms currently implemented or conceptualized across industries, including energy efficient logistics, waste reduction initiatives, circular economy practices, renewable energy adoption, and process automation. To ensure neutrality and comparability, each strategy is labeled $\mathcal{Q}_1 - \mathcal{Q}_{15}$ rather than using specific company or project names. The selected alternatives span a wide range of process designs, technological adoption levels, operational scales, and environmental interventions, each demonstrating unique strengths and limitations in terms of: resource efficiency, environmental impact reduction, energy consumption, operational autonomy, process complexity, regulatory compliance, cost effectiveness, and overall implementation readiness. Collectively, these alternatives represent the spectrum of approaches being considered for sustainable and resilient supply chain operations. A structured comparison of their key characteristics and sustainability relevant attributes is presented in Table 6, offering a high-level overview of their operational potential and suitability within the proposed FOFS-based MCGDM framework. The evaluation matrix of the experts is presented in Tables 7–11.

Table 6. Comprehensive summary of green supply chain strategy alternatives.

$\mathcal{Q}_i$	Implementation Readiness	Resource Efficiency	Environmental Impact Reduction	Autonomy and Scalability	Process Complexity	Operational Cost	Research/Adoption Level	Overall Sustainability Score (0–10)
$\mathcal{Q}_1$	Low–Medium	Very High	Medium	Medium	Very High	High	Limited Pilots	6.9

Table 6. Cont.

Q_i	Implementation Readiness	Resource Efficiency	Environmental Impact Reduction	Autonomy and Scalability	Process Complexity	Operational Cost	Research/Adoption Level	Overall Sustainability Score (0–10)
Q_2	Medium	High	High	Very High	High	Medium	Academic + Pilot Projects	7.7
Q_3	Medium–High	High	Medium	High	Medium	High	Industry Demonstrators	8.0
Q_4	Medium–High	Very High	High	Medium	Medium	Medium	Government Programs	8.4
Q_5	Low	Moderate	Low–Medium	Low–Medium	Very High	Very High	Early Experimental Research	6.0
Q_6	Low–Medium	High	Very High	High	Very High	High	Research Prototypes	7.2
Q_7	Medium	Moderate	Medium	Medium	High	Medium	Corporate Research	7.1
Q_8	High	High	High	High	Medium	Low	Mature Industry Implementation	8.5
Q_9	Medium	Moderate	Very High	Medium	Medium	Low	Pilot Environmental Studies	7.6
Q_{10}	Medium–High	High	High	Medium	Medium	Low	Demonstration Projects	8.1
Q_{11}	High	Very High	High	High	Medium	Medium	Advanced Industry Labs	8.7
Q_{12}	Medium	High	Medium	Medium	High	High	Government + Industry Pilots	7.5
Q_{13}	Low	Moderate	Low	Medium	High	Low–Medium	Early Circular Economy Research	6.3
Q_{14}	High	High	High	High	Medium	Medium	Commercial + Pilot Projects	8.2
Q_{15}	Low–Medium	High	Medium	Low	Very High	Very High	Concept-Level Studies	6.8

Table 7. Evaluation of E_1 using linguistic terms.

Q_i	$\mathcal{R}_1$	$\mathcal{R}_2$	$\mathcal{R}_3$	$\mathcal{R}_4$	$\mathcal{R}_5$	$\mathcal{R}_6$	$\mathcal{R}_7$	$\mathcal{R}_8$	$\mathcal{R}_9$	$\mathcal{R}_{10}$	$\mathcal{R}_{11}$	$\mathcal{R}_{12}$	$\mathcal{R}_{13}$	$\mathcal{R}_{14}$	$\mathcal{R}_{15}$
Q_1	S_D	M_G	E_X	P_R	A_D	P_N	S_P	U_T	E_N	O_P	D_G	R_F	B_L	M_N	M_L
Q_2	E_N	M_L	B_L	P_N	M_G	O_P	D_G	A_D	P_R	S_D	E_X	S_P	R_F	U_T	M_N
Q_3	U_T	S_P	S_D	M_G	R_F	M_L	P_N	B_L	A_D	M_N	O_P	P_R	E_N	E_X	D_G
Q_4	S_P	S_D	M_G	E_X	O_P	B_L	U_T	P_N	D_G	R_F	A_D	M_N	M_L	P_R	E_N
Q_5	R_F	O_P	A_D	D_G	P_N	E_X	M_N	P_R	S_P	B_L	U_T	M_L	M_G	E_N	S_D
Q_6	B_L	P_N	U_T	S_P	P_R	D_G	M_L	E_N	R_F	E_X	M_N	M_G	A_D	S_D	O_P
Q_7	A_D	D_G	E_N	M_L	S_P	M_N	O_P	R_F	M_G	U_T	S_D	P_N	P_R	B_L	E_X
Q_8	O_P	A_D	D_G	E_N	U_T	P_R	R_F	M_N	S_D	P_N	S_P	B_L	E_X	M_L	M_G
Q_9	E_X	P_R	M_N	R_F	E_N	S_P	M_G	S_D	B_L	D_G	M_L	A_D	U_T	O_P	P_N

Table 7. Cont.

Q_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	R_{14}	R_{15}
Q_{10}	P_R	M_N	R_F	O_P	M_L	S_D	E_X	M_G	P_N	E_N	B_L	D_G	S_P	A_D	U_T
Q_{11}	M_N	R_F	O_P	A_D	B_L	M_G	P_R	E_X	U_T	M_L	P_N	E_N	S_D	D_G	S_P
Q_{12}	D_G	E_N	M_L	B_L	S_D	R_F	A_D	O_P	E_X	S_P	M_G	U_T	M_N	P_N	P_R
Q_{13}	M_G	E_X	P_R	M_N	D_G	U_T	S_D	S_P	M_L	A_D	E_N	O_P	P_N	R_F	B_L
Q_{14}	M_L	B_L	P_N	U_T	E_X	A_D	E_N	D_G	M_N	M_G	P_R	S_D	O_P	S_P	R_F
Q_{15}	P_N	U_T	S_P	S_D	M_N	E_N	B_L	M_L	O_P	P_R	R_F	E_X	D_G	M_G	A_D

Table 8. Evaluation of E_2 using linguistic terms.

Q_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	R_{14}	R_{15}
Q_1	S_D	A_D	P_N	E_N	E_X	P_R	B_L	M_G	R_F	U_T	M_L	S_P	D_G	O_P	M_N
Q_2	O_P	U_T	R_F	D_G	M_G	S_P	P_R	M_N	A_D	E_N	B_L	E_X	S_D	M_L	P_N
Q_3	A_D	M_G	S_P	P_N	M_L	S_D	D_G	B_L	E_X	M_N	E_N	O_P	R_F	U_T	P_R
Q_4	P_R	S_D	E_N	M_L	R_F	M_N	M_G	A_D	D_G	O_P	E_X	P_N	B_L	S_P	U_T
Q_5	M_L	E_N	A_D	S_D	M_N	E_X	S_P	P_N	U_T	D_G	P_R	M_G	O_P	B_L	R_F
Q_6	E_X	M_L	S_D	P_R	U_T	R_F	P_N	E_N	O_P	B_L	M_N	A_D	S_P	M_G	D_G
Q_7	D_G	R_F	M_N	U_T	S_P	B_L	M_L	E_X	P_N	A_D	O_P	P_R	E_N	S_D	M_G
Q_8	P_N	S_P	B_L	M_G	S_D	E_N	U_T	O_P	P_R	E_X	A_D	D_G	M_N	R_F	M_L
Q_9	E_N	P_N	M_G	A_D	P_R	M_L	O_P	S_P	M_N	R_F	S_D	B_L	U_T	D_G	E_X
Q_{10}	U_T	M_N	E_X	R_F	B_L	O_P	S_D	P_R	M_G	P_N	D_G	M_L	A_D	E_N	S_P
Q_{11}	R_F	E_X	P_R	M_N	O_P	D_G	E_N	M_L	S_P	M_G	U_T	S_D	P_N	A_D	B_L
Q_{12}	M_G	B_L	O_P	S_P	E_N	A_D	R_F	D_G	M_L	P_R	P_N	U_T	E_X	M_N	S_D
Q_{13}	M_N	P_R	M_L	E_X	D_G	U_T	A_D	S_D	B_L	S_P	R_F	E_N	M_G	P_N	O_P
Q_{14}	S_P	O_P	D_G	B_L	A_D	P_N	M_N	U_T	S_D	M_L	M_G	R_F	P_R	E_X	E_N
Q_{15}	B_L	D_G	U_T	O_P	P_N	M_G	E_X	R_F	E_N	S_D	S_P	M_N	M_L	P_R	A_D

Table 9. Evaluation of E_3 using linguistic terms.

Q_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	R_{14}	R_{15}
Q_1	E_N	P_N	S_P	M_G	S_D	D_G	R_F	B_L	E_X	U_T	M_L	A_D	O_P	M_N	P_R
Q_2	M_G	E_N	M_N	P_R	P_N	A_D	E_X	S_P	B_L	O_P	D_G	U_T	M_L	R_F	S_D
Q_3	S_D	P_R	E_X	P_N	M_G	O_P	S_P	R_F	M_N	D_G	U_T	M_L	A_D	B_L	E_N
Q_4	P_R	M_G	R_F	S_D	E_N	U_T	B_L	M_N	S_P	M_L	A_D	O_P	D_G	E_X	P_N
Q_5	R_F	M_N	D_G	E_X	S_P	E_N	U_T	M_L	O_P	P_R	P_N	M_G	S_D	A_D	B_L
Q_6	S_P	B_L	O_P	M_N	E_X	S_D	D_G	U_T	A_D	E_N	P_R	P_N	M_G	M_L	R_F
Q_7	D_G	M_L	S_D	A_D	O_P	S_P	E_N	P_R	M_G	R_F	B_L	M_N	E_X	P_N	U_T
Q_8	E_X	R_F	A_D	B_L	M_N	M_G	O_P	D_G	M_L	S_D	E_N	P_R	P_N	U_T	S_P
Q_9	A_D	D_G	P_N	U_T	M_L	M_N	M_G	S_D	P_R	E_X	S_P	R_F	B_L	E_N	O_P
Q_{10}	O_P	U_T	M_G	M_L	A_D	E_X	S_D	E_N	P_N	S_P	R_F	B_L	M_N	P_R	D_G
Q_{11}	U_T	A_D	E_N	O_P	D_G	R_F	P_R	P_N	S_D	B_L	M_N	E_X	S_P	M_G	M_L
Q_{12}	M_N	S_P	M_L	R_F	B_L	P_N	A_D	O_P	U_T	M_G	S_D	E_N	P_R	D_G	E_X
Q_{13}	P_N	S_D	B_L	E_N	P_R	M_L	M_N	E_X	R_F	A_D	O_P	D_G	U_T	S_P	M_G
Q_{14}	M_L	O_P	P_R	D_G	U_T	B_L	P_N	M_G	E_N	M_N	E_X	S_P	R_F	S_D	A_D
Q_{15}	B_L	E_X	U_T	S_P	R_F	P_R	M_L	A_D	D_G	P_N	M_G	S_D	E_N	O_P	M_N

Table 10. Evaluation of E_4 using linguistic terms.

Q_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	R_{14}	R_{15}
Q_1	P_N	M_G	E_N	S_D	U_T	R_F	D_G	O_P	S_P	M_N	E_X	A_D	M_L	B_L	P_R

Table 10. Cont.

Q_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	R_{14}	R_{15}
Q_2	O_P	E_X	M_L	M_N	A_D	P_R	S_D	M_G	P_N	U_T	B_L	S_P	R_F	E_N	D_G
Q_3	E_X	E_N	P_R	A_D	P_N	S_D	U_T	B_L	M_G	S_P	M_L	O_P	D_G	R_F	M_N
Q_4	P_R	S_D	A_D	E_X	E_N	P_N	M_G	D_G	R_F	B_L	M_N	M_L	S_P	U_T	O_P
Q_5	S_P	O_P	B_L	D_G	M_N	M_L	P_R	P_N	A_D	S_D	M_G	U_T	E_N	E_X	R_F
Q_6	M_L	P_R	M_N	O_P	E_X	A_D	P_N	R_F	E_N	M_G	D_G	B_L	U_T	S_D	S_P
Q_7	B_L	M_L	D_G	S_P	O_P	M_N	A_D	E_N	E_X	P_N	R_F	M_G	S_D	P_R	U_T
Q_8	A_D	P_N	E_X	P_R	S_D	E_N	R_F	S_P	U_T	D_G	O_P	M_N	B_L	M_G	M_L
Q_9	S_D	U_T	P_N	E_N	R_F	M_G	B_L	M_N	D_G	M_L	A_D	P_R	O_P	S_P	E_X
Q_{10}	R_F	D_G	U_T	M_G	B_L	S_P	O_P	P_R	M_L	E_X	S_D	E_N	A_D	M_N	P_N
Q_{11}	M_N	A_D	O_P	M_L	P_R	E_X	E_N	U_T	S_D	R_F	S_P	D_G	M_G	P_N	B_L
Q_{12}	E_N	R_F	S_D	P_N	M_G	U_T	S_P	M_L	B_L	O_P	P_R	E_X	M_N	D_G	A_D
Q_{13}	M_G	B_L	R_F	U_T	S_P	D_G	M_N	E_X	O_P	A_D	E_N	P_N	P_R	M_L	S_D
Q_{14}	D_G	M_N	S_P	B_L	M_L	O_P	E_X	S_D	P_R	E_N	U_T	R_F	P_N	A_D	M_G
Q_{15}	U_T	S_P	M_G	R_F	D_G	B_L	M_L	A_D	M_N	P_R	P_N	S_D	E_X	O_P	E_N

Table 11. Evaluation of E_5 using linguistic terms.

Q_i	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}	R_{12}	R_{13}	R_{14}	R_{15}
Q_1	P_R	S_D	M_N	E_N	S_P	P_N	M_G	O_P	E_X	R_F	A_D	U_T	B_L	D_G	M_L
Q_2	E_N	E_X	S_P	A_D	D_G	R_F	U_T	S_D	M_G	B_L	M_N	M_L	P_R	O_P	P_N
Q_3	B_L	O_P	A_D	P_R	M_N	M_L	E_X	D_G	S_D	P_N	E_N	M_G	R_F	S_P	U_T
Q_4	M_L	M_N	B_L	P_N	P_R	E_X	D_G	A_D	S_P	M_G	R_F	O_P	U_T	E_N	S_D
Q_5	D_G	P_N	E_X	O_P	M_G	A_D	B_L	M_L	R_F	M_N	S_D	P_R	S_P	U_T	E_N
Q_6	S_P	M_L	S_D	D_G	E_X	E_N	R_F	U_T	P_N	A_D	O_P	B_L	M_N	M_G	P_R
Q_7	M_G	E_N	P_N	U_T	R_F	O_P	M_N	P_R	A_D	S_D	M_L	S_P	E_X	B_L	D_G
Q_8	P_N	S_P	P_R	R_F	E_N	M_G	O_P	M_N	D_G	U_T	B_L	S_D	M_L	A_D	E_X
Q_9	A_D	M_G	D_G	M_N	O_P	B_L	M_L	E_X	U_T	P_R	S_P	P_N	E_N	S_D	R_F
Q_{10}	S_D	B_L	U_T	E_X	M_L	S_P	E_N	R_F	P_R	D_G	M_G	A_D	O_P	P_N	M_N
Q_{11}	M_N	U_T	O_P	S_P	S_D	P_R	P_N	M_G	M_L	E_N	D_G	R_F	A_D	E_X	B_L
Q_{12}	E_X	P_R	M_L	M_G	P_N	D_G	A_D	B_L	E_N	O_P	U_T	M_N	S_D	R_F	S_P
Q_{13}	R_F	D_G	E_N	B_L	A_D	U_T	S_D	S_P	O_P	M_L	P_R	E_X	P_N	M_N	M_G
Q_{14}	U_T	A_D	R_F	M_L	B_L	S_D	S_P	E_N	M_N	E_X	P_N	D_G	M_G	P_R	O_P
Q_{15}	O_P	R_F	M_G	S_D	U_T	M_N	P_R	P_N	B_L	S_P	E_X	E_N	D_G	M_L	A_D

In the proposed MCGDM framework, each of the five experts provides a separate decision matrix reflecting their evaluations of the 15 GSCM strategies under the 15 criteria. Because expert judgments differ due to variations in domain knowledge and experience, it is necessary to combine these matrices into a single aggregated decision matrix. This unified matrix represents the collective assessment of all experts while incorporating their AHP-derived weights. Using Equation (16), the individual C_{FOFS} -based evaluations are fused into one coherent decision structure, ensuring a balanced and representative foundation for subsequent steps, including criteria weighting, normalization, and TOPSIS ranking. The aggregated decision matrix is presented in Tables 12–19.

Table 12. Aggregated decision matrix for R_1 and R_2 .

Q_i	R_1	R_2
Q_1	$(0.744610e^{i2\pi(0.073368)}, 0.262365e^{i2\pi(0.099661)})$	$(0.801172e^{i2\pi(0.076826)}, 0.234828e^{i2\pi(0.064907)})$

Table 12. Cont.

Q_i	$\mathcal{R}_1$	$\mathcal{R}_2$
Q_2	$(0.788379e^{i2\pi(0.089571)}, 0.207881e^{i2\pi(0.073965)})$	$(0.913816e^{i2\pi(0.092634)}, 0.083650e^{i2\pi(0.050396)})$
Q_3	$(0.827140e^{i2\pi(0.066147)}, 0.183397e^{i2\pi(0.067599)})$	$(0.840713e^{i2\pi(0.088344)}, 0.168957e^{i2\pi(0.086169)})$
Q_4	$(0.708234e^{i2\pi(0.077074)}, 0.299855e^{i2\pi(0.107659)})$	$(0.160298e^{i2\pi(0.044925)}, 0.873318e^{i2\pi(0.092448)})$
Q_5	$(0.851315e^{i2\pi(0.095702)}, 0.160911e^{i2\pi(0.090279)})$	$(0.905304e^{i2\pi(0.084665)}, 0.110260e^{i2\pi(0.063125)})$
Q_6	$(0.844965e^{i2\pi(0.091587)}, 0.156304e^{i2\pi(0.046421)})$	$(0.630237e^{i2\pi(0.067910)}, 0.403266e^{i2\pi(0.097920)})$
Q_7	$(0.855616e^{i2\pi(0.090404)}, 0.170153e^{i2\pi(0.074209)})$	$(0.683778e^{i2\pi(0.084487)}, 0.303906e^{i2\pi(0.085101)})$
Q_8	$(0.968301e^{i2\pi(0.102037)}, 0.041823e^{i2\pi(0.043209)})$	$(0.887949e^{i2\pi(0.092171)}, 0.116758e^{i2\pi(0.048415)})$
Q_9	$(0.910279e^{i2\pi(0.112367)}, 0.099006e^{i2\pi(0.031764)})$	$(0.897028e^{i2\pi(0.077331)}, 0.121329e^{i2\pi(0.082447)})$
Q_{10}	$(0.857662e^{i2\pi(0.072867)}, 0.149195e^{i2\pi(0.111471)})$	$(0.801204e^{i2\pi(0.045416)}, 0.205188e^{i2\pi(0.090152)})$
Q_{11}	$(0.691451e^{i2\pi(0.040454)}, 0.300217e^{i2\pi(0.085364)})$	$(0.964583e^{i2\pi(0.092079)}, 0.037472e^{i2\pi(0.048079)})$
Q_{12}	$(0.774770e^{i2\pi(0.081046)}, 0.230475e^{i2\pi(0.053640)})$	$(0.755617e^{i2\pi(0.066447)}, 0.236081e^{i2\pi(0.092680)})$
Q_{13}	$(0.698178e^{i2\pi(0.052310)}, 0.316530e^{i2\pi(0.086428)})$	$(0.869351e^{i2\pi(0.093646)}, 0.147244e^{i2\pi(0.090620)})$
Q_{14}	$(0.929788e^{i2\pi(0.083738)}, 0.074192e^{i2\pi(0.080679)})$	$(0.918422e^{i2\pi(0.103929)}, 0.095507e^{i2\pi(0.051245)})$
Q_{15}	$(0.902185e^{i2\pi(0.070028)}, 0.109350e^{i2\pi(0.092555)})$	$(0.901480e^{i2\pi(0.088277)}, 0.099480e^{i2\pi(0.073900)})$

Table 13. Aggregated decision matrix for $\mathcal{R}_3$ and $\mathcal{R}_4$.

Q_i	$\mathcal{R}_3$	$\mathcal{R}_4$
Q_1	$(0.811687e^{i2\pi(0.072780)}, 0.200572e^{i2\pi(0.051995)})$	$(0.606218e^{i2\pi(0.074427)}, 0.361453e^{i2\pi(0.077051)})$
Q_2	$(0.668400e^{i2\pi(0.064901)}, 0.325287e^{i2\pi(0.070439)})$	$(0.930985e^{i2\pi(0.105089)}, 0.083083e^{i2\pi(0.050322)})$
Q_3	$(0.905217e^{i2\pi(0.105914)}, 0.103644e^{i2\pi(0.037623)})$	$(0.924327e^{i2\pi(0.081944)}, 0.092264e^{i2\pi(0.070262)})$
Q_4	$(0.655260e^{i2\pi(0.055619)}, 0.333091e^{i2\pi(0.081399)})$	$(0.882911e^{i2\pi(0.086329)}, 0.139934e^{i2\pi(0.061642)})$
Q_5	$(0.935965e^{i2\pi(0.113366)}, 0.072918e^{i2\pi(0.037237)})$	$(0.914367e^{i2\pi(0.110525)}, 0.098847e^{i2\pi(0.073853)})$
Q_6	$(0.726334e^{i2\pi(0.069656)}, 0.294971e^{i2\pi(0.104206)})$	$(0.888660e^{i2\pi(0.097343)}, 0.126318e^{i2\pi(0.081765)})$
Q_7	$(0.868775e^{i2\pi(0.077608)}, 0.156292e^{i2\pi(0.068832)})$	$(0.972486e^{i2\pi(0.081636)}, 0.029054e^{i2\pi(0.064542)})$
Q_8	$(0.873251e^{i2\pi(0.085287)}, 0.137000e^{i2\pi(0.070460)})$	$(0.561271e^{i2\pi(0.048543)}, 0.414243e^{i2\pi(0.107688)})$
Q_9	$(0.923987e^{i2\pi(0.092746)}, 0.097292e^{i2\pi(0.069382)})$	$(0.845720e^{i2\pi(0.066322)}, 0.156008e^{i2\pi(0.061174)})$
Q_{10}	$(0.942578e^{i2\pi(0.065375)}, 0.057269e^{i2\pi(0.078472)})$	$(0.788567e^{i2\pi(0.085414)}, 0.214457e^{i2\pi(0.065977)})$
Q_{11}	$(0.903851e^{i2\pi(0.103861)}, 0.103047e^{i2\pi(0.090345)})$	$(0.837040e^{i2\pi(0.091593)}, 0.174846e^{i2\pi(0.054288)})$
Q_{12}	$(0.609875e^{i2\pi(0.086262)}, 0.429139e^{i2\pi(0.099616)})$	$(0.696109e^{i2\pi(0.058148)}, 0.315635e^{i2\pi(0.078639)})$
Q_{13}	$(0.614407e^{i2\pi(0.067278)}, 0.360687e^{i2\pi(0.089993)})$	$(0.784788e^{i2\pi(0.059259)}, 0.207203e^{i2\pi(0.069832)})$
Q_{14}	$(0.871440e^{i2\pi(0.083149)}, 0.135679e^{i2\pi(0.094403)})$	$(0.799838e^{i2\pi(0.072486)}, 0.218396e^{i2\pi(0.098148)})$
Q_{15}	$(0.890397e^{i2\pi(0.055021)}, 0.112645e^{i2\pi(0.085843)})$	$(0.725676e^{i2\pi(0.079961)}, 0.289411e^{i2\pi(0.090621)})$

Table 14. Aggregated decision matrix for $\mathcal{R}_5$ and $\mathcal{R}_6$.

$\mathcal{Q}_i$	$\mathcal{R}_5$	$\mathcal{R}_6$
$\mathcal{Q}_1$	$(0.891110e^{i2\pi(0.093010)}, 0.113079e^{i2\pi(0.048445)})$	$(0.951686e^{i2\pi(0.092418)}, 0.061355e^{i2\pi(0.075412)})$
$\mathcal{Q}_2$	$(0.918953e^{i2\pi(0.098240)}, 0.102310e^{i2\pi(0.064472)})$	$(0.857136e^{i2\pi(0.087356)}, 0.145315e^{i2\pi(0.066860)})$
$\mathcal{Q}_3$	$(0.488925e^{i2\pi(0.051420)}, 0.541121e^{i2\pi(0.081589)})$	$(0.601340e^{i2\pi(0.082348)}, 0.437810e^{i2\pi(0.103377)})$
$\mathcal{Q}_4$	$(0.774880e^{i2\pi(0.078008)}, 0.210852e^{i2\pi(0.100171)})$	$(0.909848e^{i2\pi(0.071970)}, 0.094264e^{i2\pi(0.055680)})$
$\mathcal{Q}_5$	$(0.610757e^{i2\pi(0.055267)}, 0.415503e^{i2\pi(0.065726)})$	$(0.897578e^{i2\pi(0.110208)}, 0.107950e^{i2\pi(0.033943)})$
$\mathcal{Q}_6$	$(0.942425e^{i2\pi(0.095754)}, 0.057575e^{i2\pi(0.045260)})$	$(0.760268e^{i2\pi(0.086018)}, 0.233737e^{i2\pi(0.074048)})$
$\mathcal{Q}_7$	$(0.858650e^{i2\pi(0.088498)}, 0.142586e^{i2\pi(0.079715)})$	$(0.817274e^{i2\pi(0.076789)}, 0.195442e^{i2\pi(0.074801)})$
$\mathcal{Q}_8$	$(0.649193e^{i2\pi(0.065152)}, 0.334719e^{i2\pi(0.081257)})$	$(0.477146e^{i2\pi(0.059339)}, 0.510224e^{i2\pi(0.082917)})$
$\mathcal{Q}_9$	$(0.827436e^{i2\pi(0.090912)}, 0.181072e^{i2\pi(0.100098)})$	$(0.453235e^{i2\pi(0.045777)}, 0.558636e^{i2\pi(0.085831)})$
$\mathcal{Q}_{10}$	$(0.665053e^{i2\pi(0.072430)}, 0.363512e^{i2\pi(0.073562)})$	$(0.887684e^{i2\pi(0.102064)}, 0.117416e^{i2\pi(0.049989)})$
$\mathcal{Q}_{11}$	$(0.817724e^{i2\pi(0.086611)}, 0.205727e^{i2\pi(0.104536)})$	$(0.834513e^{i2\pi(0.082070)}, 0.171799e^{i2\pi(0.098685)})$
$\mathcal{Q}_{12}$	$(0.847983e^{i2\pi(0.067206)}, 0.172355e^{i2\pi(0.071556)})$	$(0.965745e^{i2\pi(0.109717)}, 0.042756e^{i2\pi(0.058851)})$
$\mathcal{Q}_{13}$	$(0.942549e^{i2\pi(0.117883)}, 0.068280e^{i2\pi(0.049805)})$	$(0.973235e^{i2\pi(0.073364)}, 0.028055e^{i2\pi(0.097351)})$
$\mathcal{Q}_{14}$	$(0.888776e^{i2\pi(0.068303)}, 0.117383e^{i2\pi(0.065162)})$	$(0.823190e^{i2\pi(0.072821)}, 0.205693e^{i2\pi(0.078324)})$
$\mathcal{Q}_{15}$	$(0.954186e^{i2\pi(0.070162)}, 0.049977e^{i2\pi(0.085792)})$	$(0.448154e^{i2\pi(0.046108)}, 0.547364e^{i2\pi(0.087746)})$

Table 15. Aggregated decision matrix for $\mathcal{R}_7$ and $\mathcal{R}_8$.

$\mathcal{Q}_i$	$\mathcal{R}_7$	$\mathcal{R}_8$
$\mathcal{Q}_1$	$(0.635593e^{i2\pi(0.056302)}, 0.373618e^{i2\pi(0.091257)})$	$(0.879296e^{i2\pi(0.077389)}, 0.133272e^{i2\pi(0.094692)})$
$\mathcal{Q}_2$	$(0.948617e^{i2\pi(0.081666)}, 0.053397e^{i2\pi(0.082860)})$	$(0.604031e^{i2\pi(0.068222)}, 0.418117e^{i2\pi(0.067994)})$
$\mathcal{Q}_3$	$(0.951434e^{i2\pi(0.106779)}, 0.053844e^{i2\pi(0.046839)})$	$(0.831092e^{i2\pi(0.072153)}, 0.182679e^{i2\pi(0.101039)})$
$\mathcal{Q}_4$	$(0.863476e^{i2\pi(0.076384)}, 0.154573e^{i2\pi(0.090664)})$	$(0.930778e^{i2\pi(0.106976)}, 0.084881e^{i2\pi(0.033274)})$
$\mathcal{Q}_5$	$(0.839736e^{i2\pi(0.051835)}, 0.160264e^{i2\pi(0.085484)})$	$(0.809152e^{i2\pi(0.082157)}, 0.226322e^{i2\pi(0.083196)})$
$\mathcal{Q}_6$	$(0.904317e^{i2\pi(0.085241)}, 0.110764e^{i2\pi(0.084346)})$	$(0.956545e^{i2\pi(0.068499)}, 0.040439e^{i2\pi(0.087473)})$
$\mathcal{Q}_7$	$(0.645935e^{i2\pi(0.074297)}, 0.361828e^{i2\pi(0.065136)})$	$(0.813390e^{i2\pi(0.078477)}, 0.180262e^{i2\pi(0.092075)})$
$\mathcal{Q}_8$	$(0.943486e^{i2\pi(0.093059)}, 0.060974e^{i2\pi(0.099438)})$	$(0.798353e^{i2\pi(0.080317)}, 0.222234e^{i2\pi(0.071063)})$
$\mathcal{Q}_9$	$(0.593775e^{i2\pi(0.069596)}, 0.441310e^{i2\pi(0.095426)})$	$(0.768572e^{i2\pi(0.083841)}, 0.236212e^{i2\pi(0.054018)})$
$\mathcal{Q}_{10}$	$(0.688985e^{i2\pi(0.083432)}, 0.304684e^{i2\pi(0.077235)})$	$(0.671502e^{i2\pi(0.063732)}, 0.302949e^{i2\pi(0.108628)})$
$\mathcal{Q}_{11}$	$(0.902994e^{i2\pi(0.083793)}, 0.106374e^{i2\pi(0.073175)})$	$(0.825155e^{i2\pi(0.068800)}, 0.197260e^{i2\pi(0.072863)})$
$\mathcal{Q}_{12}$	$(0.927865e^{i2\pi(0.110983)}, 0.081797e^{i2\pi(0.031557)})$	$(0.860773e^{i2\pi(0.084302)}, 0.157753e^{i2\pi(0.095478)})$
$\mathcal{Q}_{13}$	$(0.556782e^{i2\pi(0.065563)}, 0.478500e^{i2\pi(0.069872)})$	$(0.846744e^{i2\pi(0.095257)}, 0.155298e^{i2\pi(0.045577)})$
$\mathcal{Q}_{14}$	$(0.866767e^{i2\pi(0.084090)}, 0.142104e^{i2\pi(0.047434)})$	$(0.840544e^{i2\pi(0.076165)}, 0.156779e^{i2\pi(0.080495)})$

Table 15. Cont.

Q_i	$\mathcal{R}_7$	$\mathcal{R}_8$
Q_{15}	$(0.733984e^{i2\pi(0.076316)}, 0.272359e^{i2\pi(0.089175)})$	$(0.932924e^{i2\pi(0.093976)}, 0.082031e^{i2\pi(0.048866)})$

Table 16. Aggregated decision matrix for $\mathcal{R}_9$ and $\mathcal{R}_{10}$.

Q_i	$\mathcal{R}_9$	$\mathcal{R}_{10}$
Q_1	$(0.865964e^{i2\pi(0.094823)}, 0.127850e^{i2\pi(0.044947)})$	$(0.923634e^{i2\pi(0.059897)}, 0.074153e^{i2\pi(0.104476)})$
Q_2	$(0.770020e^{i2\pi(0.063961)}, 0.257090e^{i2\pi(0.067647)})$	$(0.810549e^{i2\pi(0.064738)}, 0.190893e^{i2\pi(0.092877)})$
Q_3	$(0.633345e^{i2\pi(0.070145)}, 0.387164e^{i2\pi(0.064208)})$	$(0.911277e^{i2\pi(0.083621)}, 0.109396e^{i2\pi(0.059614)})$
Q_4	$(0.911543e^{i2\pi(0.107558)}, 0.095407e^{i2\pi(0.056428)})$	$(0.609302e^{i2\pi(0.064268)}, 0.414579e^{i2\pi(0.097658)})$
Q_5	$(0.917129e^{i2\pi(0.081492)}, 0.083972e^{i2\pi(0.081520)})$	$(0.692639e^{i2\pi(0.064114)}, 0.328355e^{i2\pi(0.092383)})$
Q_6	$(0.948155e^{i2\pi(0.100520)}, 0.063247e^{i2\pi(0.052622)})$	$(0.846410e^{i2\pi(0.088204)}, 0.161579e^{i2\pi(0.043792)})$
Q_7	$(0.901636e^{i2\pi(0.091973)}, 0.118186e^{i2\pi(0.040490)})$	$(0.848762e^{i2\pi(0.076116)}, 0.164884e^{i2\pi(0.075079)})$
Q_8	$(0.894746e^{i2\pi(0.096451)}, 0.119698e^{i2\pi(0.100422)})$	$(0.954455e^{i2\pi(0.082830)}, 0.049798e^{i2\pi(0.073250)})$
Q_9	$(0.918395e^{i2\pi(0.061022)}, 0.084229e^{i2\pi(0.098060)})$	$(0.823895e^{i2\pi(0.083455)}, 0.178255e^{i2\pi(0.090564)})$
Q_{10}	$(0.852613e^{i2\pi(0.071528)}, 0.170965e^{i2\pi(0.088739)})$	$(0.947449e^{i2\pi(0.113080)}, 0.062252e^{i2\pi(0.054583)})$
Q_{11}	$(0.694883e^{i2\pi(0.075764)}, 0.320078e^{i2\pi(0.087620)})$	$(0.536757e^{i2\pi(0.060213)}, 0.435320e^{i2\pi(0.084899)})$
Q_{12}	$(0.841500e^{i2\pi(0.076596)}, 0.150456e^{i2\pi(0.073231)})$	$(0.868639e^{i2\pi(0.091613)}, 0.145064e^{i2\pi(0.089980)})$
Q_{13}	$(0.837096e^{i2\pi(0.081608)}, 0.174303e^{i2\pi(0.102157)})$	$(0.860274e^{i2\pi(0.105805)}, 0.157955e^{i2\pi(0.041587)})$
Q_{14}	$(0.400079e^{i2\pi(0.053367)}, 0.585289e^{i2\pi(0.081493)})$	$(0.693067e^{i2\pi(0.078040)}, 0.307353e^{i2\pi(0.055520)})$
Q_{15}	$(0.790729e^{i2\pi(0.072668)}, 0.218320e^{i2\pi(0.084452)})$	$(0.865679e^{i2\pi(0.083389)}, 0.148087e^{i2\pi(0.068830)})$

Table 17. Aggregated decision matrix for $\mathcal{R}_{11}$ and $\mathcal{R}_{12}$.

Q_i	$\mathcal{R}_{11}$	$\mathcal{R}_{12}$
Q_1	$(0.868102e^{i2\pi(0.108708)}, 0.152374e^{i2\pi(0.047098)})$	$(0.961513e^{i2\pi(0.089997)}, 0.040720e^{i2\pi(0.051000)})$
Q_2	$(0.711176e^{i2\pi(0.059813)}, 0.306634e^{i2\pi(0.075462)})$	$(0.877414e^{i2\pi(0.086618)}, 0.125984e^{i2\pi(0.063777)})$
Q_3	$(0.867726e^{i2\pi(0.086170)}, 0.122517e^{i2\pi(0.073565)})$	$(0.718791e^{i2\pi(0.077423)}, 0.308906e^{i2\pi(0.096301)})$
Q_4	$(0.847701e^{i2\pi(0.086355)}, 0.155603e^{i2\pi(0.049573)})$	$(0.924489e^{i2\pi(0.100203)}, 0.091904e^{i2\pi(0.078343)})$
Q_5	$(0.829604e^{i2\pi(0.066263)}, 0.191055e^{i2\pi(0.097842)})$	$(0.703150e^{i2\pi(0.057796)}, 0.306406e^{i2\pi(0.108149)})$
Q_6	$(0.841502e^{i2\pi(0.084624)}, 0.174978e^{i2\pi(0.089786)})$	$(0.838508e^{i2\pi(0.060392)}, 0.185076e^{i2\pi(0.064259)})$
Q_7	$(0.649855e^{i2\pi(0.070922)}, 0.370708e^{i2\pi(0.104567)})$	$(0.791386e^{i2\pi(0.072127)}, 0.219416e^{i2\pi(0.064871)})$
Q_8	$(0.822131e^{i2\pi(0.077959)}, 0.182897e^{i2\pi(0.059763)})$	$(0.710893e^{i2\pi(0.071698)}, 0.314061e^{i2\pi(0.106223)})$
Q_9	$(0.814258e^{i2\pi(0.093247)}, 0.194457e^{i2\pi(0.051137)})$	$(0.900153e^{i2\pi(0.070189)}, 0.115562e^{i2\pi(0.072442)})$
Q_{10}	$(0.659248e^{i2\pi(0.063550)}, 0.361603e^{i2\pi(0.099809)})$	$(0.855562e^{i2\pi(0.094707)}, 0.161046e^{i2\pi(0.051847)})$
Q_{11}	$(0.945431e^{i2\pi(0.092029)}, 0.063422e^{i2\pi(0.071521)})$	$(0.762928e^{i2\pi(0.079392)}, 0.231387e^{i2\pi(0.081974)})$

Table 17. Cont.

Q_i	$\mathcal{R}_{11}$	$\mathcal{R}_{12}$
Q_{12}	$(0.936446e^{i2\pi(0.065243)}, 0.070433e^{i2\pi(0.092224)})$	$(0.863742e^{i2\pi(0.061154)}, 0.131187e^{i2\pi(0.068894)})$
Q_{13}	$(0.811471e^{i2\pi(0.081062)}, 0.183070e^{i2\pi(0.104274)})$	$(0.930403e^{i2\pi(0.111316)}, 0.075919e^{i2\pi(0.050387)})$
Q_{14}	$(0.931724e^{i2\pi(0.078843)}, 0.080229e^{i2\pi(0.061053)})$	$(0.871897e^{i2\pi(0.095588)}, 0.137546e^{i2\pi(0.084138)})$
Q_{15}	$(0.854946e^{i2\pi(0.085206)}, 0.151266e^{i2\pi(0.049462)})$	$(0.560259e^{i2\pi(0.070793)}, 0.419655e^{i2\pi(0.071379)})$

Table 18. Aggregated decision matrix for $\mathcal{R}_{13}$ and $\mathcal{R}_{14}$.

Q_i	$\mathcal{R}_{13}$	$\mathcal{R}_{14}$
Q_1	$(0.821053e^{i2\pi(0.073496)}, 0.198768e^{i2\pi(0.097589)})$	$(0.864739e^{i2\pi(0.089478)}, 0.156137e^{i2\pi(0.081154)})$
Q_2	$(0.610592e^{i2\pi(0.065777)}, 0.389175e^{i2\pi(0.124196)})$	$(0.867175e^{i2\pi(0.087942)}, 0.137506e^{i2\pi(0.095810)})$
Q_3	$(0.819573e^{i2\pi(0.081744)}, 0.177126e^{i2\pi(0.076591)})$	$(0.894253e^{i2\pi(0.071430)}, 0.104205e^{i2\pi(0.065510)})$
Q_4	$(0.942211e^{i2\pi(0.075981)}, 0.061850e^{i2\pi(0.087812)})$	$(0.875851e^{i2\pi(0.090950)}, 0.116072e^{i2\pi(0.055301)})$
Q_5	$(0.799410e^{i2\pi(0.088604)}, 0.208146e^{i2\pi(0.067586)})$	$(0.946066e^{i2\pi(0.075996)}, 0.055385e^{i2\pi(0.060312)})$
Q_6	$(0.739411e^{i2\pi(0.061352)}, 0.270198e^{i2\pi(0.059506)})$	$(0.217993e^{i2\pi(0.052877)}, 0.832324e^{i2\pi(0.097741)})$
Q_7	$(0.852102e^{i2\pi(0.096329)}, 0.143487e^{i2\pi(0.047474)})$	$(0.748682e^{i2\pi(0.048714)}, 0.277074e^{i2\pi(0.097382)})$
Q_8	$(0.736770e^{i2\pi(0.069053)}, 0.294333e^{i2\pi(0.071153)})$	$(0.909129e^{i2\pi(0.084561)}, 0.097395e^{i2\pi(0.057465)})$
Q_9	$(0.905956e^{i2\pi(0.069928)}, 0.089706e^{i2\pi(0.083313)})$	$(0.805085e^{i2\pi(0.094158)}, 0.207952e^{i2\pi(0.081931)})$
Q_{10}	$(0.905688e^{i2\pi(0.103142)}, 0.108221e^{i2\pi(0.048567)})$	$(0.907599e^{i2\pi(0.084019)}, 0.105922e^{i2\pi(0.060202)})$
Q_{11}	$(0.916255e^{i2\pi(0.098659)}, 0.100139e^{i2\pi(0.039829)})$	$(0.912683e^{i2\pi(0.101344)}, 0.099797e^{i2\pi(0.040698)})$
Q_{12}	$(0.620889e^{i2\pi(0.066194)}, 0.388248e^{i2\pi(0.082699)})$	$(0.848947e^{i2\pi(0.080029)}, 0.164686e^{i2\pi(0.088239)})$
Q_{13}	$(0.952078e^{i2\pi(0.071609)}, 0.058857e^{i2\pi(0.072745)})$	$(0.755654e^{i2\pi(0.065040)}, 0.263830e^{i2\pi(0.064532)})$
Q_{14}	$(0.737460e^{i2\pi(0.062855)}, 0.278160e^{i2\pi(0.099465)})$	$(0.827383e^{i2\pi(0.086381)}, 0.179297e^{i2\pi(0.069493)})$
Q_{15}	$(0.899007e^{i2\pi(0.114517)}, 0.113277e^{i2\pi(0.070634)})$	$(0.767590e^{i2\pi(0.086750)}, 0.254693e^{i2\pi(0.102192)})$

Table 19. Aggregated decision matrix for $\mathcal{R}_{15}$.

Q_i	$\mathcal{R}_{15}$
Q_1	$(0.517238e^{i2\pi(0.066839)}, 0.500170e^{i2\pi(0.103208)})$
Q_2	$(0.932569e^{i2\pi(0.083245)}, 0.089024e^{i2\pi(0.065333)})$
Q_3	$(0.930576e^{i2\pi(0.074217)}, 0.068969e^{i2\pi(0.090201)})$
Q_4	$(0.902185e^{i2\pi(0.076399)}, 0.109007e^{i2\pi(0.086375)})$
Q_5	$(0.596843e^{i2\pi(0.060027)}, 0.363952e^{i2\pi(0.093384)})$
Q_6	$(0.872938e^{i2\pi(0.089617)}, 0.133720e^{i2\pi(0.101858)})$
Q_7	$(0.953439e^{i2\pi(0.091900)}, 0.052386e^{i2\pi(0.078862)})$
Q_8	$(0.782688e^{i2\pi(0.091200)}, 0.223835e^{i2\pi(0.052276)})$

Table 19. Cont.

$\mathcal{Q}_i$	$\mathcal{R}_{15}$
$\mathcal{Q}_9$	$(0.887324e^{i2\pi(0.088355)}, 0.116438e^{i2\pi(0.068235)})$
$\mathcal{Q}_{10}$	$(0.879395e^{i2\pi(0.078109)}, 0.133883e^{i2\pi(0.064120)})$
$\mathcal{Q}_{11}$	$(0.548339e^{i2\pi(0.041750)}, 0.458677e^{i2\pi(0.096369)})$
$\mathcal{Q}_{12}$	$(0.849863e^{i2\pi(0.094285)}, 0.155917e^{i2\pi(0.049966)})$
$\mathcal{Q}_{13}$	$(0.557403e^{i2\pi(0.057075)}, 0.478241e^{i2\pi(0.094719)})$
$\mathcal{Q}_{14}$	$(0.882289e^{i2\pi(0.100172)}, 0.126000e^{i2\pi(0.062898)})$
$\mathcal{Q}_{15}$	$(0.903826e^{i2\pi(0.105800)}, 0.109783e^{i2\pi(0.029173)})$

After obtaining the aggregated decision matrix, the next essential step in the MCGDM process is to construct the normalized decision matrix. Normalization is required because the evaluation criteria differ in scale, measurement domain, and orientation [37]. Without normalization, criteria with larger numerical ranges would dominate the decision process and distort the final ranking [38]. In the present study, among the 15 criteria, $\mathcal{R}_3$, $\mathcal{R}_4$, $\mathcal{R}_9$, $\mathcal{R}_{11}$, $\mathcal{R}_{14}$, and $\mathcal{R}_{15}$ are cost criteria, while the remaining are benefit criteria. Using Equation (18), the aggregated C_{FOPS} -based values are transformed into a dimensionless form that allows all criteria to be compared fairly and consistently. Due to space limitations, the complete normalized decision matrix is omitted from the paper. In this part, we summarize that this step ensures each criterion contributes appropriately to the evaluation and provides a standardized foundation for subsequent weighting and TOPSIS-based ranking.

In the proposed MCGDM framework for evaluating GSCM strategies, determining the relative importance of the 15 assessment criteria is essential, as each criterion contributes differently to the overall effectiveness and sustainability of a strategy. To ensure an objective and data-driven weighting process, the entropy method [35] is employed. This method quantifies the degree of variability or dispersion present in the normalized decision matrix, allowing criteria that exhibit greater informational diversity to receive higher weights [39]. Using Equation (19), entropy values and their corresponding degrees of diversification are computed, resulting in a vector of objective criteria weights. This approach is particularly appropriate for the proposed problem because it minimizes subjective bias, reflects the actual informational content of expert evaluations, and provides a more accurate representation of how criteria such as resource efficiency, waste reduction, energy consumption, operational feasibility, scalability, product quality, regulatory compliance, and overall implementation cost influence the final ranking of GSCM strategies. The criteria weights are presented in Table 20.

Table 20. Criteria and its corresponding weights.

Criteria	Corresponding Weights	Criteria	Corresponding Weights	Criteria	Corresponding Weights
$\mathcal{R}_1$	0.05785034	$\mathcal{R}_6$	0.06340993	$\mathcal{R}_{11}$	0.06335059
$\mathcal{R}_2$	0.09337091	$\mathcal{R}_7$	0.05969790	$\mathcal{R}_{12}$	0.05997686
$\mathcal{R}_3$	0.06180154	$\mathcal{R}_8$	0.06101757	$\mathcal{R}_{13}$	0.07031635
$\mathcal{R}_4$	0.05469479	$\mathcal{R}_9$	0.07068265	$\mathcal{R}_{14}$	0.09168510
$\mathcal{R}_5$	0.06340226	$\mathcal{R}_{10}$	0.06123785	$\mathcal{R}_{15}$	0.06750638

This step ensures that each criterion's influence on the evaluation of GSCM strategies is proportional to its computed importance. Using Equation (16), the weighted aggregated

decision matrix is obtained, in which highly informative criteria such as resource efficiency, waste reduction, energy consumption, operational feasibility, scalability, product quality, and regulatory compliance exert greater impact on the final assessment. The weighted aggregated decision matrix thus integrates both expert evaluations and objective criteria significance, forming the essential input for the subsequent TOPSIS ranking of the fifteen GSCM strategy alternatives. The weighted aggregated decision matrix is presented in Tables 21–28.

Table 21. Weighted aggregated decision matrix for $\mathcal{R}_1$ and $\mathcal{R}_2$.

Q_i	$\mathcal{R}_1$	$\mathcal{R}_2$
Q_1	$(0.076650e^{i2\pi(0.004442)}, 0.924805e^{i2\pi(0.873957)})$	$(0.141297e^{i2\pi(0.007510)}, 0.872286e^{i2\pi(0.772670)})$
Q_2	$(0.086736e^{i2\pi(0.005467)}, 0.912314e^{i2\pi(0.858863)})$	$(0.206392e^{i2\pi(0.009125)}, 0.791377e^{i2\pi(0.754449)})$
Q_3	$(0.097467e^{i2\pi(0.003990)}, 0.905659e^{i2\pi(0.854359)})$	$(0.159066e^{i2\pi(0.008685)}, 0.845621e^{i2\pi(0.793595)})$
Q_4	$(0.069438e^{i2\pi(0.004675)}, 0.932050e^{i2\pi(0.877907)})$	$(0.016341e^{i2\pi(0.004325)}, 0.987307e^{i2\pi(0.798876)})$
Q_5	$(0.105376e^{i2\pi(0.005860)}, 0.898764e^{i2\pi(0.868923)})$	$(0.199312e^{i2\pi(0.008308)}, 0.812261e^{i2\pi(0.770643)})$
Q_6	$(0.103187e^{i2\pi(0.005596)}, 0.897240e^{i2\pi(0.835803)})$	$(0.089556e^{i2\pi(0.006610)}, 0.917921e^{i2\pi(0.803220)})$
Q_7	$(0.106909e^{i2\pi(0.005521)}, 0.901701e^{i2\pi(0.859029)})$	$(0.102887e^{i2\pi(0.008290)}, 0.893758e^{i2\pi(0.792661)})$
Q_8	$(0.182617e^{i2\pi(0.006268)}, 0.830726e^{i2\pi(0.832310)})$	$(0.186504e^{i2\pi(0.009078)}, 0.816659e^{i2\pi(0.751602)})$
Q_9	$(0.131392e^{i2\pi(0.006940)}, 0.873620e^{i2\pi(0.817480)})$	$(0.192960e^{i2\pi(0.007561)}, 0.819622e^{i2\pi(0.790297)})$
Q_{10}	$(0.107653e^{i2\pi(0.004410)}, 0.894803e^{i2\pi(0.879694)})$	$(0.141309e^{i2\pi(0.004374)}, 0.861257e^{i2\pi(0.796983)})$
Q_{11}	$(0.066393e^{i2\pi(0.002410)}, 0.932116e^{i2\pi(0.866086)})$	$(0.270233e^{i2\pi(0.009068)}, 0.733659e^{i2\pi(0.751108)})$
Q_{12}	$(0.083404e^{i2\pi(0.004926)}, 0.917830e^{i2\pi(0.842892)})$	$(0.124427e^{i2\pi(0.006463)}, 0.872724e^{i2\pi(0.799065)})$
Q_{13}	$(0.067594e^{i2\pi(0.003134)}, 0.935002e^{i2\pi(0.866713)})$	$(0.174638e^{i2\pi(0.009230)}, 0.834722e^{i2\pi(0.797373)})$
Q_{14}	$(0.143746e^{i2\pi(0.005096)}, 0.859017e^{i2\pi(0.863235)})$	$(0.210493e^{i2\pi(0.010295)}, 0.801332e^{i2\pi(0.755639)})$
Q_{15}	$(0.126997e^{i2\pi(0.004233)}, 0.878707e^{i2\pi(0.870188)})$	$(0.196317e^{i2\pi(0.008678)}, 0.804418e^{i2\pi(0.782183)})$

Table 22. Weighted aggregated decision matrix for $\mathcal{R}_3$ and $\mathcal{R}_4$.

Q_i	$\mathcal{R}_3$	$\mathcal{R}_4$
Q_1	$(0.013875e^{i2\pi(0.003327)}, 0.987062e^{i2\pi(0.849123)})$	$(0.024473e^{i2\pi(0.004419)}, 0.972731e^{i2\pi(0.866315)})$
Q_2	$(0.024260e^{i2\pi(0.004549)}, 0.975168e^{i2\pi(0.843072)})$	$(0.004780e^{i2\pi(0.002848)}, 0.996058e^{i2\pi(0.882983)})$
Q_3	$(0.006806e^{i2\pi(0.002391)}, 0.993804e^{i2\pi(0.869242)})$	$(0.005333e^{i2\pi(0.004016)}, 0.995663e^{i2\pi(0.870932)})$
Q_4	$(0.024968e^{i2\pi(0.005285)}, 0.973960e^{i2\pi(0.834990)})$	$(0.008292e^{i2\pi(0.003508)}, 0.993145e^{i2\pi(0.873443)})$
Q_5	$(0.004715e^{i2\pi(0.002366)}, 0.995878e^{i2\pi(0.872939)})$	$(0.005733e^{i2\pi(0.004229)}, 0.995067e^{i2\pi(0.885446)})$
Q_6	$(0.021579e^{i2\pi(0.006845)}, 0.980240e^{i2\pi(0.846801)})$	$(0.007432e^{i2\pi(0.004701)}, 0.993501e^{i2\pi(0.879256)})$
Q_7	$(0.010552e^{i2\pi(0.004441)}, 0.991258e^{i2\pi(0.852534)})$	$(0.001627e^{i2\pi(0.003679)}, 0.998460e^{i2\pi(0.870750)})$
Q_8	$(0.009154e^{i2\pi(0.004550)}, 0.991576e^{i2\pi(0.857570)})$	$(0.029112e^{i2\pi(0.006274)}, 0.968600e^{i2\pi(0.846103)})$
Q_9	$(0.006368e^{i2\pi(0.004478)}, 0.995078e^{i2\pi(0.862069)})$	$(0.009325e^{i2\pi(0.003481)}, 0.990787e^{i2\pi(0.860815)})$

Table 22. Cont.

Q_i	$\mathcal{R}_3$	$\mathcal{R}_4$
Q_{10}	$(0.003674e^{i2\pi(0.005088)}, 0.996316e^{i2\pi(0.843455)})$	$(0.013245e^{i2\pi(0.003763)}, 0.986964e^{i2\pi(0.872929)})$
Q_{11}	$(0.006765e^{i2\pi(0.005893)}, 0.993710e^{i2\pi(0.868181)})$	$(0.010560e^{i2\pi(0.003078)}, 0.990222e^{i2\pi(0.876304)})$
Q_{12}	$(0.034386e^{i2\pi(0.006528)}, 0.969606e^{i2\pi(0.858179)})$	$(0.020732e^{i2\pi(0.004514)}, 0.980189e^{i2\pi(0.854584)})$
Q_{13}	$(0.027537e^{i2\pi(0.005869)}, 0.970055e^{i2\pi(0.844968)})$	$(0.012744e^{i2\pi(0.003991)}, 0.986703e^{i2\pi(0.855477)})$
Q_{14}	$(0.009060e^{i2\pi(0.006170)}, 0.991448e^{i2\pi(0.856212)})$	$(0.013519e^{i2\pi(0.005690)}, 0.987738e^{i2\pi(0.865051)})$
Q_{15}	$(0.007432e^{i2\pi(0.005586)}, 0.992780e^{i2\pi(0.834427)})$	$(0.018696e^{i2\pi(0.005234)}, 0.982444e^{i2\pi(0.869754)})$

Table 23. Weighted aggregated decision matrix for $\mathcal{R}_5$ and $\mathcal{R}_6$.

Q_i	$\mathcal{R}_5$	$\mathcal{R}_6$
Q_1	$(0.132376e^{i2\pi(0.006232)}, 0.869723e^{i2\pi(0.823772)})$	$(0.176391e^{i2\pi(0.006191)}, 0.836311e^{i2\pi(0.847434)})$
Q_2	$(0.148630e^{i2\pi(0.006600)}, 0.864168e^{i2\pi(0.838987)})$	$(0.117170e^{i2\pi(0.005837)}, 0.883792e^{i2\pi(0.840926)})$
Q_3	$(0.042074e^{i2\pi(0.003375)}, 0.961437e^{i2\pi(0.851734)})$	$(0.057198e^{i2\pi(0.005489)}, 0.948476e^{i2\pi(0.864727)})$
Q_4	$(0.091070e^{i2\pi(0.005188)}, 0.905127e^{i2\pi(0.862999)})$	$(0.142821e^{i2\pi(0.004772)}, 0.859631e^{i2\pi(0.831129)})$
Q_5	$(0.058633e^{i2\pi(0.003634)}, 0.945311e^{i2\pi(0.840023)})$	$(0.135788e^{i2\pi(0.007451)}, 0.867127e^{i2\pi(0.805197)})$
Q_6	$(0.167069e^{i2\pi(0.006425)}, 0.832931e^{i2\pi(0.820192)})$	$(0.087413e^{i2\pi(0.005744)}, 0.911109e^{i2\pi(0.846444)})$
Q_7	$(0.117759e^{i2\pi(0.005916)}, 0.882733e^{i2\pi(0.850467)})$	$(0.103146e^{i2\pi(0.005104)}, 0.900727e^{i2\pi(0.846992)})$
Q_8	$(0.064880e^{i2\pi(0.004305)}, 0.932313e^{i2\pi(0.851511)})$	$(0.040680e^{i2\pi(0.003910)}, 0.957819e^{i2\pi(0.852598)})$
Q_9	$(0.106414e^{i2\pi(0.006085)}, 0.896344e^{i2\pi(0.862958)})$	$(0.037928e^{i2\pi(0.002997)}, 0.963396e^{i2\pi(0.854487)})$
Q_{10}	$(0.067646e^{i2\pi(0.004803)}, 0.937253e^{i2\pi(0.846104)})$	$(0.130668e^{i2\pi(0.006871)}, 0.871808e^{i2\pi(0.825410)})$
Q_{11}	$(0.103275e^{i2\pi(0.005785)}, 0.903702e^{i2\pi(0.865359)})$	$(0.108819e^{i2\pi(0.005469)}, 0.893320e^{i2\pi(0.862158)})$
Q_{12}	$(0.113639e^{i2\pi(0.004445)}, 0.893517e^{i2\pi(0.844607)})$	$(0.194332e^{i2\pi(0.007415)}, 0.817188e^{i2\pi(0.834083)})$
Q_{13}	$(0.167184e^{i2\pi(0.008000)}, 0.842076e^{i2\pi(0.825233)})$	$(0.206963e^{i2\pi(0.004868)}, 0.795431e^{i2\pi(0.861407)})$
Q_{14}	$(0.131197e^{i2\pi(0.004520)}, 0.871807e^{i2\pi(0.839559)})$	$(0.105034e^{i2\pi(0.004831)}, 0.903681e^{i2\pi(0.849492)})$
Q_{15}	$(0.179169e^{i2\pi(0.004648)}, 0.825416e^{i2\pi(0.854478)})$	$(0.037358e^{i2\pi(0.003019)}, 0.962139e^{i2\pi(0.855695)})$

Table 24. Weighted aggregated decision matrix for $\mathcal{R}_7$ and $\mathcal{R}_8$.

Q_i	$\mathcal{R}_7$	$\mathcal{R}_8$
Q_1	$(0.059051e^{i2\pi(0.003488)}, 0.942366e^{i2\pi(0.865584)})$	$(0.122179e^{i2\pi(0.004952)}, 0.883196e^{i2\pi(0.864787)})$
Q_2	$(0.163880e^{i2\pi(0.005124)}, 0.838061e^{i2\pi(0.860561)})$	$(0.055497e^{i2\pi(0.004345)}, 0.947677e^{i2\pi(0.847314)})$
Q_3	$(0.166717e^{i2\pi(0.006785)}, 0.838483e^{i2\pi(0.831466)})$	$(0.103811e^{i2\pi(0.004605)}, 0.900528e^{i2\pi(0.868252)})$
Q_4	$(0.113135e^{i2\pi(0.004780)}, 0.893529e^{i2\pi(0.865244)})$	$(0.151751e^{i2\pi(0.006949)}, 0.858977e^{i2\pi(0.810804)})$
Q_5	$(0.104520e^{i2\pi(0.003204)}, 0.895480e^{i2\pi(0.862180)})$	$(0.097041e^{i2\pi(0.005270)}, 0.912497e^{i2\pi(0.857917)})$
Q_6	$(0.131941e^{i2\pi(0.005358)}, 0.875754e^{i2\pi(0.861484)})$	$(0.175745e^{i2\pi(0.004364)}, 0.820609e^{i2\pi(0.860571)})$

Table 24. Cont.

Q_i	$\mathcal{R}_7$	$\mathcal{R}_8$
Q_7	$(0.060683e^{i2\pi(0.004644)}, 0.940546e^{i2\pi(0.848163)})$	$(0.098289e^{i2\pi(0.005024)}, 0.899789e^{i2\pi(0.863295)})$
Q_8	$(0.159067e^{i2\pi(0.005872)}, 0.844793e^{i2\pi(0.870077)})$	$(0.093972e^{i2\pi(0.005147)}, 0.911472e^{i2\pi(0.849623)})$
Q_9	$(0.052868e^{i2\pi(0.004340)}, 0.951875e^{i2\pi(0.867919)})$	$(0.086248e^{i2\pi(0.005382)}, 0.914905e^{i2\pi(0.835383)})$
Q_{10}	$(0.067997e^{i2\pi(0.005239)}, 0.930848e^{i2\pi(0.856921)})$	$(0.066308e^{i2\pi(0.004050)}, 0.929044e^{i2\pi(0.872137)})$
Q_{11}	$(0.131221e^{i2\pi(0.005263)}, 0.873621e^{i2\pi(0.854135)})$	$(0.101901e^{i2\pi(0.004384)}, 0.904800e^{i2\pi(0.850933)})$
Q_{12}	$(0.146601e^{i2\pi(0.007068)}, 0.859891e^{i2\pi(0.811901)})$	$(0.114422e^{i2\pi(0.005413)}, 0.892423e^{i2\pi(0.865228)})$
Q_{13}	$(0.047877e^{i2\pi(0.004080)}, 0.956530e^{i2\pi(0.851760)})$	$(0.109166e^{i2\pi(0.006151)}, 0.891561e^{i2\pi(0.826680)})$
Q_{14}	$(0.114439e^{i2\pi(0.005282)}, 0.889010e^{i2\pi(0.832099)})$	$(0.106986e^{i2\pi(0.004871)}, 0.892082e^{i2\pi(0.856173)})$
Q_{15}	$(0.076738e^{i2\pi(0.004775)}, 0.924575e^{i2\pi(0.864381)})$	$(0.153396e^{i2\pi(0.006064)}, 0.857172e^{i2\pi(0.830238)})$

Table 25. Weighted aggregated decision matrix for $\mathcal{R}_9$ and $\mathcal{R}_{10}$.

Q_i	$\mathcal{R}_9$	$\mathcal{R}_{10}$
Q_1	$(0.009718e^{i2\pi(0.003278)}, 0.989779e^{i2\pi(0.845212)})$	$(0.147083e^{i2\pi(0.003813)}, 0.851368e^{i2\pi(0.869613)})$
Q_2	$(0.020991e^{i2\pi(0.004988)}, 0.981517e^{i2\pi(0.821786)})$	$(0.097779e^{i2\pi(0.004131)}, 0.902644e^{i2\pi(0.863306)})$
Q_3	$(0.034351e^{i2\pi(0.004726)}, 0.967921e^{i2\pi(0.827218)})$	$(0.139133e^{i2\pi(0.005387)}, 0.872091e^{i2\pi(0.839953)})$
Q_4	$(0.007132e^{i2\pi(0.004138)}, 0.993410e^{i2\pi(0.852849)})$	$(0.056471e^{i2\pi(0.004100)}, 0.946998e^{i2\pi(0.865991)})$
Q_5	$(0.006242e^{i2\pi(0.006052)}, 0.993844e^{i2\pi(0.836119)})$	$(0.070368e^{i2\pi(0.004090)}, 0.933439e^{i2\pi(0.863021)})$
Q_6	$(0.004653e^{i2\pi(0.003852)}, 0.996207e^{i2\pi(0.848739)})$	$(0.109413e^{i2\pi(0.005695)}, 0.893384e^{i2\pi(0.824081)})$
Q_7	$(0.008938e^{i2\pi(0.002946)}, 0.992636e^{i2\pi(0.843372)})$	$(0.110263e^{i2\pi(0.004885)}, 0.894504e^{i2\pi(0.852021)})$
Q_8	$(0.009060e^{i2\pi(0.007526)}, 0.992092e^{i2\pi(0.846239)})$	$(0.173916e^{i2\pi(0.005333)}, 0.830658e^{i2\pi(0.850723)})$
Q_9	$(0.006262e^{i2\pi(0.007341)}, 0.993941e^{i2\pi(0.819031)})$	$(0.101846e^{i2\pi(0.005375)}, 0.898828e^{i2\pi(0.861961)})$
Q_{10}	$(0.013295e^{i2\pi(0.006612)}, 0.988682e^{i2\pi(0.828372)})$	$(0.166572e^{i2\pi(0.007395)}, 0.842206e^{i2\pi(0.835385)})$
Q_{11}	$(0.027164e^{i2\pi(0.006525)}, 0.974349e^{i2\pi(0.831780)})$	$(0.046479e^{i2\pi(0.003834)}, 0.949861e^{i2\pi(0.858524)})$
Q_{12}	$(0.011572e^{i2\pi(0.005414)}, 0.987756e^{i2\pi(0.832429)})$	$(0.117983e^{i2\pi(0.005925)}, 0.887447e^{i2\pi(0.861616)})$
Q_{13}	$(0.013579e^{i2\pi(0.007663)}, 0.987387e^{i2\pi(0.836205)})$	$(0.114609e^{i2\pi(0.006893)}, 0.892132e^{i2\pi(0.821453)})$
Q_{14}	$(0.060899e^{i2\pi(0.006050)}, 0.936696e^{i2\pi(0.811230)})$	$(0.070448e^{i2\pi(0.005013)}, 0.929630e^{i2\pi(0.836265)})$
Q_{15}	$(0.017430e^{i2\pi(0.006279)}, 0.983378e^{i2\pi(0.829307)})$	$(0.116766e^{i2\pi(0.005371)}, 0.888580e^{i2\pi(0.847455)})$

Table 26. Weighted aggregated decision matrix for $\mathcal{R}_{11}$ and $\mathcal{R}_{12}$.

Q_i	$\mathcal{R}_{11}$	$\mathcal{R}_{12}$
Q_1	$(0.010523e^{i2\pi(0.003082)}, 0.990990e^{i2\pi(0.867623)})$	$(0.179084e^{i2\pi(0.005697)}, 0.823726e^{i2\pi(0.835036)})$
Q_2	$(0.023160e^{i2\pi(0.005008)}, 0.978426e^{i2\pi(0.835080)})$	$(0.119401e^{i2\pi(0.005474)}, 0.882059e^{i2\pi(0.846422)})$

Table 26. Cont.

Q_i	$\mathcal{R}_{11}$	$\mathcal{R}_{12}$
Q_3	$(0.008328e^{i2\pi(0.004878)}, 0.990962e^{i2\pi(0.854819)})$	$(0.073976e^{i2\pi(0.004870)}, 0.931309e^{i2\pi(0.867818)})$
Q_4	$(0.010764e^{i2\pi(0.003248)}, 0.989483e^{i2\pi(0.854937)})$	$(0.144874e^{i2\pi(0.006376)}, 0.865365e^{i2\pi(0.857036)})$
Q_5	$(0.013476e^{i2\pi(0.006567)}, 0.988118e^{i2\pi(0.840571)})$	$(0.070934e^{i2\pi(0.003600)}, 0.930851e^{i2\pi(0.873940)})$
Q_6	$(0.012233e^{i2\pi(0.006002)}, 0.989018e^{i2\pi(0.853829)})$	$(0.104573e^{i2\pi(0.003767)}, 0.902851e^{i2\pi(0.846809)})$
Q_7	$(0.029202e^{i2\pi(0.007043)}, 0.972797e^{i2\pi(0.844233)})$	$(0.090577e^{i2\pi(0.004525)}, 0.912209e^{i2\pi(0.847295)})$
Q_8	$(0.012842e^{i2\pi(0.003935)}, 0.987546e^{i2\pi(0.849360)})$	$(0.072420e^{i2\pi(0.004497)}, 0.932243e^{i2\pi(0.872989)})$
Q_9	$(0.013742e^{i2\pi(0.003353)}, 0.986938e^{i2\pi(0.859148)})$	$(0.130279e^{i2\pi(0.004399)}, 0.877457e^{i2\pi(0.852980)})$
Q_{10}	$(0.028310e^{i2\pi(0.006706)}, 0.973691e^{i2\pi(0.838325)})$	$(0.110607e^{i2\pi(0.006009)}, 0.895277e^{i2\pi(0.835869)})$
Q_{11}	$(0.004184e^{i2\pi(0.004737)}, 0.996416e^{i2\pi(0.858425)})$	$(0.083504e^{i2\pi(0.004999)}, 0.915149e^{i2\pi(0.859391)})$
Q_{12}	$(0.004663e^{i2\pi(0.006172)}, 0.995807e^{i2\pi(0.839736)})$	$(0.113743e^{i2\pi(0.003815)}, 0.884224e^{i2\pi(0.850388)})$
Q_{13}	$(0.012855e^{i2\pi(0.007022)}, 0.986721e^{i2\pi(0.851484)})$	$(0.149088e^{i2\pi(0.007124)}, 0.855405e^{i2\pi(0.834425)})$
Q_{14}	$(0.005337e^{i2\pi(0.004023)}, 0.995485e^{i2\pi(0.849972)})$	$(0.117050e^{i2\pi(0.006068)}, 0.886763e^{i2\pi(0.860749)})$
Q_{15}	$(0.010440e^{i2\pi(0.003241)}, 0.990022e^{i2\pi(0.854204)})$	$(0.048552e^{i2\pi(0.004438)}, 0.948757e^{i2\pi(0.852216)})$

Table 27. Weighted aggregated decision matrix for $\mathcal{R}_{13}$ and $\mathcal{R}_{14}$.

Q_i	$\mathcal{R}_{13}$	$\mathcal{R}_{14}$
Q_1	$(0.099672e^{i2\pi(0.004647)}, 0.906118e^{i2\pi(0.867626)})$	$(0.015598e^{i2\pi(0.007807)}, 0.986633e^{i2\pi(0.799700)})$
Q_2	$(0.055925e^{i2\pi(0.004143)}, 0.944040e^{i2\pi(0.880485)})$	$(0.013605e^{i2\pi(0.009283)}, 0.986890e^{i2\pi(0.798418)})$
Q_3	$(0.099219e^{i2\pi(0.005190)}, 0.899767e^{i2\pi(0.854893)})$	$(0.010139e^{i2\pi(0.006255)}, 0.989704e^{i2\pi(0.783190)})$
Q_4	$(0.159675e^{i2\pi(0.004810)}, 0.843815e^{i2\pi(0.862055)})$	$(0.011360e^{i2\pi(0.005254)}, 0.987800e^{i2\pi(0.800909)})$
Q_5	$(0.093377e^{i2\pi(0.005645)}, 0.908671e^{i2\pi(0.848394)})$	$(0.005262e^{i2\pi(0.005744)}, 0.994879e^{i2\pi(0.787697)})$
Q_6	$(0.078784e^{i2\pi(0.003856)}, 0.923254e^{i2\pi(0.841827)})$	$(0.152413e^{i2\pi(0.009479)}, 0.868437e^{i2\pi(0.761679)})$
Q_7	$(0.110081e^{i2\pi(0.006162)}, 0.888277e^{i2\pi(0.830303)})$	$(0.029598e^{i2\pi(0.009443)}, 0.973553e^{i2\pi(0.755917)})$
Q_8	$(0.078217e^{i2\pi(0.004357)}, 0.928086e^{i2\pi(0.851060)})$	$(0.009444e^{i2\pi(0.005465)}, 0.991217e^{i2\pi(0.795525)})$
Q_9	$(0.134331e^{i2\pi(0.004414)}, 0.863179e^{i2\pi(0.859293)})$	$(0.021357e^{i2\pi(0.007885)}, 0.980123e^{i2\pi(0.803484)})$
Q_{10}	$(0.134180e^{i2\pi(0.006621)}, 0.873118e^{i2\pi(0.831458)})$	$(0.010314e^{i2\pi(0.005733)}, 0.991062e^{i2\pi(0.795051)})$
Q_{11}	$(0.140436e^{i2\pi(0.006318)}, 0.868993e^{i2\pi(0.821454)})$	$(0.009689e^{i2\pi(0.003840)}, 0.991575e^{i2\pi(0.808974)})$
Q_{12}	$(0.057468e^{i2\pi(0.004170)}, 0.943903e^{i2\pi(0.858905)})$	$(0.016525e^{i2\pi(0.008518)}, 0.984950e^{i2\pi(0.791477)})$
Q_{13}	$(0.169221e^{i2\pi(0.004524)}, 0.841264e^{i2\pi(0.852210)})$	$(0.027965e^{i2\pi(0.006158)}, 0.974389e^{i2\pi(0.776422)})$
Q_{14}	$(0.078365e^{i2\pi(0.003953)}, 0.924891e^{i2\pi(0.868635)})$	$(0.018131e^{i2\pi(0.006647)}, 0.982606e^{i2\pi(0.797095)})$
Q_{15}	$(0.130556e^{i2\pi(0.007394)}, 0.875555e^{i2\pi(0.850680)})$	$(0.026854e^{i2\pi(0.009933)}, 0.975804e^{i2\pi(0.797410)})$

Table 28. Weighted aggregated decision matrix for $\mathcal{R}_{15}$.

$\mathcal{Q}_i$	$\mathcal{R}_{15}$
$\mathcal{Q}_1$	$(0.046182e^{i2\pi(0.007399)}, 0.956047e^{i2\pi(0.831554)})$
$\mathcal{Q}_2$	$(0.006337e^{i2\pi(0.004596)}, 0.995251e^{i2\pi(0.844092)})$
$\mathcal{Q}_3$	$(0.004861e^{i2\pi(0.006424)}, 0.995106e^{i2\pi(0.837511)})$
$\mathcal{Q}_4$	$(0.007838e^{i2\pi(0.006140)}, 0.993006e^{i2\pi(0.839167)})$
$\mathcal{Q}_5$	$(0.030379e^{i2\pi(0.006662)}, 0.965424e^{i2\pi(0.825482)})$
$\mathcal{Q}_6$	$(0.009739e^{i2\pi(0.007298)}, 0.990778e^{i2\pi(0.848347)})$
$\mathcal{Q}_7$	$(0.003662e^{i2\pi(0.005585)}, 0.996754e^{i2\pi(0.849803)})$
$\mathcal{Q}_8$	$(0.017128e^{i2\pi(0.003654)}, 0.983433e^{i2\pi(0.849361)})$
$\mathcal{Q}_9$	$(0.008405e^{i2\pi(0.004807)}, 0.991882e^{i2\pi(0.847527)})$
$\mathcal{Q}_{10}$	$(0.009752e^{i2\pi(0.004508)}, 0.991276e^{i2\pi(0.840434)})$
$\mathcal{Q}_{11}$	$(0.040982e^{i2\pi(0.006885)}, 0.959861e^{i2\pi(0.805296)})$
$\mathcal{Q}_{12}$	$(0.011490e^{i2\pi(0.003489)}, 0.988970e^{i2\pi(0.851289)})$
$\mathcal{Q}_{13}$	$(0.043385e^{i2\pi(0.006762)}, 0.960934e^{i2\pi(0.822648)})$
$\mathcal{Q}_{14}$	$(0.009140e^{i2\pi(0.004419)}, 0.991498e^{i2\pi(0.854812)})$
$\mathcal{Q}_{15}$	$(0.007897e^{i2\pi(0.002017)}, 0.993129e^{i2\pi(0.858003)})$

In the TOPSIS stage of the proposed MCGDM framework, the PIS and NIS are constructed to evaluate how each GSCM strategy compares with the best and worst possible performance across all criteria [40]. The PIS represents the optimal values for benefit criteria and the minimal values for cost criteria [41], corresponding to the most desirable performance outcomes for sustainable and efficient supply chain strategies. Conversely, the NIS captures the least favorable values of minimum performance for benefit criteria and maximum performance for cost criteria. Using Equations (21) and (22), the PISs and NISs are derived from the weighted aggregated decision matrix, forming the reference points against which all fifteen GSCM strategies are compared. These PISs and NISs enable a clear, structured comparison of alternatives based on their proximity to optimal performance across environmental, operational, economic, and regulatory criteria. The PISs and NISs are presented in Table 29.

Table 29. Positive ideal solutions and negative ideal solutions.

$\mathcal{Q}_i$	$\mathcal{P}^+$	$\mathcal{P}^-$
$\mathcal{Q}_1$	$(0.2664e^{i2\pi(0.2024)}, 0.8350e^{i2\pi(0.8797)})$	$(0.1826e^{i2\pi(0.1469)}, 0.9307e^{i2\pi(0.9175)})$
$\mathcal{Q}_2$	$(0.3163e^{i2\pi(0.3043)}, 0.7873e^{i2\pi(0.8032)})$	$(0.2702e^{i2\pi(0.2503)}, 0.9037e^{i2\pi(0.9011)})$
$\mathcal{Q}_3$	$(0.3372e^{i2\pi(0.3124)}, 0.7963e^{i2\pi(0.8129)})$	$(0.2344e^{i2\pi(0.2168)}, 0.9196e^{i2\pi(0.8944)})$
$\mathcal{Q}_4$	$(0.3416e^{i2\pi(0.3128)}, 0.8085e^{i2\pi(0.8154)})$	$(0.2217e^{i2\pi(0.2063)}, 0.9286e^{i2\pi(0.9061)})$
$\mathcal{Q}_5$	$(0.3421e^{i2\pi(0.3334)}, 0.8014e^{i2\pi(0.8155)})$	$(0.2192e^{i2\pi(0.2093)}, 0.9254e^{i2\pi(0.9024)})$
$\mathcal{Q}_6$	$(0.3474e^{i2\pi(0.3335)}, 0.8016e^{i2\pi(0.8157)})$	$(0.2070e^{i2\pi(0.2074)}, 0.9256e^{i2\pi(0.9052)})$

Table 29. Cont.

Q_i	$\mathcal{P}^+$	$\mathcal{P}^-$
Q_7	$(0.3479e^{i2\pi(0.3339)}, 0.8019e^{i2\pi(0.8161)})$	$(0.2072e^{i2\pi(0.2079)}, 0.9261e^{i2\pi(0.9043)})$
Q_8	$(0.3523e^{i2\pi(0.3441)}, 0.8021e^{i2\pi(0.8123)})$	$(0.2075e^{i2\pi(0.2081)}, 0.9265e^{i2\pi(0.9048)})$
Q_9	$(0.3531e^{i2\pi(0.3529)}, 0.8024e^{i2\pi(0.8125)})$	$(0.2079e^{i2\pi(0.2077)}, 0.9267e^{i2\pi(0.9012)})$
Q_{10}	$(0.3493e^{i2\pi(0.3488)}, 0.8193e^{i2\pi(0.8296)})$	$(0.1739e^{i2\pi(0.1574)}, 0.9306e^{i2\pi(0.9185)})$
Q_{11}	$(0.3490e^{i2\pi(0.3491)}, 0.8194e^{i2\pi(0.8297)})$	$(0.1743e^{i2\pi(0.1577)}, 0.9308e^{i2\pi(0.9115)})$
Q_{12}	$(0.3486e^{i2\pi(0.3476)}, 0.8188e^{i2\pi(0.8213)})$	$(0.1745e^{i2\pi(0.1578)}, 0.9312e^{i2\pi(0.9119)})$
Q_{13}	$(0.3459e^{i2\pi(0.3449)}, 0.8182e^{i2\pi(0.8247)})$	$(0.1712e^{i2\pi(0.1574)}, 0.9311e^{i2\pi(0.9115)})$
Q_{14}	$(0.3453e^{i2\pi(0.3438)}, 0.8179e^{i2\pi(0.8241)})$	$(0.1711e^{i2\pi(0.1572)}, 0.9310e^{i2\pi(0.9114)})$
Q_{15}	$(0.3451e^{i2\pi(0.3420)}, 0.8168e^{i2\pi(0.8238)})$	$(0.1710e^{i2\pi(0.1570)}, 0.9309e^{i2\pi(0.9113)})$

After determining the $\mathcal{P}^+$ and $\mathcal{P}^-$, the TOPSIS method evaluates each GSCM strategy by measuring its Euclidean distance from these two reference points. Using Equation (23), the distance from the PIS reflects how close a technology is to the optimal performance across all benefit and cost criteria, while using Equation (24), the distance from the NIS indicates how far it is from the least desirable performance outcomes. For each of the 15 GSCM strategies, these distances capture the overall alignment of their characteristics, such as extraction efficiency, autonomy, environmental resilience, and contamination risk, with mission objectives. To derive the final ranking, a closeness coefficient $\mathcal{G}_i$ is computed, which represents the relative proximity of each alternative to the ideal solution. A higher $\mathcal{G}_i$ value indicates a strategy that is nearer to the $\mathcal{P}^+$ and farther from the $\mathcal{P}^-$, and therefore more suitable for implementation. By applying Equation (25), the $\mathcal{G}_i$ of all alternatives are obtained and sorted in descending order, producing a clear and interpretable ranking of the 15 green supply chains. The $\mathcal{G}_i$ and ranking of alternatives is presented in Table 30.

Table 30. Distance between the PIS, NIS, and ranking.

Q_i	$\mathcal{D}(Q_i, \mathcal{P}^+)$	$\mathcal{D}(Q_i, \mathcal{P}^-)$	$\mathcal{G}_i$	Ranking
Q_1	1.4748	1.4831	−0.5260	13
Q_2	1.3988	1.3988	−0.2450	8
Q_3	1.1542	1.1613	−0.1083	3
Q_4	1.2580	1.2634	−0.1301	4
Q_5	1.1974	1.2081	−0.1267	2
Q_6	1.599	1.588	−0.5327	14
Q_7	1.060	1.080	0.0003	1
Q_8	1.3793	1.3804	−0.2414	7
Q_9	1.3400	1.3513	−0.1998	5
Q_{10}	1.3414	1.3619	−0.2294	6
Q_{11}	1.4137	1.4238	−0.3573	9
Q_{12}	1.4431	1.4591	−0.4733	11
Q_{13}	1.6783	1.6103	−0.6828	15
Q_{14}	1.4638	1.4643	−0.5163	12
Q_{15}	1.4152	1.4231	−0.3959	10

The final results indicate that strategy Q_7 achieved the highest overall performance score, demonstrating superior effectiveness within the proposed C_{FOFS} -based MCGDM

framework for evaluating GSCM strategies. Its top ranking reflects strong performance across critical criteria, including resource efficiency, operational feasibility, energy consumption, regulatory compliance, and overall sustainability. Compared to other alternatives, Q_7 exhibits higher scalability, process efficiency, and implementation maturity, making it a more reliable and readily deployable solution in real-world supply chain environments. From a managerial perspective, this result suggests that organizations should prioritize strategies similar to Q_7 for immediate implementation, as they offer a balanced combination of environmental performance and operational feasibility under uncertainty. The strong performance of Q_7 indicates that decision-makers can achieve maximum sustainability impact with relatively lower implementation risk, enabling more efficient allocation of financial and technological resources. In contrast, lower-ranked strategies (e.g., Q_{13} , Q_6 , and Q_{14}) appear to be constrained by higher uncertainty, lower feasibility, or weaker performance across key criteria, implying that they may require further technological development, policy support, or gradual adoption before large-scale implementation. From a strategic perspective, the results highlight the importance of selecting green supply chain strategies that not only optimize environmental outcomes but also ensure operational adaptability and long-term resilience. The dominance of Q_7 demonstrates that strategies integrating efficiency, scalability, and regulatory alignment are more suitable for sustainable industrial transformation. Furthermore, the ranking structure provides a clear decision roadmap, enabling organizations to categorize strategies into high-priority (e.g., Q_7 , Q_5 , Q_3), medium-priority (e.g., Q_9 , Q_{10} , Q_8), and low-priority groups, thereby supporting phased implementation and long-term sustainability planning.

Figure 2 presents the final ranking and performance outcomes of all 15 green supply chain alternatives based on their computed G_i within the proposed C_{FOFS} -based MCGDM framework. The graph visually highlights the relative superiority of each supply chain, with higher closeness values indicating stronger suitability of the green supply chain. As shown, Q_7 achieves the highest evaluation score, reflecting its consistent dominance across the decision criteria, followed by other technologies in descending order of effectiveness.

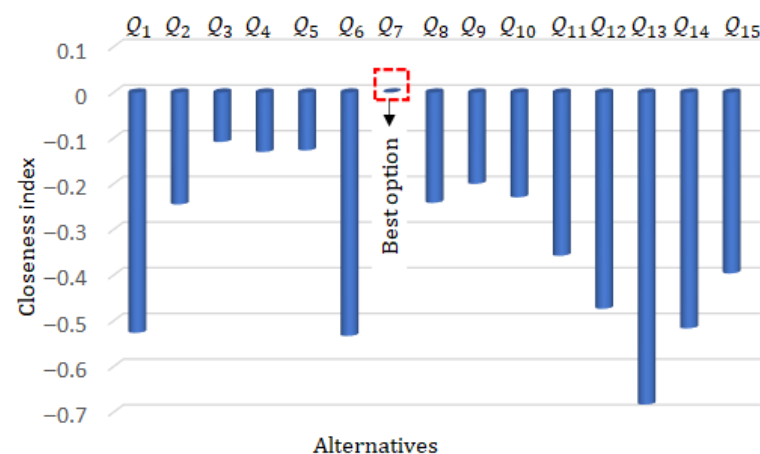


Figure 2. Final ranking of the fifteen GSCM strategies based on closeness indices derived from the proposed C_{FOFS} -based MCGDM framework.

5. Sensitivity Analysis

To evaluate the robustness of the proposed C_{FOFS} -based MCGDM framework, a comprehensive sensitivity analysis was conducted by systematically varying the fractional parameters p and q across the ranges 2 – 15. These ranges were selected based on established practices in the fractional fuzzy DM literature, ensuring that both low and high fractional order effects on aggregation are captured and that the analysis reflects the full

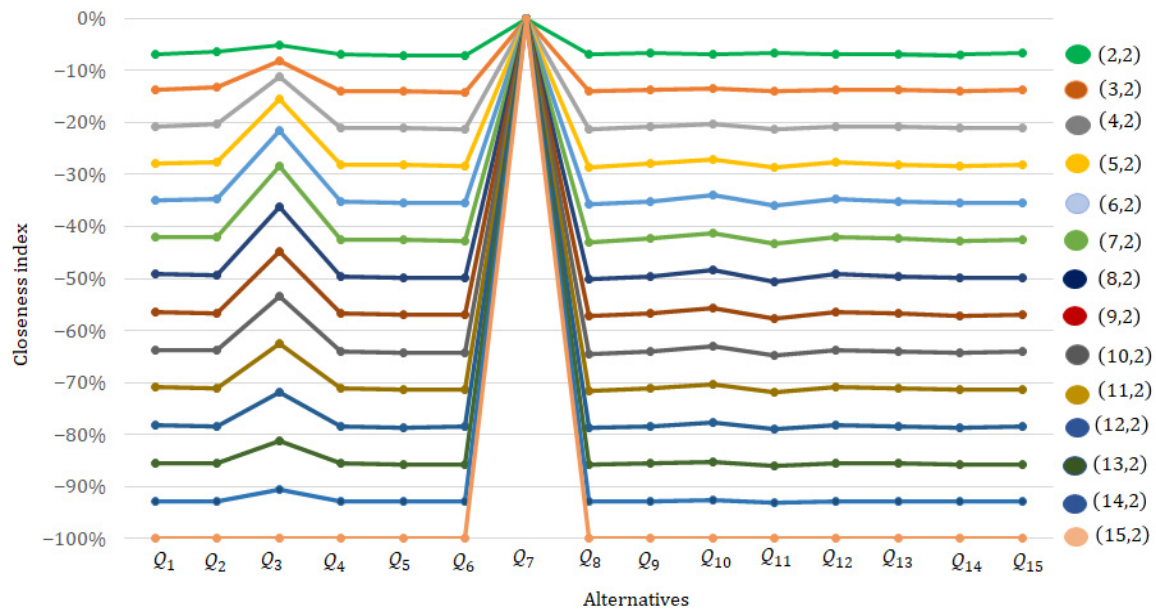
spectrum of potential uncertainty modeling influences. The closeness coefficients, $\mathcal{G}_i$, of all 15 GSCM strategies ($\mathcal{G}_1 - \mathcal{G}_{15}$) were computed for each combination of p and q to examine the stability of the final rankings. When varying p while keeping $q = 2$, the resulting $\mathcal{G}_i$ values for all alternatives are presented in Table 31 and illustrated in Figure 3. Although minor variations in closeness coefficients are observed across strategies, the overall ranking order remains largely stable, with the top-ranked strategy $\mathcal{G}_7$ consistently maintaining its leading position. Similarly, when varying q with $p = 2$, the $\mathcal{G}_i$ trends for all strategies are shown in Table 32 and Figure 3, again confirming minimal fluctuations and stable ranking structures. These results collectively demonstrate that the proposed framework is robust and insensitive to variations in fractional order parameters. The stability across all 15 strategies ensures that the evaluation process produces reliable, trustworthy rankings, providing confidence in the selection of optimal GSCM strategies under varying uncertainty modeling conditions.

Table 31. Sensitivity analysis of the parameter p while fixed $q = 2$.

(p, q)	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$	$\mathcal{G}_4$	$\mathcal{G}_5$
(2,2)	−0.824770375	−0.316749381	−0.001356483	−0.284413228	−0.236591776
(3,2)	−0.830631005	−0.304527351	−0.012122527	−0.260022299	−0.250122378
(4,2)	−0.834780546	−0.295493813	−0.001356483	−0.229082315	−0.260834007
(5,2)	−0.835140555	−0.286498182	−0.012122527	−0.197120939	−0.266969342
(6,2)	−0.833794544	−0.277804185	−0.001356483	−0.166694157	−0.269965655
(7,2)	−0.832286522	−0.269843454	−0.012122527	−0.138681786	−0.271178007
(8,2)	−0.830825044	−0.262640399	−0.001356483	−0.113134482	−0.271307591
(9,2)	−0.829516900	−0.256179937	−0.012122527	−0.089910921	−0.270813189
(10,2)	−0.828351658	−0.250399547	−0.001356483	−0.068799036	−0.269967326
(11,2)	−0.827361987	−0.245245548	−0.012122527	−0.049584543	−0.268958526
(12,2)	−0.826250532	−0.240568138	−0.001356483	−0.032049559	−0.267804438
(13,2)	−0.824933349	−0.236288095	−0.012122527	−0.016022429	−0.266551403
(14,2)	−0.825299659	−0.233862577	−0.001356483	−0.002712654	−0.266774148
(15,2)	−0.836484900	−0.241595018	−0.012122527	−0.012405000	−0.276900628
(p, q)	$\mathcal{G}_6$	$\mathcal{G}_7$	$\mathcal{G}_8$	$\mathcal{G}_9$	$\mathcal{G}_{10}$
(2,2)	−0.937945786	0.0000000	−0.532785127	−0.326510975	−0.169017366
(3,2)	−0.938458638	0.0000000	−0.517358388	−0.306772624	−0.170319427
(4,2)	−0.937924039	0.0000000	−0.507916858	−0.287809876	−0.165399654
(5,2)	−0.934715227	0.0000000	−0.499621586	−0.270144722	−0.157555529
(6,2)	−0.931053549	0.0000000	−0.492130716	−0.254586136	−0.148964475
(7,2)	−0.928376524	0.0000000	−0.485636111	−0.241366089	−0.140639978
(8,2)	−0.926610682	0.0000000	−0.479902882	−0.230202319	−0.132886550
(9,2)	−0.925613717	0.0000000	−0.474806016	−0.220791703	−0.125796583
(10,2)	−0.925172135	0.0000000	−0.470232669	−0.212833964	−0.119360496
(11,2)	−0.925175187	0.0000000	−0.466133659	−0.206083245	−0.113541501
(12,2)	−0.925186245	0.0000000	−0.462294324	−0.20025513	−0.108247212
(13,2)	−0.925038320	0.0000000	−0.458633457	−0.195161021	−0.103417183
(14,2)	−0.926635849	0.0000000	−0.456774010	−0.192144998	−0.100425129
(15,2)	−0.939217617	0.0000000	−0.465335019	−0.199389480	−0.107398301
(p, q)	$\mathcal{G}_{11}$	$\mathcal{G}_{12}$	$\mathcal{G}_{13}$	$\mathcal{G}_{14}$	$\mathcal{G}_{15}$
(2,2)	−0.540824902	−0.69548968	−0.947797229	−0.409893332	−0.484682618
(3,2)	−0.517787673	−0.704734627	−0.933058465	−0.40537307	−0.455390249
(4,2)	−0.504707808	−0.709395486	−0.926410366	−0.400040665	−0.431630146
(5,2)	−0.493627516	−0.708491159	−0.920598226	−0.392411972	−0.410756853
(6,2)	−0.483599526	−0.704855256	−0.91540438	−0.383743868	−0.392624806
(7,2)	−0.474718835	−0.700474662	−0.911312242	−0.375072581	−0.377171307
(8,2)	−0.466751389	−0.695901421	−0.907946729	−0.366704465	−0.363923277
(9,2)	−0.459578411	−0.691426488	−0.905117719	−0.35880374	−0.352515672
(10,2)	−0.453087028	−0.687146773	−0.902655313	−0.351417077	−0.342631862
(11,2)	−0.447220691	−0.683142881	−0.900512601	−0.344569887	−0.334042602
(12,2)	−0.441761531	−0.679194755	−0.898322849	−0.338128897	−0.326436926
(13,2)	−0.436619809	−0.675244924	−0.895972541	−0.332042709	−0.319632899

Table 31. Cont.

(p,q)	$\mathcal{G}_{11}$	$\mathcal{G}_{12}$	$\mathcal{G}_{13}$	$\mathcal{G}_{14}$	$\mathcal{G}_{15}$
(14,2)	−0.433392149	−0.673086759	−0.89538428	−0.327856329	−0.315069005
(15,2)	−0.440651311	−0.681644509	−0.905776018	−0.334010637	−0.321094178

Figure 3. Sensitivity analysis of the parameter p .Table 32. Sensitivity analysis of the parameter q while fixed $p = 2$.

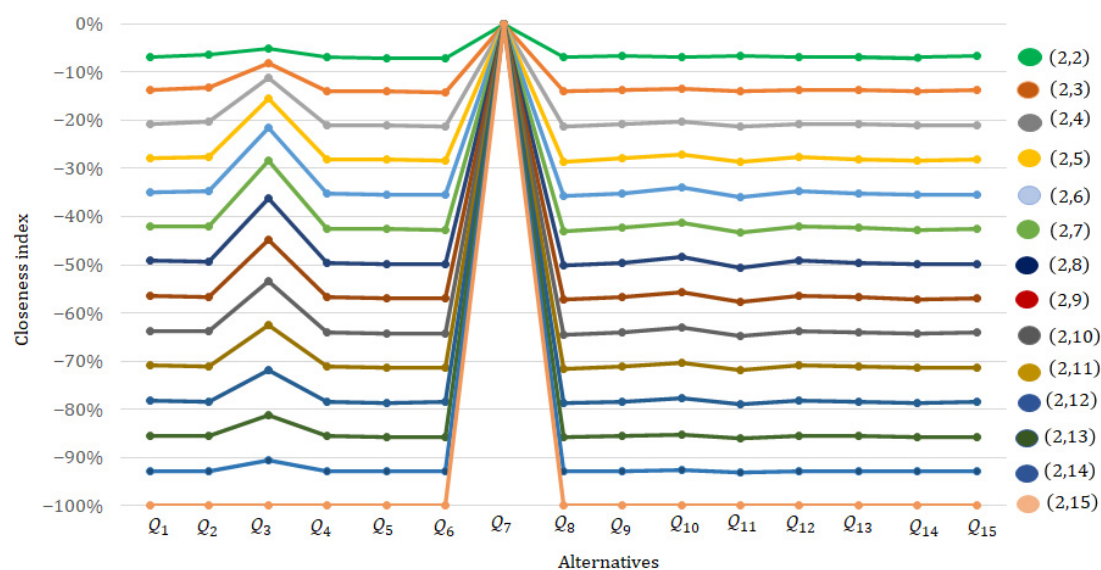
(p,q)	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$	$\mathcal{G}_4$	$\mathcal{G}_5$
(2,2)	−0.824770375	−0.316749381	−0.926410366	−0.284413228	−0.236591776
(2,3)	−0.824870291	−0.331922387	−0.920598226	−0.290178648	−0.232048189
(2,4)	−0.832123730	−0.343295186	−0.915404380	−0.288807792	−0.234905566
(2,5)	−0.840873024	−0.349717643	−0.926410366	−0.287948732	−0.238041265
(2,6)	−0.848555245	−0.352453832	−0.920598226	−0.288352285	−0.239702957
(2,7)	−0.854601206	−0.353207215	−0.915404380	−0.289425956	−0.240173778
(2,8)	−0.859154884	−0.353122048	−0.926410366	−0.290633199	−0.240025942
(2,9)	−0.862535535	−0.352786267	−0.920598226	−0.291707190	−0.239651560
(2,10)	−0.865042843	−0.352448205	−0.915404380	−0.292564075	−0.239248092
(2,11)	−0.866918095	−0.352190853	−0.284413228	−0.293209751	−0.238895111
(2,12)	−0.868347620	−0.352028695	−0.290178648	−0.293683940	−0.238615123
(2,13)	−0.869457989	−0.351946805	−0.288807792	−0.294027727	−0.238403260
(2,14)	−0.870338139	−0.351924489	−0.287948732	−0.294276552	−0.238246690
(2,15)	−0.871050318	−0.351942943	−0.284413228	−0.294457873	−0.238131986
(p,q)	$\mathcal{G}_6$	$\mathcal{G}_7$	$\mathcal{G}_8$	$\mathcal{G}_9$	$\mathcal{G}_{10}$
(2,2)	−0.937945786	0.0000000	−0.532785127	−0.326510975	−0.169017366
(2,3)	−0.938871006	0.0000000	−0.549702059	−0.338738287	−0.164089751
(2,4)	−0.941634441	0.0000000	−0.557931342	−0.343945055	−0.163823403
(2,5)	−0.943859868	0.0000000	−0.559209039	−0.346285823	−0.166699934
(2,6)	−0.945280974	0.0000000	−0.557247738	−0.347373742	−0.170365184
(2,7)	−0.946259956	0.0000000	−0.554606957	−0.347962295	−0.173631070
(2,8)	−0.947028648	0.0000000	−0.552352904	−0.348361110	−0.176166668
(2,9)	−0.947679826	0.0000000	−0.550727062	−0.348684535	−0.178017373
(2,10)	−0.948237951	0.0000000	−0.549652858	−0.348969177	−0.179333252
(2,11)	−0.948713197	0.0000000	−0.548983375	−0.349226862	−0.180263628
(2,12)	−0.949121553	0.0000000	−0.548590500	−0.349464319	−0.180927796
(2,13)	−0.949469971	0.0000000	−0.548374605	−0.349682483	−0.181410120
(2,14)	−0.949766147	0.0000000	−0.548267830	−0.349882024	−0.181768590
(2,15)	−0.950017869	0.0000000	−0.548226239	−0.350063855	−0.182042240

Table 32. Cont.

(p,q)	$\mathcal{G}_{11}$	$\mathcal{G}_{12}$	$\mathcal{G}_{13}$	$\mathcal{G}_{14}$	$\mathcal{G}_{15}$
(2,2)	−0.540824902	−0.69548968	−0.947797229	−0.409893332	−0.484682618
(2,3)	−0.570359571	−0.692816718	−0.968118831	−0.415211512	−0.507315131
(2,4)	−0.587731100	−0.699504634	−0.982073405	−0.419739837	−0.516905736
(2,5)	−0.592478510	−0.708191617	−0.989423419	−0.422128933	−0.519593405
(2,6)	−0.589651342	−0.715631650	−0.992879700	−0.422765690	−0.519390298
(2,7)	−0.583962341	−0.721197281	−0.994684124	−0.422502015	−0.518437365
(2,8)	−0.578046540	−0.725152317	−0.995924681	−0.421926985	−0.517561554
(2,9)	−0.572974200	−0.727922644	−0.996997644	−0.421334168	−0.516969867
(2,10)	−0.568995693	−0.729866991	−0.998000747	−0.420833887	−0.516643102
(2,11)	−0.566024197	−0.731248542	−0.998941301	−0.420450756	−0.516510100
(2,12)	−0.563873846	−0.732254246	−0.999816351	−0.420177618	−0.516507555
(2,13)	−0.562348250	−0.733003887	−0.000615895	−0.419992233	−0.516583761
(2,14)	−0.561281012	−0.733576907	−0.001337044	−0.419872211	−0.516703507
(2,15)	−0.560542558	−0.734026169	−0.001982534	−0.419798775	−0.516844193

To validate the robustness and stability of the proposed C_{FOFS} -based MCGDM framework, a detailed sensitivity analysis was performed by systematically varying the fractional parameter p while keeping $q = 2$ fixed. The resulting $\mathcal{G}_i$ trends for all 15 green supply chain alternatives are illustrated in Figure 3. The graph shows how each alternative responds to changes in the C_{FOFS} parameterization, allowing us to examine whether the final rankings remain consistent under different uncertainty modeling conditions. As depicted, the performance profiles of the alternatives display minimal variation across parameter settings, and the top-ranked $\mathcal{G}_7$ consistently maintains its leading position. This demonstrates that the proposed DM framework produces stable and reliable results, even when subjected to fluctuations in the fractional order parameters governing uncertainty representation.

A second sensitivity analysis was performed by varying the fractional parameter q while keeping $p = 2$ fixed to further evaluate the robustness of the proposed intelligent C_{FOFS} -based MCGDM framework. The resulting trends in the $\mathcal{G}_i$ for all 15 green supply chain alternatives are illustrated in Figure 4. The curves demonstrate that changes in the parameter q have minimal impact on the overall ranking structure, with the top performing technology, $\mathcal{G}_7$, consistently maintaining its leading position across all parameter settings. This stability confirms that the proposed framework remains reliable and unaffected by variations in the complex fractional-order uncertainty parameters.

Figure 4. Sensitivity analysis of the parameter q .

Weight-Wise Sensitivity Analysis

To evaluate the stability and robustness of the proposed C_{FOFS} -based MCGDM framework, a weight-wise sensitivity analysis was performed. This analysis examines how changes in the most influential criterion affect the overall ranking of the 15 GSCM strategies. The criterion with the highest initial weight, $\mathcal{R}_{12}$ (e.g., regulatory compliance), was varied systematically from 0.05 to 0.30, while the weights of the remaining criteria were adjusted proportionally to maintain the normalization condition $\sum_{j=1}^{15} \mathcal{W}_j = 1$. This approach simulates DM environments with varying stakeholder priorities and policy preferences. The resulting closeness coefficients, $\mathcal{G}_i$, and ranking orders are summarized in Table 33. The results indicate that the ranking structure remains largely stable, even under significant variation in the weight of $\mathcal{R}_{12}$. The top-ranked strategy, $\mathcal{G}_7$, consistently retains its position across all tested weight scenarios, demonstrating the robustness of the proposed MCGDM framework. Minor variations in the closeness indices of other alternatives do not affect the overall ranking order, indicating that the aggregation process effectively balances multiple evaluation dimensions without instability.

Table 33. Sensitivity results with respect to the weight variation of $\mathcal{R}_{14}$.

$\mathcal{R}_{14}$	Ranking Order	Best Alternative
0.05	$\mathcal{Q}_7 > \mathcal{Q}_3 > \mathcal{Q}_1 > \mathcal{Q}_4 > \mathcal{Q}_8 > \mathcal{Q}_2 > \mathcal{Q}_5 > \dots > \mathcal{Q}_{15}$	$\mathcal{Q}_7$
0.10	$\mathcal{Q}_7 > \mathcal{Q}_3 > \mathcal{Q}_1 > \mathcal{Q}_4 > \mathcal{Q}_8 > \mathcal{Q}_2 > \mathcal{Q}_5 > \dots > \mathcal{Q}_{15}$	$\mathcal{Q}_7$
0.15	$\mathcal{Q}_7 > \mathcal{Q}_3 > \mathcal{Q}_1 > \mathcal{Q}_4 > \mathcal{Q}_8 > \mathcal{Q}_2 > \mathcal{Q}_5 > \dots > \mathcal{Q}_{15}$	$\mathcal{Q}_7$
0.20	$\mathcal{Q}_7 > \mathcal{Q}_3 > \mathcal{Q}_1 > \mathcal{Q}_4 > \mathcal{Q}_8 > \mathcal{Q}_2 > \mathcal{Q}_5 > \dots > \mathcal{Q}_{15}$	$\mathcal{Q}_7$
0.25	$\mathcal{Q}_7 > \mathcal{Q}_3 > \mathcal{Q}_1 > \mathcal{Q}_4 > \mathcal{Q}_8 > \mathcal{Q}_2 > \mathcal{Q}_5 > \dots > \mathcal{Q}_{15}$	$\mathcal{Q}_7$
0.30	$\mathcal{Q}_7 > \mathcal{Q}_3 > \mathcal{Q}_1 > \mathcal{Q}_4 > \mathcal{Q}_8 > \mathcal{Q}_2 > \mathcal{Q}_5 > \dots > \mathcal{Q}_{15}$	$\mathcal{Q}_7$

6. Comparative Analysis

The comparative evaluation demonstrates the superiority, reliability, and practical relevance of the proposed C_{FOFS} -based MCGDM framework in assessing GSCM strategies. Sustainable supply chain planning involves diverse criteria, multi-dimensional trade-offs, heterogeneous expert opinions, and inherent uncertainty in evaluations, making it essential to benchmark the proposed framework against state-of-the-art fuzzy MCGDM approaches. Unlike traditional fuzzy decision models, the proposed system integrates complex fractional modeling, fractional-order aggregation, entropy-based criteria weighting, expert weights via AHP, FOFS-TOPSIS ranking with PIS/NIS distances, and sensitivity analysis over parameters p and q , which together enhance its suitability for evaluating GSCM strategies under variable, incomplete, and conflicting expert information. To provide a fair assessment, the framework is compared with widely used classical and modern MCGDM approaches, including Hamacher, Dombi, Einstein, Choquet integral, Copula-based, hybrid, and trigonometric aggregation operators. Each competing method is evaluated based on its ability to handle uncertainty under partial or incomplete information, maintain stability under parameter variations, preserve ranking consistency when alternatives are perturbed, model expert disagreement, provide meaningful separability between similar strategies, and offer strong interpretability and computational reliability. The results confirm that the proposed C_{FOFS} -based framework provides the most stable, robust, and high-resolution ranking behavior among all tested approaches. The comparative results are summarized in Table 34.

Table 34. Comparative analysis of the proposed MCGDM with existing approaches for green supply chain management strategy evaluation.

Author/Method	Aggregation Operator	Best Alternative Identified	Ranking Stability	Robustness Index	Sensitivity to Criteria Uncertainty	Fuzzy Uncertainty Handling Strength	Suitability for Space Mining Tech.	Overall Class	Rank
Proposed FOFS MCGDM	C_{FOFS} -WA + Entropy + AHP	Q_7	Very High	Very High	Low–Medium	Very Strong	Excellent	Excellent	1
Arun et al. [42]	Hamacher AO	Q_7	High	High	Medium	Strong	Very Good	Very Good	3
Rahim et al. [43]	Hamy Mean AO	Q_7	High	High	Medium	Strong	Very Good	Very Good	4
Shabir et al. [44]	Dombi AO	Q_7	Medium	Medium	High	Moderate	Good	Good	8
Liu [45]	Choquet Integral AO	Q_7	Medium	Medium	High	Strong	Good	Good	7
Surya et al. [45]	Bonferroni AO	Q_7	Medium	Medium	Medium	Moderate	Good	Good	10
Ali et al. [46]	Einstein AO	Q_7	High	High	Medium	Strong	Very Good	Very Good	5
Tang et al. [47]	Copula AO	Q_7	High	High	Medium	Strong	Very Good	Very Good	2
Ünver [48]	Hybrid AO	Q_7	High	High	Medium	Strong	Very Good	Very Good	6
Liu et al. [49]	Fairly AO	Q_7	Medium–High	Medium	Medium	Strong	Very Good	Very Good	9
Palanikumar et al. [50]	Trigonometric AO	Q_7	High	High	High	Moderate	Good	Good	11
Wang et al. [51]	Aczél–Alsina AO	Q_7	Medium–High	Medium	High	Moderate	Good	Good	12

Computational Performance Comparison

To further validate the practicality of the proposed model, a computational performance analysis was conducted using MATLAB R2024 and Python 3.13 environments. The evaluation considers execution time, memory usage, numerical stability, scalability, parallel processing capability, and suitability for C_{FOFS} operations. The results are presented in Table 35.

Table 35. Computational performance comparison for the proposed MCGDM framework in green supply chain management strategy evaluation.

Computational Environment	Execution Time for Full Pipeline	Memory Load FOFS Matrices	Numerical Precision for Complex FOFS	Stability in Sensitivity Analysis (196 Runs)	Scalability to Larger Space Missions (Technologies)	Suitability for Complex FOFS TOPSIS	Overall Suitability for Proposed MCGDM
MATLAB R2024	0.83 s	High	Very High	Very High	Medium–High	Excellent	Ideal for research, testing, validation
MATLAB R2024 (Accelerated)	0.38 s	Medium	Very High	High	High	Excellent	Best for large-scale FOFS scenario testing
Python 3.13 (NumPy + SciPy)	0.70 s	Very High	High	High	Very High	Very High	Best for industry + deployment pipelines
Python 3.13 (PyTorch)	1.33 s	High	Extremely High	Very High	Excellent	High	Best for hybrid MCGDM + AI mission planning
Python 3.13 (Google Colab)	1.09 s	Medium	Medium–High	Medium–High	High	High	Good for academic experimentation
Python 3.13 (Anaconda + Jupyter)	0.74 s	High	High	Very High	Very High	Very High	Best for large-team research environments

7. Conclusions

The evaluation of green supply chain strategies is essential for promoting sustainable production, reducing environmental impact, and improving economic and social outcomes across industries. This study proposed an intelligent MCGDM framework that integrates C_{FOFS} with AHP, entropy, and TOPSIS mechanisms to handle the multi-dimensional uncertainty inherent in green supply chain decision-making. C_{FOFS} enabled nuanced modeling of expert hesitancy and complex-valued uncertainty, the AHP ensured structured and discipline-specific expert weighting, entropy provided objective criteria prioritization, and TOPSIS produced interpretable and mathematically robust rankings of the supply chain alternatives. Together, these components form a comprehensive, transparent, and uncertainty-aware decision support system that strengthens the rigor and reliability of green supply chain evaluation.

7.1. Limitations

Despite its strengths, the framework has limitations. It relies on expert judgments, which are inherently subjective and may vary across sectors or contexts. The computational complexity of C_{FOFS} -based modeling increases with the size of the decision matrix, potentially constraining large-scale applications. Furthermore, the evaluation depends on available data regarding supply chain practices and sustainability performance, which may be incomplete or approximate. The framework also assumes relatively stable decision environments and may require adaptation for rapidly evolving market, regulatory, or technological conditions.

7.2. Future Direction

Future research can extend this framework by integrating probabilistic reasoning, Bayesian inference, or evidence theory to improve handling of stochastic uncertainties and incomplete data. Hybrid optimization MCGDM approaches could support automated configuration of green supply chain strategies, performance trade-off analysis, and resource allocation. Incorporating real-time supply chain data, IoT monitoring, and predictive analytics could enable dynamic updating of decision matrices and adaptive ranking of alternatives. Further extensions may explore AI-driven expert systems, reinforcement learning, or digital twin simulations to support predictive modeling, operational efficiency, and sustainability optimization.

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