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A Robust Multi-Dimensional Evaluation Framework for the Zero-Carbon Transformation of Industrial Parks: Diagnosis and Developmental Disparities

Tianqing Shen [1], Long Sun [2*]

[1] School of Urban Construction and Transportation, Hefei University, 230601 Hefei, China
[2] Anhui Provincial Key Laboratory of Urban Rail Transit Safety and Emergency Management, Hefei University, 230601 Hefei, China

[*] Correspondence: Long Sun (sunlong@stu.hfuu.edu.cn)

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Abstract: Industrial parks represent one of the most significant contributors to carbon emissions, making their transition toward zero-carbon operations a critical priority. Achieving this goal requires scientific, phased evaluation tools capable of guiding differentiated emission reduction strategies. This study introduces an integrated assessment framework that combines interval-valued triangular fuzzy sets, an enhanced CRITIC weighting method, and matter-element extension theory to provide robust and diagnostic insights into carbon performance. Sensitivity and comparative analyses confirm the model's reliability and resilience. An empirical application involving five industrial parks in China's Yangtze River Delta demonstrates the framework's effectiveness. The results indicate that Park C has approached a near-zero-carbon status, while Parks D and E remain in high-emission stages. Notable disparities are observed among the parks: high-performing parks benefit from strong governance and energy synergy, whereas underperforming parks face bottlenecks due to weak carbon management and limited adoption of circular economy practices. The proposed model maintains stable ranking outcomes even under weight perturbations and aligns closely with alternative evaluation methods. These findings suggest that successful zero-carbon transformation depends on coordinated progress across multiple dimensions rather than isolated improvements in specific indicators. This research offers a scientific foundation for targeted, phase-based decarbonization strategies in industrial parks.

Keywords: Industrial park; Decarbonization process; Evaluation indicator system; Empirical analysis; Development strategy

1. Introduction

Global warming presents profound challenges to economic and social systems worldwide. According to the IPCC Sixth Assessment Report, the energy and industrial sectors collectively account for approximately 73% of global greenhouse gas emissions (Masson-Delmotte et al., 2021). Within these sectors, industrial parks are critical leverage points for emission reduction due to their intensive energy consumption and concentrated industrial chains. China's Dual-Carbon Target underscores that the low-carbon transition of industrial parks is crucial for achieving the national goals of carbon peak and neutrality. The International Energy Agency (IEA) estimates that, through systematic strategies—including enhanced energy efficiency, waste heat recovery, renewable energy integration, and carbon capture, utilization, and storage (CCUS)—industrial parks could cumulatively reduce carbon emissions by over 20% by 2050 (IEA, 2021). Furthermore, international trade policies, such as the European Union's Carbon Border Adjustment Mechanism (CBAM), are elevating carbon management to a critical factor in global competitiveness (European Union., 2023) compelling industrial parks worldwide to accelerate their low-carbon transformation.

China's "14th Five-Year Plan for Industrial Green Development" explicitly advocates for establishing numerous near-zero and zero-carbon demonstration parks, with phased targets to significantly reduce carbon intensity before

2030. The transition to a zero-carbon park represents a progressive evolution through "low-carbon to near-zero carbon to zero-carbon" stages (Yu et al., 2018), rather than a mere matter of technological accumulation. Therefore, accurately determining a park's current stage of carbon development is a critical prerequisite for formulating differentiated emission reduction pathways and optimizing policy resource allocation (Zhao et al., 2024). This task is particularly urgent due to the diverse transformation pathways and complex influencing mechanisms involved in the transition of industrial parks. From a strategic perspective, Qian et al. (2022) developed an integrated "Land-Industry-Carbon" (LIC) model to simulate and validate the central role of industrial restructuring in achieving carbon peak, highlighting the value of multidimensional solutions. Through a comparative multi-case study, Sun et al. (2024) identified a systematic carbon neutrality pathway encompassing 12 key areas, including energy substitution and carbon capture. Regarding driving mechanisms, Meng et al. (2024) employed a configurational analysis based on the Technology-Organization-Environment (TOE) framework. Their analysis revealed that the effectiveness of green transformation in parks depends on the complex interactions among technological capability, organizational structure, and environmental factors, rather than on any single linear factor.

While the importance of the low-carbon transition in industrial parks is widely recognized, as evidenced by previous studies, a systematic assessment of their development levels remains inadequate. Existing evaluation systems are limited in framework completeness, indicator coverage, and technical application (Huang et al., 2023). First, universal indicator systems that can adapt to diverse energy structures and industrial characteristics are lacking. In particular, dynamic inter-indicator mechanisms (e.g., the negative correlation between industrial agglomeration and emission reduction costs (Langie et al., 2022) and complex interactions among technological, organizational, and environmental factors (Zhang et al., 2025) have received insufficient attention. Second, weighting methods have notable shortcomings: subjective weighting is susceptible to expert bias, objective weighting fails to reflect strategic priorities, and combined weighting methods often rely on simplistic averaging, which cannot capture the context-dependent dynamics of indicator importance (Huang et al., 2023). Third, most studies continue to use linear evaluation frameworks, which are ill-suited to capture the nonlinear coupling characteristics of energy-carbon systems. This limitation is particularly evident in modeling complex feedback mechanisms, such as carbon flows and energy-waste recycling loops. Finally, the validation of assessment results is often limited to individual case studies and lacks systematic, cross-regional, or cross-industrial verification, which undermines the generalizability and reliability of the conclusions (Du et al., 2024; Feng et al., 2018).

To address these limitations, this study proposes an integrated and practically applicable evaluation framework for assessing the carbon transition stage of industrial parks. This framework integrates interval-valued triangular fuzzy sets with an enhanced CRITIC weighting model. This integration balances expert knowledge with objective data characteristics and incorporates a dynamic mechanism to characterize the contextual importance of indicators for weight determination. We improve the matter-element extension theory to enable phase identification under multi-indicator, nonlinear, and fuzzy conditions. Furthermore, methods including TOPSIS, grey relational analysis (GRA), and Kullback-Leibler (KL) divergence are employed for multi-dimensional consistency verification of the assessment results. Global sensitivity analysis is further applied to test the model's robustness and adaptability. This approach scientifically determines the carbon development stage of industrial parks, thereby systematically revealing common shortcomings and key drivers across different park types during their zero-carbon transition. It provides quantitative evidence for formulating differentiated policies and designing precise transition pathways. Moreover, it facilitates the effective implementation of zero-carbon park assessments by bridging theoretical methodology and management practice.

2. Literature Review

2.1 Development Stages of Zero-Carbon Parks

Zero-carbon industrial parks are vital vehicles for addressing climate change and advancing green industrial transformation. They are typically viewed as evolving through a gradual developmental process. This progression involves phased transitions from low-carbon to near-zero-carbon and, ultimately, to zero-carbon parks (Zhang et al., 2024). This evolutionary logic demonstrates global universality. According to a recent International Energy Agency (IEA) assessment, deep decarbonization of the industrial sector is a central challenge for achieving global net-zero emissions targets, with industrial parks identified as critical leverage points (IEA, 2021). Globally, diverse zero-carbon park practices have emerged, ranging from the industrial symbiosis paradigm in the Netherlands (Eilering et al., 2004) to emission reduction strategic planning for industrial estates in Singapore (Wong et al., 2008), and integrated hydrogen energy storage exploration in China's Ordos (Zou et al., 2024).

In the low-carbon phase, research and practice focused primarily on enhancing energy efficiency and replacing fossil fuels with renewable energy sources. Representative measures included energy-efficient building retrofits (Zhang et al., 2023b), industrial waste heat recovery, and the initial adoption of renewable energy (Adebayo & Ağa, 2022). Although these efforts effectively reduced carbon intensity, they often relied on isolated technological measures and remained dependent on fossil fuels, thereby creating a ceiling for emissions reduction. Limitations in systemic integration were recognized even at this early stage. Early research on eco-industrial parks similarly focused on enterprise-level clean production and park-level waste exchange models (Chertow, 2000). The European Union's early promotion of best practices initially focused on energy-saving retrofits of individual facilities (Feng et al., 2018) and later shifted towards helping park enterprises identify and improve energy efficiency opportunities (Miśkiewicz et al., 2021). This approach parallels the initial practices in China's low-carbon parks.A case study of Canada's Debert Aerospace Industrial Park exemplifies this shift in perspective (Côté & Liu, 2016). This pioneering research moved beyond isolated technologies, highlighting the critical importance of a systemic approach. This approach integrated land use, infrastructure, buildings, energy, vegetation management, and policy mechanisms to achieve deep emissions reductions within the park.

Amid intensifying emission reduction pressures and accelerated technological advancements, some industrial parks have progressed to the near-zero carbon development phase. This phase is characterized by the deep integration of multi-energy systems and information technologies. On one hand, distributed photovoltaics, energy storage systems, and smart microgrids form the foundation of new energy supply systems (Aziz et al., 2023). On the other hand, energy-carbon management platforms leveraging IoT and big data provide core support for system optimization. For instance, Luo et al. (2024) proposed a multi-energy coupling system that utilizes by-product hydrogen. Through four case studies, they quantified the differences in economic and environmental benefits among various by-product hydrogen utilization methods, demonstrating the positive impact of multi-energy coupling on emissions reduction.

Conceptually, this work aligns closely with the energy hub optimization model (Olgyay & Campbell, 2018). In recent years, integrated with artificial intelligence, this concept has been further developed to solve dynamic optimal scheduling problems for park-level integrated energy systems (Wang et al., 2024). Furthermore, pilot "Smart Energy Park" projects, which integrate distributed energy resources through digital technologies to optimize the overall park energy system, represent advanced practices in the near-zero-carbon stage (Yu & Liu, 2024). Their findings indicate that selecting and optimizing innovative energy utilization approaches is crucial for enhancing the overall emissions reduction performance of industrial parks. However, it should be noted that near-zero-carbon industrial parks still face challenges such as immature key technologies like carbon capture and green hydrogen production, as well as high cost burdens (Irham et al., 2024; Urbina, 2023).

Zero-carbon industrial parks represent the ultimate developmental goal, characterized by achieving net-zero emissions through complete reliance on carbon-free energy, carbon capture and removal, and cross-industry circular coupling (Zhang et al., 2024). For example, a German energy industrial park has established a zero-carbon demonstration model spanning the building, transportation, and industrial energy sectors via the systematic integration of distributed renewables and energy storage technologies (Côté & Liu, 2016).

It is noteworthy that the exploration of zero-carbon parks is a global endeavor. In developing countries such as India, Green Industrial Park Initiatives provide infrastructure subsidies to encourage low-carbon technology adoption. However, the challenges they face differ markedly from those in developed countries, focusing more on financing access, technology acquisition, and grid stability (Jain, 2021). This disparity reveals the distinct political-economic contexts that economies at different development stages face during the zero-carbon transition. China's Ordos Zero-Carbon Industrial Park and Suzhou Industrial Park have explored integrated pathways for renewables, energy storage, and hydrogen utilization using a “wind-solar-hydrogen-storage-vehicle” model (Xiao et al., 2018). These cases demonstrate that zero-carbon park development has progressed from concept validation to large-scale implementation, although challenges persist in standardization, systemic coordination, and policy incentives.

In summary, the evolution through carbon development stages in industrial parks results from not only technological accumulation but also the combined influence of policy, market forces, and industrial chains. Accurately identifying each park's developmental stage facilitates the formulation of tailored transformation pathways, prevents the inefficacy of one-size-fits-all policies, and optimizes resource allocation across different park types.

2.2 Evaluation Criteria and Indicator Systems

The scientific identification and quantitative assessment of the carbon development stage in industrial parks depend on a robust indicator system. Early indicator systems primarily focused on single dimensions, such as energy consumption and carbon emissions, using conventional static metrics like energy consumption per unit of industrial output and carbon intensity (Huang et al., 2016). Although these indicators enable macro-level comparability, they often fail to capture variations in energy structures, industrial characteristics, and technological levels across different parks, thus providing limited insight into the overall transition process. As research has advanced, evaluation frameworks have expanded to incorporate multiple dimensions, including energy, environment, and economy. For instance, Huang et al. (2023) developed a comprehensive evaluation framework for low-carbon development in industrial parks. This framework includes energy and emission metrics, alongside indicators such as the clean energy proportion and waste recycling rate, demonstrating an increased emphasis on industrial circularity and resource efficiency. Similarly, the European Union’s guidelines for low-carbon park assessment incorporate institutional and management factors—such as governance mechanisms and policy implementation effectiveness—highlighting the critical role of management systems in emission reduction efforts (Fragkos et al., 2021).

Table 1. Indicator system for assessing zero-carbon levels in industrial parks

Core Dimensions	**Primary Indicator**	**Secondary Indicators**	**Specific Source/Basis**
Energy structure and efficiency	Renewable Energy Utilization	Distributed Energy Coverage Rate (C1)	The international RE100 initiative, China's "Pilot Program for Green Power Trading" (Fait et al., 2022)
		Share of Renewable Energy in Installed Capacity (C2)	
	Energy Efficiency Optimization	Electricity consumption per unit area in public buildings (C3)	(Zhang et al., 2023a)
		Green Travel Ratio (C4)	(Zhang et al., 2024)
		Intelligence Level of Energy Management Systems (C5)	China's Smart Park Construction Guide (Wang et al., 2019)
Carbon management and emissions reduction	Direct Carbon Emissions Control	Carbon Emission Intensity Reduction Rate (C6）	ISO 14064 China's Carbon Emission Trading Management Measures (Côté & Liu, 2016)
		Carbon Capture Technology Adoption Rate (C7)	(Prajapati et al., 2024) China's Science and Technology Roadmap for Carbon Peaking and Carbon Neutrality
	Indirect Carbon Emissions Management	Energy consumption per unit of product (C8)	(Tian et al., 2023)
		Proportion of Carbon Emissions Offset by Green Certificates (C9)	Standard Specifications: ISO 14067 SBTi (Zhu et al., 2025)
		Comprehensive Energy Consumption per Unit of Industrial Value Added (C10)	CDM Administrative Measures for China's CCER (Olgyay & Campbell, 2018)
		Carbon Allowance Compliance Rate (C11)	China's Regulations on the Administration of Carbon Emission Trading (Côté & Liu, 2016)
Circular economy and resource utilization	Industrial Solid Waste Comprehensive Utilization Rate	Industrial Solid Waste Comprehensive Utilization Rate	GB/T 39198-2020(Fragkos et al., 2021)
		Industrial Water Recycling Rat (C13)	ISO 46001 (Roberts, 2004)
		Household Waste Sorting Collection Rate (C14)	China's Water Pollution Prevention and Control Action Plan (Hu et al., 2019)
	Infrastructure	Green Space Ratio (C15)	(Xiao et al., 2018)
		Industrial Value Added per Unit of Construction Land (C16)	Administrative Measures for Green Product Labels (While & Eadson, 2022)
Governance and innovation capabilities	Policy and Planning	Low-Carbon Development Special Fund Investment Rate (C17)	China's "Green Development Guidelines for Industrial Parks" and "National Low-Carbon Industrial Park Pilot Implementation Plan" (While & Eadson, 2022)
		Frequency of Carbon Disclosure (C18)	TCFD (Task Force on Climate-related Financial Disclosures) Framework (Lee et al., 2015; Prajapati et al., 2024)
		Carbon Management System Certification Rate (C19)	United Nations SDG 11 (Sustainable Cities and Communities)
	Technological Innovation and Digitalization	Digital Carbon Management Platform Coverage Rate (C20)	Guiding Opinions on Promoting the Development of "Internet Plus" Smart Energy in China (Wang et al., 2019)
		Implementation Rate of Zero-Carbon Production Audits in Enterprises (C21)	China's 14^{th} Five-Year Plan for Green Industrial Development (Lee et al., 2015)

To construct an internationally comparable evaluation system, a systematic review of major global assessment standards is essential. Currently, widely applied international frameworks can be categorized into three types: policy-regulated standards, market-driven standards, and certification and reporting standards, including the ISO 14064 series for greenhouse gas accounting, which provide methodologies or certification labels. In recent years, indicator systems have evolved toward greater systematicity and dynamic characterization. Scholars have attempted to integrate life cycle assessment (Zhang et al., 2023a), carbon footprint accounting, and multi-dimensional composite indicators into a unified framework. This framework incorporates energy supply (Wang et al., 2019), upstream-downstream industrial synergy (Zhu et al., 2025), digital management, and policy implementation. While this trend has improved the coverage and refinement of indicator systems, it has also introduced challenges, including subjective weight allocation and increased complexity in inter-indicator couplings. For instance, studies have revealed nonlinear trade-offs between energy substitution rates and economic output. These complex relationships are often oversimplified by the additive weighting methods used in existing frameworks, which fail to capture their actual dynamic interactions (Adebayo & Ağa, 2022).

In summary, although existing research has made substantial progress in identifying developmental stages and constructing indicator systems for zero-carbon industrial parks, critical limitations persist. To address these gaps, this study establishes an indicator system across four key dimensions: (1) energy structure and efficiency, (2) carbon management and emission reduction, (3) circular economy and resource utilization, and (4) governance and innovation capability. This integrated framework is designed to balance universality with specificity and to accommodate the characteristics of dynamic, complex systems, as detailed in Table 1 and Figure 1. Consequently, the proposed system provides a methodological foundation for the scientifically robust assessment of developmental stages in zero-carbon industrial parks.

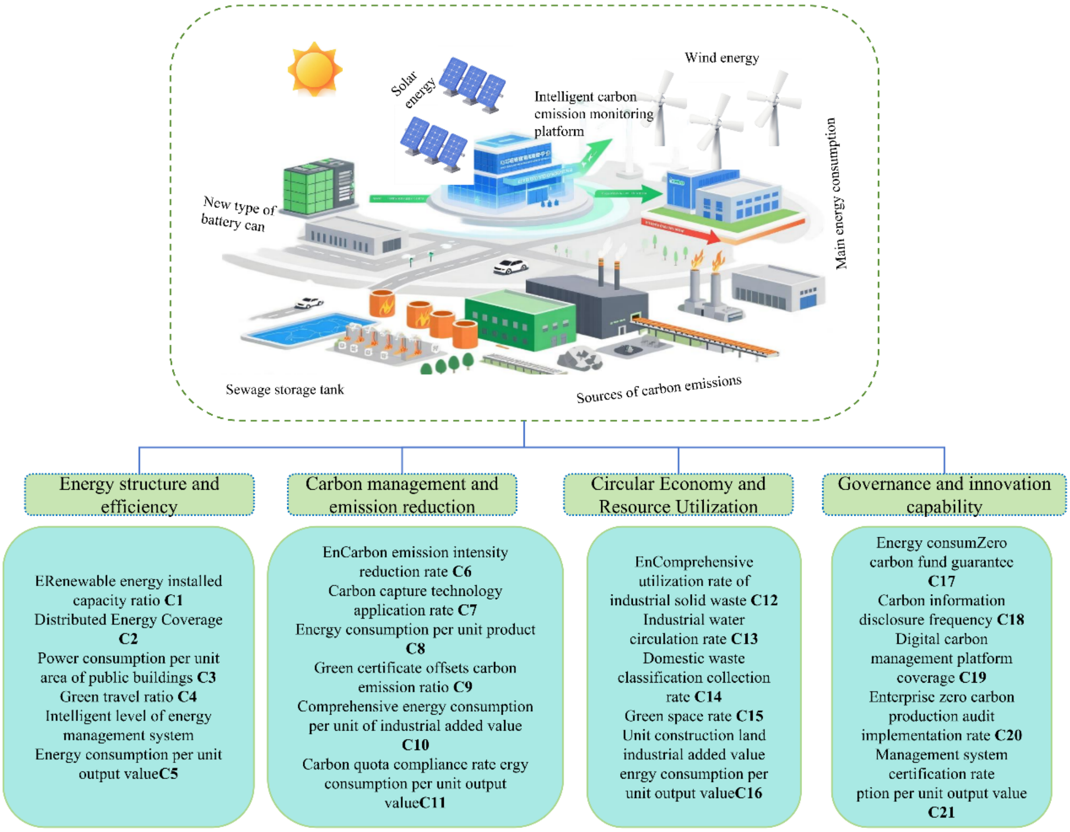

Figure 1. Integrated framework

3. Methodology

To address the challenges of data ambiguity, indicator heterogeneity, and the conflicts between subjective and objective weighting in assessing the low-carbon performance of industrial parks, this study proposes an integrated evaluation framework. The framework combines expert-derived weights, interval-valued fuzzy data processing, and extension-based decision modeling. The overall methodological workflow is illustrated in Figure 2, and the specific computational procedures are detailed in the following subsections.

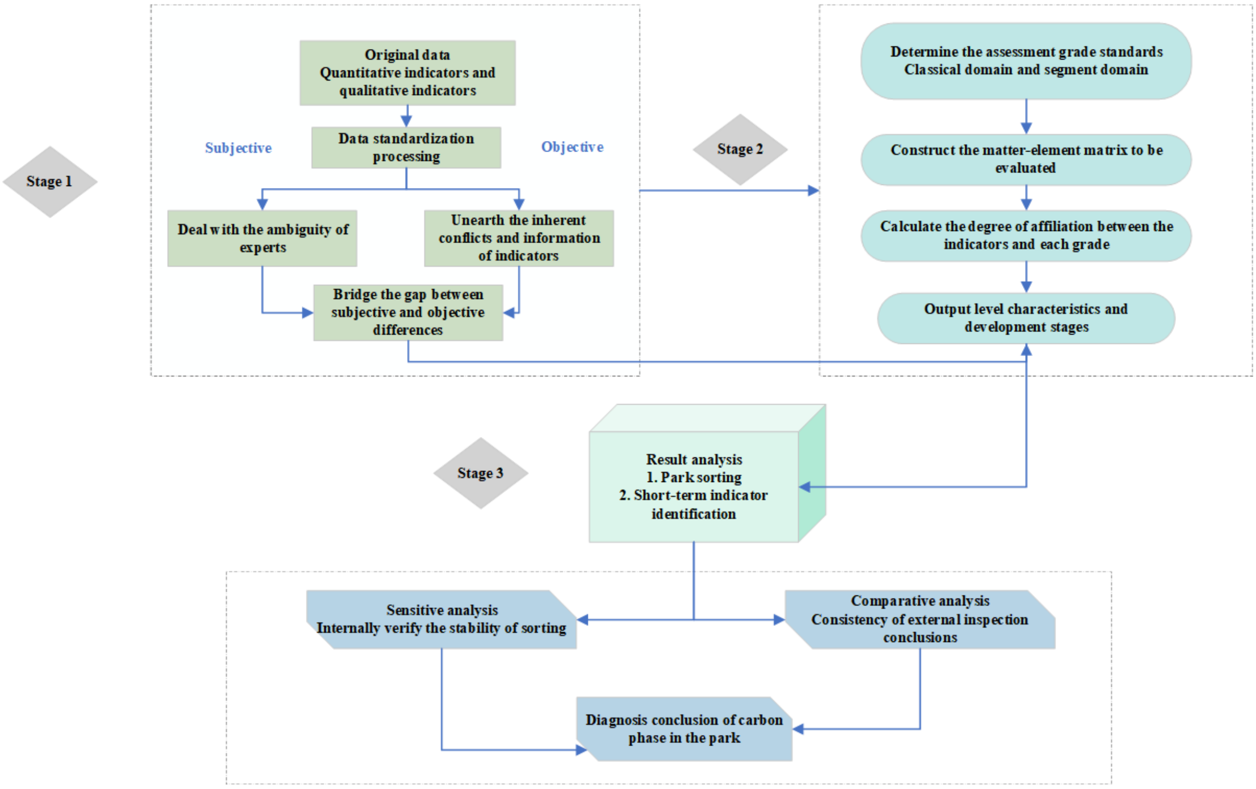

Figure 2. Carbon phase assessment framework for the park

3.1 Expert Weight Quantification Based on Intuitionistic Fuzzy Sets

The accuracy of expert-derived weights directly determines the credibility of the evaluation results. Traditional methods, which often rely on direct assignment, fail to capture the cognitive uncertainty inherent in expert judgments. Assessing the low-carbon performance of industrial parks involves multidimensional, heterogeneous indicators (e.g., energy structure, process-level carbon efficiency, and management policies). This complexity leads to significant disparities in expert knowledge, especially concerning emerging technologies such as carbon capture. Although classical fuzzy sets use membership functions to represent degrees of expert endorsement, they lack mathematical representations of opposition (non-membership) and uncertainty (hesitancy). This limitation can introduce bias into weight allocation. To overcome these limitations, we introduce intuitionistic fuzzy sets (IFS). IFS comprehensively capture the importance assigned by experts through a triple structure (μ, v, π). As an extension of traditional fuzzy set theory, IFS provides enhanced capabilities for processing fuzzy and imperfect information.

3.1.1 Relevant definition

Definition 1: Let X be a non-empty universe of discourse. An intuitionistic fuzzy set (IFS) A on X is defined as:

$$A = \{(x, \mu_A(x), v_A(x)) | x \in X\} \tag{1}$$

where, $\mu_A(x): X \to [0,1]$ denotes the degree of membership of element x in set A, and $v_A(x): X \to [0,1]$ denotes the degree of non-membership, satisfying the condition: $0 \le \mu_A(x) + v_A(x) \le 1$.

Definition 2: The third parameter of IFS is the hesitancy degree $\pi_A(x)$ calculated by the following Eq. (2):

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) \tag{2}$$

A smaller value of $\pi_A(x)$ indicates clearer decision information regarding X. while a larger value reflects greater uncertainty. When $\pi_A(x) = 0$ the intuitionistic fuzzy set reduces to an ordinary fuzzy set.

3.1.2 Implementation steps

Step 1: The Delphi method is employed to invite K experts to evaluate each other's authoritative level using a five-level intuitionistic fuzzy scale, as shown in Table 2:

Table 2. Linguistic terms for ranking the importance of Decision-Makers (DMs)

Linguistic Terms	Intuitionistic Fuzzy Numbers (IFNs)
Very important	(0.90,0.10)
Important	(0.75,0.20)
Medium	(0.50,0.45)
Unimportant	(0.35,0.60)
Very Unimportant	(0.10,0.90)

Step 2: Determine expert weights

The relative importance among experts is expressed through linguistic terms represented by intuitionistic fuzzy numbers. Let the evaluation of the k-th expert be denoted as $D_k = [\mu_k, v_k, \pi_k]$ The weight of each expert is then calculated using the following formula:

$$w_k = \frac{\mu_k + \pi_k \cdot \left(\frac{\mu_k}{\mu_k + v_k}\right)}{\sum_{k=1}^{K}\left[\mu_k + \pi_k \cdot \left(\frac{\mu_k}{\mu_k + v_k}\right)\right]} \tag{3}$$

3.2 Subjective Weighting of Indicators Based on Interval Triangular Fuzzy Numbers

Triangular fuzzy numbers (TFNs), a class of fuzzy sets characterized by convexity and normality, are widely used to process fuzzy decision information. However, TFNs rely on fixed value boundaries. In contrast, interval-valued triangular fuzzy numbers allow different experts to define varying membership degree intervals for the same indicator. This approach better accommodates the data gaps and fluctuations commonly found in industrial park data. This method not only preserves the integrity of fuzzy decision information but also ensures that its constituent elements are more readily obtainable than those of trapezoidal fuzzy numbers, as shown in Table 3.

Table 3. The importance and scoring of language terms for each criterion

The Importance of Linguistic Terms	Fuzzy Number of Triangular Interval Values
Very low (VL)	[(0,0),0, (0.1,0.15)]
Low (L)	[(0,0.05),0.1, (0.25,0.35)]
Medium low (ML)	[(0,0.15),0.3, (0.45,0.55)]
Medium (M)	[(0.25,0.35),0.5, (0.65,0.75)]
Medium high (MH)	[(0.45,0.55),0.7, (0.8,0.95))
High (H)	[(0.55,0.75),0.9, (0.95,1)]
Very high (VH)	[(0.85,0.95),1, (1,1)]

3.2.1. Relevant definitions

Definition 3: Let X be a set of real numbers. An interval triangular fuzzy set $\tilde{A}$ is defined as:

$$\tilde{A} = x, \left[\mu_{A^{\sim L}}(x), \mu_{A^{\sim U}}(x)\right], x \in X, \mu_{A^{\sim L}}, \mu_{A^{\sim U}}: X \to [0,1] \tag{4}$$

where, $Al^{\mu}_{\sim}(x)$ and $AU^{\mu}_{\sim}(x)$represent the lower and upper bounds of the interval-valued membership degree, respectively, satisfying:

$$\mu_{A^{\sim}}(x) \le \mu_{A^{\sim \cup}}(x), \forall x \in X \tag{5}$$

$$\mu_{A^{\sim}}(x) = [\mu_{A \sim L}(x), \mu_{A^{\sim \cup}}(x)], \forall x \in X \tag{6}$$

An interval triangular fuzzy set can be defined as $\tilde{A} = [\tilde{A}^L, \tilde{A}^U] = [(1^x_L, 2^x_L, 3^x_L; A^{\mu}_{\sim}(x)), (1^x_U, 2^x_U, 3^x_U; AU^{\mu}_U(x))]$ where, $\tilde{A}^L$ and $\tilde{A}^U$ denote the lower and upper interval-valued triangular fuzzy numbers, respectively, with $\tilde{A}^L \subset \tilde{A}^U$. When $\mu_{A^L}(x) = A^{U\mu}_{\sim}(x) = 1$ and $2^X_L = 2^X_U$, the interval triangular fuzzy set can be simplified as:

$$\tilde{A} = \left[\tilde{A}^L, \tilde{A}^U\right] = [(1_U^x, 1_L^x), x_2, (3_L^x, 3_U^x)] \tag{7}$$

Geometrically, unlike conventional triangular fuzzy numbers with a deterministic membership value, the membership degree in this representation becomes an interval, allowing more flexible and accurate expression of fuzzy information.

Definition 4: Based on the definition by Liu et al. (2019) for two interval triangular fuzzy numbers: TIVFNs $\tilde{A} = [\tilde{A}^L, \tilde{A}^U] = [(1_U^x, 1_L^x), x_2, (3_L^x, 3_U^x)]$ and $\tilde{B} = [\tilde{B}^L, \tilde{B}^U] = [(1_U^y, 1_L^y), y_2, (3_L^y, 3_U^y)]$ the following arithmetic operations apply:

$$\begin{aligned} \tilde{A} + \tilde{B} &= [(1_U^x, 1_L^x), x_2, (3_L^x, 3_U^x)] + \left[\left(1_U^y, 1_L^y\right), y_2, \left(3_L^y, 3_U^y\right)\right] \\ &= \left[\left(1_U^x + 1_U^y, 1_L^x + 1_L^y\right), x_2 + y_2, \left(3_L^x + 3_L^y, 3_U^x + 3_U^y\right)\right] \end{aligned} \tag{8}$$

$$\begin{aligned} \tilde{A} - \tilde{B} &= [(1_U^x, 1_L^x), x_2, (3_L^x, 3_U^x)] - \left[\left(1_U^y, 1_L^y\right), y_2, \left(3_L^y, 3_U^y\right)\right] \\ &= \left[\left(1_U^x - 1_U^y, 1_L^x - 1_L^y\right), x_2 - y_2, \left(3_L^x - 3_L^y, 3_U^x - 3_U^y\right)\right] \end{aligned} \tag{9}$$

Definition 5: The defuzzification of an interval triangular fuzzy number $\tilde{A}$ can be performed using the following formula to obtain a crisp value:

$$h\left(\tilde{A}\right) = \frac{(1_U^x + 1_L^x) + 2x_2 + (3_L^x + 3_U^x)}{6} \tag{10}$$

3.3 Enhanced CRITIC Method

Determining the weight of each evaluation indicator is central to multi-criteria comprehensive evaluation. The accuracy and objectivity of these weights critically influence the credibility of low-carbon performance assessments for industrial parks. The entropy weight method determines weights based on indicator variability, is free from subjective influence, and involves a straightforward computational process. However, for low-carbon assessment of industrial parks, cost-based indicators exhibit both variability and certain intercorrelations. Relying solely on the entropy method fails to adequately capture inter-indicator correlations. Therefore, this study integrates the CRITIC and entropy methods to establish an improved CRITIC-entropy weight fing approach. This combined method enables a more scientific and comprehensive evaluation of low-carbon performance in industrial parks.

Assume there are **i** samples and **j** indicators, forming an evaluation matrix **X**:

$$\mathrm{X} = \begin{bmatrix} \mathrm{x}_{11} & \mathrm{x}_{12} & \cdots & \mathrm{x}_{1j} \\ \mathrm{x}_{21} & \mathrm{x}_{22} & \cdots & \mathrm{x}_{2j} \\ \vdots & \vdots & \cdots & \vdots \\ \mathrm{x}_{i1} & \mathrm{x}_{i2} & \cdots & \mathrm{x}_{ij} \end{bmatrix} \tag{11}$$

Standardize the indicators using Eq. (12) to obtain the normalized matrix $\mathbf{X'} = [\mathbf{ij}_{\prime}^{\mathbf{x}}]$.

$$\mathrm{x}_{ij} = \begin{cases} \dfrac{\mathrm{x}_{ij} - \mathrm{minx}_j}{\mathrm{maxx}_j - \mathrm{minyx}_j} & \text{Positive indicator} \\ \dfrac{\mathrm{maxx}_j - \mathrm{x}_{ij}}{\mathrm{maxx}_j - \mathrm{minx}_j} & \text{Reverse indicator} \end{cases} \tag{12}$$

Calculate the correlation coefficients between evaluation indicators using the Pearson product-moment correlation coefficient, resulting in the correlation matrix:

$$R=\left[r_{pq}\right]_{n\times n}=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \tag{13}$$

$$r_{pq}=\frac{\sum_{i=1}^{n}\left(x_{kp}-\bar{x}_p\right)\left(x_{kq}-\bar{x}_q\right)}{\sqrt{\sum_{i=1}^{n}\left(x_{kp}-\bar{x}_p\right)}\cdot\sqrt{\sum_{i=1}^{n}\left(x_{kq}-\bar{x}_q\right)}} \tag{14}$$

where, $\bar{x}_p$ and $\bar{x}_q$ are the average values of the normalized $p\text{-}th$ and $q\text{-}th$ indicators, respectively; x_{kp} and x_{kq} are the normalized values of the $p\text{-}th$ and $q\text{-}th$ indicators for the $k\text{-}th$ industrial park. In general, the closer r_{pq} to 1 the stronger the correlation between the indicators.

Compute the information content T_j contained in the cost-based indicators:

$$T_j=u_j\sum_{i=1}^{n}\left(1-\left|r_{pj}\right|\right) \tag{15}$$

where, u_j is the standard deviation of the $j-th$ cost-based indicator, and r_{pj} is the correlation coefficient between the $p-th$ and the $p-th$ cost-based indicators.

Calculate the entropy value s_j of the evaluation indicators:

$$s_j=-\frac{\sum_{i=1}^{m}x_{ij}ln\ x_{ij}}{lnm} \tag{16}$$

The final improved CRITIC-entropy combined weight W_j is obtained as:

$$W_j=\frac{1-s_j+T_j}{\sum_{j=1}^{n}\left(1-s_j+T_j\right)} \tag{17}$$

3.4 Combined Weighting Based on Minimum Deviation Method

Let the subjective weight derived from interval fuzzy sets be denoted as w_1 and the objective weight from the improved CRITIC method as w_2. The combined weight ω is calculated as:

$$w=\alpha^{*}w_1+\beta^{*}w_2 \tag{18}$$

where, the coefficients α and β satisfy the following constrained optimization problem:

$$\begin{cases} maxF(\alpha,\beta)=\sum_{l=1}^{m}\left(\sum_{k=1}^{n}\left(\alpha w_1+\beta w_2\right)\right) \\ s.t.\alpha^2+\beta^2=1 \end{cases} \tag{19}$$

Using the Lagrange multiplier method under extreme value conditions, the coefficients α and β are computed as:

$$
\begin{cases}
\alpha = \dfrac{\sum_{l=1}^{m}\sum_{k=1}^{n} w_1 b_{lk}}{\sqrt{(\sum_{l=1}^{m}\sum_{k=1}^{n} w_1 b_{lk})^2 + (\sum_{l=1}^{m}\sum_{k=1}^{n} w_2 b_{lk})^2}} \\
\beta = \dfrac{\sum_{1=1}^{m}\sum_{k=1}^{n} w_2 b_{1k}}{\sqrt{(\sum_{l=1}^{m}\sum_{k=1}^{n} w_1 b_{lk})^2 + (\sum_{l=1}^{m}\sum_{k=1}^{n} w_2 b_{lk})^2}}
\end{cases}
\tag{20}
$$

Finally, α and β are normalized to obtain α*and β*

$$
\begin{cases}
\alpha^* = \alpha/(\alpha+\beta) \\
\beta^* = \beta/(\alpha+\beta)
\end{cases}
\tag{21}
$$

3.5 Improved Mater -Element Extension Model

Matter-element extension theory provides a theoretical foundation for handling uncertain and fuzzy information. By constructing matter-element models, this approach can accurately describe the key characteristics of industrial parks. Meanwhile, the calculation of correlation degrees quantifies how well indicator values align with different performance levels. This theoretical approach has been widely adopted in the fields of multi-criteria decision-making and comprehensive evaluation.

(1) Definition of Classical Domain

For the 21 secondary indicators, four zero-carbon development levels are defined based on international standards, policy documents, and academic research, as shown in Table 1, Table 4 and Appendix.

Table 4. Evaluation index system for carbon stage in the park

Dimension	Secondary Indicators	Net-zero Carbonization (I)	Near-zero Carbonization (II)	Low zero Carbonization (III)	High Carbonization (IV)
Energy structure and efficiency	C1	[50%,70%)	[30%,50%)	[15%,30%)	[0,15%)
	C2	[90%,100%)	[50%,90%)	[15%, 50%)	[0%,15%)
	C3	[0.8,1)	[0.5,0.8)	[0.2,0.5)	[0, 0.2)
	C4	[90%,100%)	[80%,90%)	[60%,80%)	[50,60%)
	C5	[90,100)	[75,90)	[60,75)	[50,60)
Carbon management and emission reduction	C6	[6%,7.5%)	[4.5%,6%)	[3.5%,4.5%)	[0%,3.5%)
	C7	[70%,100%)	[50%,70%)	[30%,50%)	[0,30%)
	C8	[80%,100%)	[60%,80%)	[40%,60%)	[20,40%)
	C9	[80%,100%)	(60%,70%)	(30%,60%)	[0%,30%)
	C10	[0， 0.35)	[0.35,0.5)	[0.5,0.7)	[0.7,1)
Circular economy and resource utilization	C11	[90%,100%)	[80%,90%)	[70%,80%)	[60,70%)
	C12	[90%,100%)	[85%,90%)	[50%,85%)	[0,50%)
	C13	[80%,100%)	[70%,80%)	[0.6%,70%)	[50,60%)
	C14	[90%,100%)	[65%,90%)	[50%,65%)	[35%,50%)
	C15	[40%,100%)	[35%,40%)	[30%,35%)	[0,30%)
Governance and innovation capabilities	C16	[1,1.5)	[0.6,1)	[0.3,0.6)	[0,0.3)
	C17	[7%， 10%)	[0.06,0.07)	[5%， 6%)	[4%,5%)
	C18	[3,4)	[3,2)	[2,1)	[0,1)
	C19	[90%,100%)	[70%,90%)	[50%,70%)	[30,50%)
	C20	[80%,100%)	[50%,80%)	[15%,50%)	[0,15%)
	C21	[90%,100%)	[70%,90%)	[30%,70%)	[0,30%)

The classical domain matter-element matrix is constructed as follows:

$$R_j = (N_j, E_i, V_{ij}) = \begin{bmatrix} N_j & E_1 & v_{1j} \\ & E_2 & v_{2j} \\ & \vdots & \vdots \\ & E_n & v_{ij} \end{bmatrix} = \begin{bmatrix} N_j & E_1 & [a_{1j} & b_{1j}] \\ & E_2 & [a_{2j} & b_{2j}] \\ & \vdots & & \vdots \\ & E_n & [a_{nj} & b_{nj}] \end{bmatrix} \tag{22}$$

where, N_j denotes the $j\text{-}th$ evaluation level . $E_1, E_2, \cdots, E_n$ are the evaluation indicators $v_{1j}, v_{2j}, \cdots, v_{nj}$ represent the dimensionless value intervals of the evaluation indicators for the $j\text{-}th$ level; and $[a_{nj}, b_{nj}]$ is the threshold interval of indicator E_n under level N_j.

(2) Definition of Section Domain

The minimum and maximum values of each indicator across all evaluation levels define the section domain matter-element matrix, as shown in Eq. (23):

$$R_p = (N_p, E_n, V_p) = \begin{bmatrix} N_p & E_1 & v_{p1} \\ & E_2 & v_{p2} \\ & \vdots & \vdots \\ & E_n & v_{pn} \end{bmatrix} = \begin{bmatrix} N_j & E_1 & [a_{p1} & b_{p1}] \\ & E_2 & [a_{p2} & b_{p2}] \\ & \vdots & & \vdots \\ & E_n & [a_{pn} & b_{pn}] \end{bmatrix} \tag{23}$$

Here, N_p represents all evaluation levels, $E_1, E_2, \cdots, E_n$ are the evaluation indicators, v_{pn} is the dimensionless value range of the evaluation indicators; and $[a_{pn} \quad b_{pn}]$denotes the value interval.

(3) Determining the Matter-Element to be Evaluated

For a set of m indicators evaluating the zero-carbon level of an industrial park, the matter-element for the *t-th* indicator is given by:

$$R_t = (N_t, E_n, V_t) = \begin{bmatrix} N_t & E_1 & v_{t1} \\ & E_2 & v_{t2} \\ & \vdots & \vdots \\ & E_n & v_{tn} \end{bmatrix} \tag{24}$$

where, R_t(t=1, 2, ⋯ m) is the matter-element to be evaluated, and V_t represents the actual data of the zero-carbon indicators.

(4) Data Normalization

To eliminate dimensional differences, R_j and R_t are normalized using Eqs. (25)-(26):

$$j_{\prime}^{R} = (N_j, E_i, ij_{\prime}^{V}) = \begin{bmatrix} N_j & E_1 & \left[\frac{a_{1j}}{a_{p1}}, \frac{b_{1j}}{b_{p1}}\right] \\ & E_2 & \left[\frac{a_{2j}}{a_{p2}}, \frac{b_{2j}}{b_{p2}}\right] \\ & \vdots & \vdots \\ & E_n & \left[\frac{a_{nj}}{a_{pn}}, \frac{b_{nj}}{b_{pn}}\right] \end{bmatrix} \tag{25}$$

$$t_{\prime}^{R} = (N_t, E_n, t_{\prime}^{V}) = \begin{bmatrix} N_t & E_1 & \frac{v_{t1}}{b_{p1}} \\ & E_2 & \frac{v_{t2}}{b_{p2}} \\ & \vdots & \vdots \\ & E_n & \frac{v_{tn}}{b_{pn}} \end{bmatrix} \tag{26}$$

(5) Calculation of Indicator Correlation Degree

The correlation degree $H_{s^*}(v_{kj})$ between the actual value of each indicator and the classical domain is calculated as:

$$H_{s^*}(v_{kj}) = 1 - \frac{1}{n(n+1)}\sum_{j=1}^{n} \rho_j(v_{kj})\omega_j \tag{27}$$

Here, $\rho(v_i, v_{ij})$ denotes the distance between the matter-element and the classical domain, computed as:

$$\begin{aligned} \rho(v_i v_{ij}) &= \left|v_i - \frac{1}{2}(a_{ij} + b_{ij})\right| - \frac{1}{2}(b_{ij} + a_{ij}) \\ \rho(v_i v_{ip}) &= |v_i - \frac{1}{2}(a_{ip} + b_{ip})| - \frac{1}{2}(b_{ip} + a_{ip}) \end{aligned} \tag{28}$$

In the equations, $\rho(V_i, V_{ij})$ represents the distance between V_i and the interval V_{ij} ,and $\rho(v_i v_{ip})$ represents the distance between V_i and the interval V_{ip}.

(6) Determining the Evaluation Level

$$\bar{H}_{S^*}(v_{kj}) = \frac{H_{S^*}(v_{ki}) - \frac{5}{sin1}\left(H_{S^*}(v_{ki})\right)}{\underset{s^*=1}{\overset{4}{max}}\ \{H_{S^*}(v_{ki})\} - \underset{s^*=1}{\overset{4}{min}}\ \{H_{S^*}(v_{ki})\}} \tag{29}$$

$$s^{**} = \frac{\sum_{s=1}^{5} s^* \bar{H}_{S^*}(v_{kj})}{\sum_{s=1}^{5} \bar{H}_{S^*}(v_{kj})} \tag{30}$$

In Eq. (30), s^{**} is the variable characteristic value of the matter-element to be evaluated. It determines the degree of deviation toward adjacent levels and enables the ranking of objects within the same evaluation level.

3.6 Limitations of Model Application

Although the comprehensive evaluation framework proposed in this study offers theoretical advantages, its practical application requires careful consideration of specific contexts. However, it must be acknowledged that the model's effectiveness is highly dependent on the completeness, accuracy, and consistency of the underlying data. To enhance operational practicality, a tiered application strategy is proposed: (1) For parks with comprehensive data, the full model can be applied to obtain precise diagnostic results. (2) For parks with partially missing data, a fuzzy comprehensive evaluation method can be employed to estimate the missing values before model application. Specifically, interval-valued triangular fuzzy numbers can handle quantitative indicators, whereas expert scoring or analogy with similar parks is suitable for qualitative indicators. (3) For parks with a critically inadequate data foundation, the priority should be to monitor core indicators (e.g., C1, C6, C12, C17) and conduct a qualitative stage assessment.

4 Results and Discussion

Based on geographical distribution and socio-economic development levels, this study selected five industrial parks in the Yangtze River Delta region as research subjects. Due to the large number of parks in the region, conducting a comprehensive analysis of all parks would be resource- and time-prohibitive. Therefore, following the Yangtze River Delta Urban Agglomeration Development Plan and using publicly available geographic information platforms, we selected five representative parks: one industrial park each in Suzhou, Shanghai, and Ningbo, and one science park each in Wuxi and Hefei. The evaluation results from these representative parks will provide insights into the overall regional situation.

4.1 Indicator Weight Calculation

First, a panel of three experts was assembled to assess and select the most appropriate indicators for evaluating the low-carbon performance of industrial parks. The relative weight of each expert was determined based on three criteria: (1) experience and knowledge in low-carbon development, (2) professional and educational background in relevant fields, and (3) organizational position. The relative weights of the three experts are provided as linguistic terms in Table 5. These linguistic terms were then converted into intuitionistic fuzzy numbers. Expert weights were derived from these conversions.

Table 5. The importance and weight of experts

Expert	DM1	DM2	DM3
Language term weight	Important (0.318)	Very important (0.363)	Important (0.318)

Table 6. The index weights are transformed into interval triangular fuzzy numbers and weighted averages

Indicators	Expert			Weighted Average
	DM1	DM2	DM3	
C1	[(0.85,0.95), 1, (1,1)]	[(0.45,0.55), 0.7, (0.8,0.9	[(0.85,0.95), 1, (1,1)]	[(0.704,0.804), 0.89, (0.926,0.98
C2	[(0.55,0.75), 0.9, (0.95,1)	[(0.45,0.55), 0.7, (0.8,0.9	[(0.55,0.75), 0.9, (0.95,1)]	[(0.513,0.677), 0.827, (0.895,0.9
C3	[(0.45,0.55), 0.7, (0.8,0.9	[(0.25,0.35), 0.5, (0.65,0.	[(0.55,0.75), 0.9, (0.95,1)]	[(0.409,0.540), 0.69, (0.792,0.89
C4	[(0.55,0.75), 0.9, (0.95,1)	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.481,0.613), 0.763, (0.847,0.9
C5	[(0.85,0.95), 1, (1,1)]	[(0.45,0.55), 0.7, (0.8,0.9	[(0.55,0.75), 0.9, (0.95,1)]	[(0.609,0.740), 0.858, (0.911,0.9
C6	[(0.55,0.75), 0.9, (0.95,1)	[(0.85,0.95), 1, (1,1)]	[(0.85,0.95), 1, (1,1)]	[(0.754,0.885), 0.967, (0.983,0.9
C7	[(0.25,0.35), 0.5, (0.65,0.	[(0,0.15), 0.3, (0.45,0.55)	[(0.85,0.95), 1, (1,1)]	[(0.35,0.468), 0.586, (0.688,0.75
C8	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.450,0.549), 0.699, (0.799,0.9
C9	[(0.45,0.55), 0.7, (0.8,0.9	[(0.85,0.95), 1, (1,1)]	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.595,0.695)0.808, (0.872,0.96
C10	[(0,0.15), 0.3, (0.45,0.55)	[(0.25,0.35), 0.5, (0.65,0.	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.234,0.350), 0.5, (0.633,0.749
C11	[(0.85,0.95), 1, (1,1)]	[(0.25,0.35), 0.5, (0.65,0.	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.504,0.604), 0.722, (0.808,0.9
C12	[(0.55,0.75), 0.9, (0.95,1)	[(0.45,0.55), 0.7, (0.8,0.9	[(0.85,0.95), 1, (1,1)]	[(0.609,0.740), 0.858, (0.911,0.9
C13	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.450,0.549), 0.699, (0.799,0.9
C14	[(0.45,0.55), 0.7, (0.8,0.9	[(0.25,0.35), 0.5, (0.65,0.	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.377,0.477), 0.627, (0.745,0.8
C15	[(0.25,0.35), 0.5, (0.65,0.	[(0.45,0.55), 0.7, (0.8,0.9	[(0.85,0.95), 1, (1,1)]	[(0.513,0.613), 0.731, (0.815,0.9
C16	[(0.25,0.35), 0.5, (0.65,0.	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.386,0.486), 0.636, (0.752,0.8
C17	[(0.85,0.95), 1, (1,1)]	[(0.85,0.95), 1, (1,1)]	[(0.85,0.95), 1, (1,1)]	[(0.849,0.949), 0.999, (0.999,0.9
C18	[(0.45,0.55), 0.7, (0.8,0.9	[(0.85,0.95), 1, (1,1)]	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.595,0.695), 0.808, (0.872, .96
C19	[(0.85,0.95), 1, (1,1)]	[(0.45,0.55), 0.7, (0.8,0.9	[(0.85,0.95), 1, (1,1)]	[(0.704,0.84), 0.890, (0.926,0.98
C20	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.450,0.549), 0.699, (0.799,0.9
C21	[(0.85,0.95), 1, (1,1)]	[(0.45,0.55), 0.7, (0.8,0.9	[(0.45,0.55), 0.7, (0.8,0.95)]	[(0.577,0.677), 0.795, (0.863,0.9

The subjective weights of the indicators were calculated according to the procedures described in Sections 3.1 and 3.2. The expert weights, determined using intuitionistic fuzzy sets, were applied to transform the linguistic evaluations of indicator importance into interval-valued triangular fuzzy numbers. The resulting data are summarized in Table 6.

The subjective weights were obtained by defuzzifying the triangular fuzzy weighted averages of the indicators. The objective weights were determined using the improved CRITIC method described in Section 3.3. Using the maximum-minimum deviation method, the optimal combination coefficients for the subjective and objective weighting methods were determined as 0.533 and 0.467, respectively. This determination was based on the principles of maximizing deviation from the ideal solution and minimizing the worst-case deviation. These coefficients were then substituted into Eqs. (20)-(21) to calculate the combined weights, as shown in Table 7.

Table 7. The weight results of the secondary indicators in three cases

Target Layer	Secondary Indicators	Triangular Interval Fuzzy Function	Improve CRITIC	Combined Weight
The carbon phase level of the park	C1	0.055	0.028	0.041
	C2	0.050	0.040	0.045
	C3	0.043	0.043	0.043

C4	0.047	0.036	0.041
C5	0.053	0.063	0.058
C6	0.059	0.039	0.048
C7	0.037	0.053	0.046
C8	0.044	0.062	0.054
C9	0.050	0.045	0.047
C10	0.032	0.040	0.037
C11	0.046	0.054	0.050
C12	0.053	0.044	0.048
C13	0.044	0.055	0.050
C14	0.040	0.067	0.054
C15	0.046	0.049	0.048
C16	0.041	0.081	0.062
C17	0.061	0.065	0.063
C18	0.050	0.054	0.052
C19	0.055	0.044	0.049
C20	0.044	0.016	0.029
C21	0.050	0.023	0.035

As shown in Table 7, the improved CRITIC method captures information through the comparative strength and conflict among indicators. This approach highlights the influence of highly variable and strongly correlated indicators—such as carbon emission intensity and energy structure—on the parks' low-carbon performance. Indicators such as the smartness level of energy management systems, comprehensive utilization rate of industrial solid waste, and value-added output per unit of construction land typically receive higher weights. This tendency may bias the evaluation results toward the high-carbon end of the spectrum. Therefore, weighting based on triangular fuzzy functions within the intuitionistic fuzzy set framework was employed. This method incorporates experts' degrees of hesitation and membership regarding indicator importance by using triangular fuzzy numbers to represent semantic judgments. This approach makes the weights more representative of the parks' actual low-carbon operational characteristics. The combined weights fall between those derived from the individual methods, indicating that the weighting scheme has been moderated through integration. This integration mitigates biases inherent in any single method and enhances the objectivity and robustness of the low-carbon performance evaluation.

4.2 Comprehensive Evaluation and Level Diagnosis

Through field investigations and literature reviews, current values for each low-carbon indicator were collected and calculated. By integrating the evaluation criteria with Eq. (22), Eqs. (25)-(26), the normalized matter-element matrix for the classical domain of the evaluated subjects was constructed as follows:

$$N_{\square}^{R}=\begin{bmatrix} N_A & C_1 & 0.28 \\ & C_2 & 0.15 \\ & \vdots & \vdots \\ & C_{21} & 0.56 \end{bmatrix} N_{\square}^{R}=\begin{bmatrix} N_B & C_1 & 0.47 \\ & C_2 & 0.12 \\ & \vdots & \vdots \\ & C_{21} & 0.64 \end{bmatrix} N_{\square}^{R}=\begin{bmatrix} N_C & C_1 & 0.68 \\ & C_2 & 0.28 \\ & \vdots & \vdots \\ & C_{21} & 0.77 \end{bmatrix} \tag{31}$$

$$N_{\square}^{R}=\begin{bmatrix} N_A & C_1 & 0.72 \\ & C_2 & 0.40 \\ & \vdots & \vdots \\ & C_{21} & 0.80 \end{bmatrix} N_{\square}^{R}=\begin{bmatrix} N_A & C_1 & 0.58 \\ & C_2 & 0.35 \\ & \vdots & \vdots \\ & C_{21} & 0.60 \end{bmatrix} \tag{32}$$

The correlation coefficients for each indicator across all grades were calculated using the methodology described in Section 3.5. The correlation coefficient values for each indicator and the comprehensive evaluation results for the five parks were determined based on the maximum correlation principle, as shown in Figure 3.

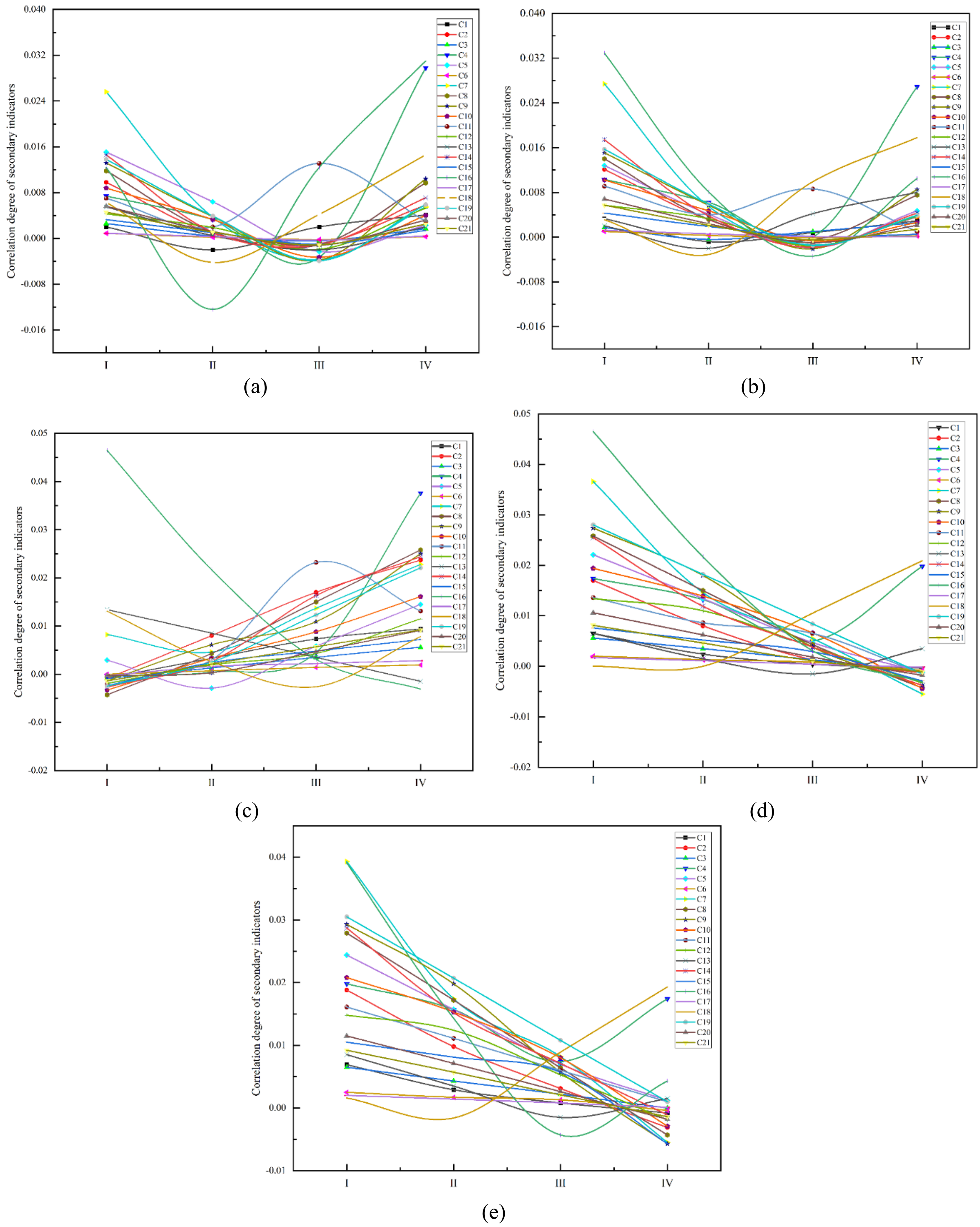

Figure 3. The correlation degree and evaluation grades of the index layers of each park

As can be seen from Figure 3, the index correlation graph of the five parks clearly reveals the imbalance in their internal development, which directly supports the core finding of this paper regarding the bottleneck effect. The proportions of indicators rated at Level III or above were 71.43%, 80.95%, 19.05%, 90.48%, and 95.24% for Parks A through E, respectively. Parks A, B, D, and E exhibited relatively weaker overall indicator performance, whereas Park C demonstrated consistently stronger performance across most indicators. Further analysis revealed that although Parks E and D met Level I standards for key indicators (e.g., C1, C8, C19), they lacked clearly defined and systematic net-zero carbon pathways. Parks B and A were in transition from high-carbon to low-carbon development. Park B showed potential for improvement in process efficiency indicators such as C4 and C15. Park A demonstrated strong performance in end-of-pipe emission control indicators (e.g., C7, C10), indicating a current focus on downstream measures rather than process optimization and systemic coordination. Park C maintained most indicators at Level III or above, with particularly strong performance in foundational metrics such as C3 and C21. This indicates advantages not only in distributed energy technologies but also in management systems, transparency, and public engagement. These visualized data strongly demonstrate that the zero-carbon transformation of the park is not a simultaneous improvement of all indicators, but rather a process of overcoming shortcomings in key dimensions.

Table 8. The relevance of each park for each level

Park	Net-Zero Carbonization Standard	Near-Zero Carbon Standard	Low-Carbon Standards	High Carbonization Standard
A	0.804	0.971	1.002	0.836
B	0.778	0.943	0.987	0.863
C	0.925	0.943	0.847	0.708
D	0.676	0.826	0.903	0.937
E	0.642	0.793	0.896	0.931

Based on the comprehensive correlation scores for each level in Table 8, the development levels of the parks were calculated using Eqs. (29)-(30) and ranked by their s^{**} values, as shown in Table 9. For example, Park E's s^{**} value of 3.199 indicates a relatively low level of low-carbon development, while Park D's s^{**} value of 3.174 suggests above-average carbon emissions, albeit lower than Park E's.

Table 9. Comprehensive correlation and ranking of each park

Park	S'	Evaluation Results	s^{**}	Rank
A	1.002	Low-Carbon Park	2.660	2
B	0.987	Near-Zero Carbon Park	2.824	3
C	0.943	Near-Zero Carbon Park	1.868	1
D	0.937	High-Carbon Park	3.174	4
E	0.931	High-Carbon Park	3.199	5

From a dimensional perspective, all parks demonstrated relatively strong performance in governance and innovation capabilities, suggesting established policy support and social consensus. However, significant disparities emerged in the dimensions of carbon management and emission reduction, as well as circular economy and resource utilization. This finding suggests that the current low-carbon transformation remains primarily technology-driven, with market mechanisms and resource circulation coordination not yet fully leveraged.

4.3 Sensitivity Analysis

To ensure the reliability of the conclusions derived from the combined weights determined by the maximum-minimum deviation method, a sensitivity analysis was conducted. This analysis tested the robustness of the evaluation results against variations in the subjective-objective weight allocation ratio. A sensitivity coefficient λ was introduced, varying within the range [0,1] with an increment of $\Delta\lambda = 0.2$, to generate different combined weighting schemes. The comprehensive scores were recalculated for each scheme, yielding new ranking sequences as shown in Table 10 and Figure 4.

The sensitivity analysis results presented in Figure 4 provide critical evidence for the robustness of the evaluation conclusions in this study. The results demonstrate that when λ varies across [0,1], simulating scenarios from complete reliance on objective data to complete reliance on expert judgment—the comprehensive scores exhibit minor fluctuations. However, the final ranking order (C > A > B > D > E) remains unchanged. This indicates that the evaluation results are robust and insensitive to the choice of weight allocation strategy. This finding is significant because it demonstrates that the disparities in park development levels identified in this study originate not from the arbitrary choice of subjective weighting schemes, but from objective, structural performance gaps across multiple indicators.

Table 10. The comprehensive correlation degree of the combined weights under different interval coefficients

Interval	[0,1]	[0.2,0.8]	[0.4,0.6]	[0.6,0.4]	[0.8,0.2]	[1,0]
A	2.562	2.567	2.572	2.578	2.583	2.589
B	2.883	2.879	2.874	2.869	2.864	2.858
C	1.822	1.815	1.809	1.804	1.798	1.793
D	3.251	3.252	3.253	3.254	3.255	3.256

E	3.255	3.259	3.262	3.266	3.270	3.274

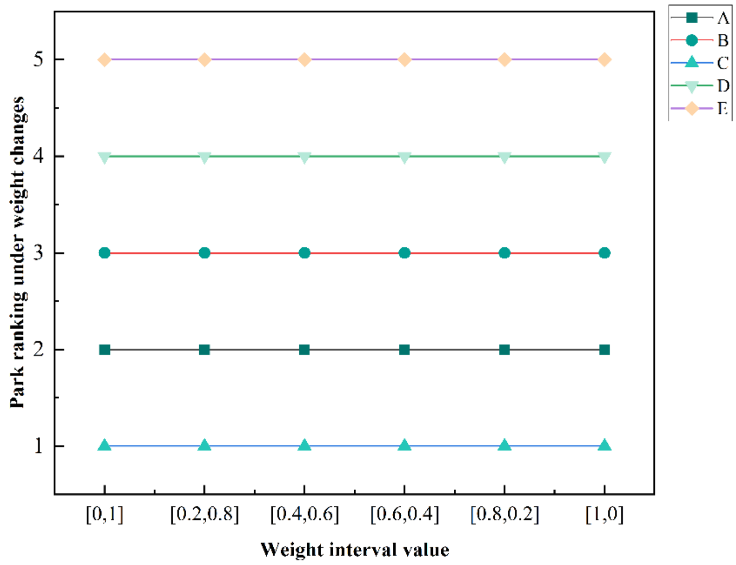

Figure 4. Sort after the weight interval changes

The robustness of these results fundamentally originates from the inherent structural disparities in net-zero carbon development levels among the parks. As previously discussed, Parks D and E have achieved Level III or higher for over 90% of their indicators, establishing a comprehensive leading advantage. Conversely, Park C remains at Level III or below for over 80% of its indicators, indicating systemic developmental lag.

This fundamental heterogeneity implies that the excellence of high-performing parks derives from synergistic improvements across multiple indicators, not from outstanding performance in isolated metrics. Similarly, the shortcomings of lagging parks manifest as multidimensional, concurrent challenges. Consequently, weight reallocation can only induce minor fluctuations in the internal score structures of individual parks; it cannot overturn their inherent hierarchical ranking determined by comprehensive performance. The reliability of this study's evaluation conclusions is rooted not in the specific weighting scheme, but in the objectively existing, fundamental developmental gradient among the research subjects.

4.4 Comparative Analysis

To verify the robustness of this study's conclusions at the model framework level, the GRA-KL-TOPSIS integrated model was selected as a benchmark for comparison. This choice is scientifically justified by the fundamental theoretical differences between the models. The matter-element extension model, based on extension set theory, achieves grade diagnosis through correlation functions and represents an absolute evaluation paradigm. In contrast, the GRA-KL-TOPSIS model integrates grey relational analysis with the ideal solution method, performing rankings by measuring relative closeness to the ideal solution, and represents a relative evaluation paradigm. The specific algorithmic steps of the GRA-KL-TOPSIS model are as follows:

Step 1: Calculate the weighted normalized matrix Z.by multiplying the normalized matrix P by the weight vector ω. Then, determine the positive ideal solution (Z^+) and the negative ideal solution (Z^-) from the alternatives.

$$Z = (z_{ij})_{txz} = (w_k P_{lk})_{txz} \tag{33}$$

$$j_+^z = \left\{ \max_i z_{ij} \middle| z_{ij} \in Z^+, \min_i z_{ij} \middle| z_{ij} \in Z^- \right\} = \{1_+^z, 2_+^z \dots i_+^z\} \tag{34}$$

$$j_-^z = \left\{ \min_i z_{ij} \middle| z_{ij} \in Z^+, \max_i z_{ij} \middle| z_{ij} \in Z^- \right\} = \{1_-^z, 2_-^z \dots i_-^z\} \tag{35}$$

where, j_+^Z denotes that a larger value is better for the *j-th* indicator (benefit-type), and j_-^Z denotes that a smaller value is better (cost-type).

Step 2: Calculate the grey correlation coefficients ij_+^ζ and ij_-^ζ between the value of the j *-th* indicator for the *i-th* alternative and j_+^Z or j_-^Z, respectively.

$$ij_{+}^{\zeta} = \frac{\underset{i}{min}\underset{j}{min}\left|z_{ij} - j_{+}^{z}\right| + \rho \underset{i}{max}\underset{j}{max}\left|z_{ij} - j_{+}^{z}\right|}{\left|z_{ij} - j_{+}^{z}\right| + \rho \underset{i}{max}\underset{j}{max}\left|z_{ij} - j_{+}^{z}\right|} \tag{36}$$

$$ij_{-}^{\zeta} = \frac{\underset{i}{min}\underset{j}{min}\left|z_{ij} - j_{-}^{Z}\right| + \rho \underset{i}{max}\underset{j}{max}\left|z_{ij} - j_{-}^{Z}\right|}{\left|z_{ij} - j_{-}^{Z}\right| + \rho \underset{i}{max}\, max_{j}\left|z_{j} - j_{-}^{Z}\right|} \tag{37}$$

where, ρ is the distinguishing coefficient, set to 0.5 based on research experience.

Step 3: Calculate the grey correlation degrees i_{+}^{γ} and i_{-}^{γ} for the *i-th* alternative with respect to j_{+}^{z} and j_{-}^{z}.

$$i_{+}^{\gamma} = \sum_{j=1}^{n} w_{j} ij_{+}^{\zeta} \tag{38}$$

$$\gamma_{i} = \sum_{j=1}^{n} w_{j} ij_{-}^{\xi} \tag{39}$$

Step 4: Calculate the Kullback - Leibler (KL) divergence i_{+}^{d} and i_{-}^{d} from the indicator values of the evaluated object to the positive and negative ideal solutions of matrix *F*.

$$i_{+}^{d} = \sum_{j=1}^{n} \left[j_{+}^{f}\, lg\frac{j_{+}^{f}}{f_{ij}} + \left(1 - j_{+}^{f}\right) lg\frac{1 - j_{+}^{f}}{1 - f_{ij}} \right] \tag{40}$$

$$i_{-}^{d} = \sum_{j=1}^{n} \left\{ j_{-}^{f}\, lg\frac{j_{-}^{f}}{f_{ij}} + \left(1 - j_{-}^{f}\right) lg\frac{1 - j_{-}^{f}}{1 - f_{ij}} \right\} \tag{41}$$

Step 5: Determine the comprehensive relative closeness Cr_{i} for each evaluation target.

$$Cr_{i} = \frac{i_{+}^{d}}{i_{+}^{d} + i_{-}^{d}} \tag{42}$$

The model comparison results presented in Figure 5 verify the reliability of this study from a methodological perspective and reveal the inherent value orientations of different modeling approaches.

Although the matter-element extension model and the GRA-KL-TOPSIS model differ in their theoretical foundations—the former focuses on absolute grade evaluation, whereas the latter emphasizes relative ranking—they exhibit a high degree of consistency in the overall ranking (Spearman's $\rho = 0.8$). This consistency cross-validates the objectivity of the differences in the carbon development stages among the industrial parks. It is worth noting that slight differences exist in the rankings of Parks A and C between the two models. Specifically, the GRA-KL-TOPSIS model ranked Park A first due to its highest proximity to the ideal solution (0.5720). In contrast, the matter-element extension model ranked Park C first, based on its more balanced overall development and superior comprehensive score (1.868), as detailed in Table 11. Furthermore, except for Park E, the adjusted rankings of the other parks exhibit a fluctuating trend in the line chart in Figure 5. This observed volatility provides valuable insights.

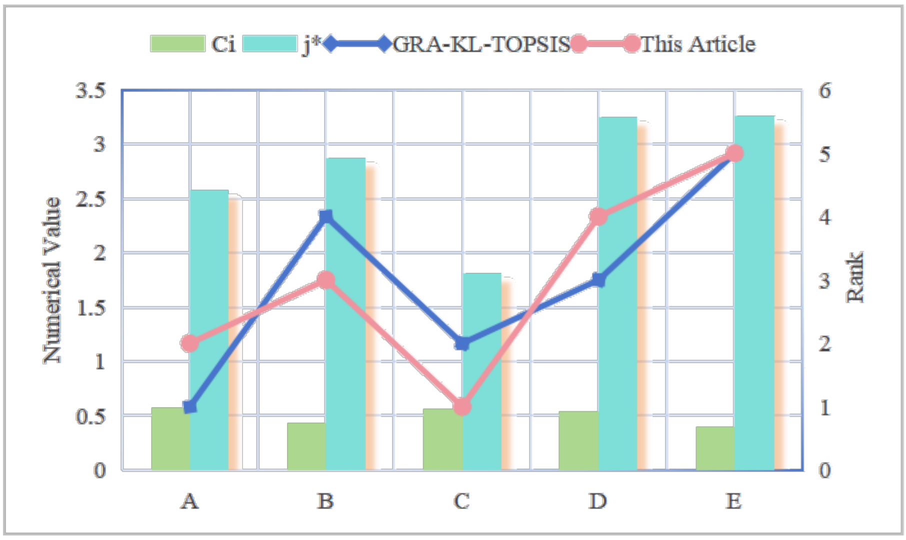

Figure 5. Comparison of matter-element extension and TOPSIS evaluation results

The TOPSIS model is more sensitive to exceptionally performing indicators, whereas the matter-element extension model places greater emphasis on the overall balance of the indicator system. This contrast highlights a key advantage of using the matter-element extension model for "diagnosis" over simple "ranking": it can effectively identify parks that achieve high comprehensive scores yet retain critical weaknesses. This capability provides deeper insights for formulating targeted policies. Collectively, the results from multiple perspectives confirm that inherent disparities in the development levels of industrial parks are the dominant factor determining the evaluation conclusions. The choice of research methodology does not alter this fundamental conclusion but reveals its characteristics from different dimensions.

Table 11. The comprehensive Posting progress and ranking under comparative analysis

Park	i_+^d	i_-^d	Cr_i	Rank
A	0.1966	0.1471	0.5720	1
B	0.1498	0.1981	0.4036	4
C	0.2009	0.1568	0.5616	2
D	0.2499	0.2128	0.5402	3
E	0.2027	0.3032	0.4006	5

The fundamental cause of these discrepancies is the uneven development of carbon management levels across industrial parks. The TOPSIS method tends to over-reward outstanding strengths, whereas the matter-element extension model over-penalizes weaknesses. The ultimate goal is to guide all parks toward a balanced, high-quality low-carbon development model that addresses all aspects, rather than pursuing excellence in any single metric.

5. Conclusion

Accurately assessing the zero-carbon development stage of industrial parks is fundamental for formulating effective emission reduction strategies. This study constructs a comprehensive evaluation model that integrates interval-valued triangular fuzzy sets, an improved CRITIC method, and matter-element extension theory. This model enables a methodological shift from traditional "ranking" to precise "diagnostics." An empirical analysis of five industrial parks in the Yangtze River Delta revealed that Park C has entered a near-zero-carbon stage, whereas Parks D and E remain in a high-carbon stage, with significant disparities observed across all parks.

The advantages of leading parks stem from the synergy between governance innovation and energy structure optimization. In contrast, bottlenecks in lagging parks are concentrated in dimensions such as carbon management and the circular economy. Consequently, the zero-carbon transition of industrial parks must follow differentiated pathways. For high-carbon parks, the immediate priority is to consolidate data and management foundations. This involves prioritizing the deployment of a comprehensive carbon accounting system, initiating energy-saving retrofits for key high-consumption equipment, and rapidly installing distributed photovoltaic systems and solid waste disposal facilities. For near-zero- and low-carbon parks, the focus shifts to systemic coordination and value capture. Deep decarbonization can be achieved by establishing carbon performance incentive mechanisms, developing smart microgrids with multi-energy coordination, and managing supply chain carbon footprints. At the policy level, we recommend implementing park-specific carbon budget management and differentiated performance evaluation based on this assessment framework. Market mechanisms should be leveraged to drive cost-effective emission reductions.

Methodologically, this study demonstrates the model's robustness and interpretability. Sensitivity analysis confirmed that perturbations in weight assignments did not alter the ranking outcomes. Furthermore, a comparative analysis with the GRA-KL-TOPSIS model revealed a high degree of consistency. This indicates that the robustness of the conclusions stems not from arbitrary weight allocation but from intrinsic structural development disparities among the parks—reflecting fundamental differences rather than methodological bias.

The primary contributions of this study are threefold: (1) proposing a robust and diagnosable framework for assessing the carbon development stage of industrial parks; (2) empirically identifying and explaining bottleneck patterns in zero-carbon transformation; and (3) offering differentiated transformation pathways based on diagnostic findings. For parks with leading advantages, strengths in governance and energy should be extended to carbon management and circular economy dimensions. For high-carbon parks, foundational capabilities must be prioritized to prevent the amplification of bottleneck effects. It should be noted that the conclusions are derived from a sample in the Yangtze River Delta; thus, their generalizability requires further validation in resource-based and heavy industrial parks. Future research should expand this framework to multiple types of industrial parks, compare and simulate their differentiated low-carbon transition paths. Furthermore, the ultimate goal of industrial park diagnosis is to promote the transformation of the management paradigm from post-hoc evaluation to real-time decision-making. Therefore, future studies should explore the construction of a carbon management platform based on digital twins and artificial intelligence, to realize real-time perception, predictive early warning, and adaptive optimization of carbon flows, thereby providing intelligent decision support for industrial parks throughout the entire life cycle of planning, construction, and operation.

Author Contribution

Conceptualization, Shen, T. and Sun, L.; methodology, Shen, T.; software, Shen, T.; validation, Shen, T., Sun, L.; formal analysis, Shen, T.; investigation, Shen, T.; resources, Shen, T.; data curation, Shen, T.; writing—original draft preparation, Shen, T.; writing—review and editing, Shen, T.; visualization, Shen, T.; supervision, Shen, T.; project administration, Shen, T.; funding acquisition, Sun, L. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest related to this study.

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Appendix A:

Table A1. The Definition and Quantification of Indicators for Carbon Development Stages in Industrial Parks

Indicator	Definition & Quantification Method	Threshold Rationale
C1	The proportion of energy-consuming units equipped with distributed energy systems. Formula: $C_1 = \left(\frac{Number\ of\ units\ with\ distributed\ systems}{Total\ number\ of\ units}\right) \times 100\%$	Aligned with the development goals outlined in China's "14th Five-Year Plan for Modern Energy Systems" and benchmarked against practical targets (e.g., >50% for large-scale application) from leading parks like Suzhou Industrial Park and Shanghai Jinqiao Export Processing Zone.
C2	The percentage of total installed electricity capacity derived from renewable sources. Formula: $C_2 =$	Derived from the International Energy Agency's (IEA) "Net Zero by 2050: A Roadmap for the Global

Indicator	Definition & Quantification Method	Threshold Rationale
	$\left(\frac{Installed\ renewable\ capacity}{Total\ installed\ electricity\ capacity}\right)$×100%.	Energy Sector", which recommends that renewable generation shares reach 60% by 2030 and nearly 90% by 2050 in advanced economies. Thresholds are adapted for the Chinese context.
C3	The electricity consumption per unit area of public buildings relative to the industry benchmark. Formula: $C_3 = \left(\frac{Park's\ building\ energy\ intensity}{Benchmark\ value} \times 100\%\right)$. The benchmark is the "constraint value" specified for the corresponding climate zone and building type in the Chinese national standard "Standard for energy consumption of building"(GB/T 51161-2016).	Directly based on the mandatory national standard GB/T 51161. A ratio of 1.0 indicates compliance, while a ratio below 0.5 represents a "leading" performance level.
C4	The percentage of trips made using low-carbon modes (walking, cycling, new energy vehicles, public transport). Formula: $C_4 = \left(\frac{Number\ of\ low-carbon\ trips}{Total\ number\ of\ trips}\right) \times 100\%$.	References the EU's Sustainable Urban Mobility Plans (SUMPs), which set a target of 70-80% or higher for green travel modal share in core cities as a key indicator of sustainability
C5	A score (0-100) evaluating the level of system intelligence, determined by expert assessment based on guidelines such as China's "Smart Park Construction Guide".	According to the "Smart Park Construction Guide", a score above 75 signifies an "Integrated and Optimized" level, and above 90 represents an "Innovation and Leadership" level.
C6	The average annual reduction rate of CO2 emissions per unit of industrial added value compared to a base year (e.g., the final year of the 13th Five-Year Plan). Formula: $C_6 = \left[1 - \left(\frac{I_t}{I_o}\right)^{\frac{1}{n}}\right]$×100% .Where I_t current year carbon intensity I_o base year n is the number of years.	Based on China's "Action Plan for Carbon Dioxide Peaking Before 2030", which mandates a reduction of over 18% during the 14th Five-Year Plan period and over 15% in the 15th, translating to an average annual reduction rate of 4-4.5%. A threshold of 4.5% is set as an ambitious target.
C7	The proportion of fossil fuel CO2 emissions captured by CCUS technology. Formula: C7 = (*Annual CO2 captured by CCUS / Total fossil fuel CO2 emissions*) × 100%. This indicator is particularly relevant for high-emission parks (e.g., chemical, steel).	Based on the IEA's "Energy Technology Perspectives" report, which indicates that CCUS application rates in industry need to scale up from around 10% by 2030 to nearly 40-70% by 2050 to achieve net-zero goals.
C8	The carbon emissions per unit of product relative to an industry benchmark. Formula: $C_8 = \left(\frac{Product\ carbon\ intensity}{Industry\ benchmark\ value}\right)$	The methodology is aligned with the benchmark approach core to China's national Emissions Trading Scheme (ETS), an internationally recognized method for ensuring fairness and efficiency. Thresholds directly reflect carbon efficiency competitiveness within the sector.
C9	The proportion of the park's total carbon emissions offset by purchasing Green Electricity Certificates (GECs). Formula: C9 = $\left(\frac{Emission\ reduction\ equivalent\ of\ GECs}{Total\ park\ emissions}\right) \times 100\%$	The reliance on off-site mitigation instruments like GECs is expected to increase as decarbonization deepens, making this a key indicator for advanced stages.
C10	The park's energy consumption per unit of industrial added value relative to the average of its host province/municipality. Formula: C10 = $\left(\frac{Park's\ energy\ intensity}{Regional\ average\ energy\ intensity}\right) \times 100\%$	Using a relative value helps benchmark the park's performance against its regional peers, reflecting achievements in both technological and structural energy savings.
C11	he percentage of enterprises covered by the emissions trading system that fully and timely surrender their carbon quotas. Formula: C11 = $\left(\frac{Number\ of\ compliant\ enterprises}{Total\ number\ of\ enterprises\ obligated\ to\ comply}\right) \times 100\%$	While 100% compliance is the legal requirement per China's "Interim Regulations on Carbon Emissions Trading", a Tier I threshold of 90% acknowledges the high national compliance rate (>99.5% in the first cycle) while allowing for minor, non-systemic delays.
C12	The proportion of industrial solid waste that is comprehensively utilized. Formula: C12 = $\left(\frac{Amount\ utilized}{Amount\ generated + previous\ years'\ stockpiles}\right) \times 100\%$	Based on China's "Standard for National Eco-industrial Demonstration Parks" (HJ 274-2015) and the "Indicator System for 'Zero-Waste City' Construction", which identify a utilization rate exceeding 90% as an international advanced level.

Indicator	Definition & Quantification Method	Threshold Rationale
C13	The proportion of water reused in industrial processes. Formula: C13 = (*Volume of water reused / Total water intake*)×100%	The World Business Council for Sustainable Development's (WBCSD) "Water Tool" considers an industrial water recycling rate above 80% as "best practice".
C14	The proportion of domestically generated waste that is separately collected at source. Formula: C14 = $(\frac{Amount\ of\ separately\ collected\ waste}{Total\ amount\ of\ waste\ transported})$×100%	None
C15	The percentage of construction land area dedicated to green space. Formula: C15 = (*Green space area / Total construction land area*) × 100%	References China's "Urban Greening Planning and Construction Indicators" and standards for eco-industrial parks.
C16	The economic output density, measured as industrial added value generated per unit area of construction land. Formula: C16 = $(\frac{Industrial\ added\ value}{Construction\ land\ area})$×100%	Benchmarked against world-class parks like Singapore's Industrial Estate and Japan's Kawasaki Eco-Town, which demonstrate significantly higher land productivity through intensive development.
C17	The share of the park administration's budget allocated specifically to low-carbon development initiatives.	Reflects the level of financial commitment and resource allocation by the park management authority towards the green transition, often influenced by local government support intensity.
C18	The frequency of carbon-related information disclosure. Scored ordinally: 0=None, 1=Annual, 2=Semi-annual, 3=Quarterly, 4=Monthly/Near-real-time. Assessed via park websites, sustainability reports, or public platforms.	Aligned with the Task Force on Climate-related Financial Disclosures (TCFD) recommendation for more frequent and timely disclosure, as well as guidance from bodies like the Shanghai Stock Exchange on environmental disclosure frequency.
C19	The proportion of enterprises that have established and operate a certified carbon management system. Formula: C19 = $(\frac{Number\ of\ certified\ enterprises}{Total\ number\ of\ enterprises\ targeted\ for\ certification})$ × 100%.	Consistent with China's policy direction of promoting carbon management system construction in key enterprises.
C20	The percentage of key emission sources (as defined by the park based on energy consumption/emission levels) connected to a unified digital carbon management platform. Formula: C20 = $(\frac{Number\ of\ connected\ sources}{Total\ number\ of\ key\ sources}$ /) × 100%.	Emphasizes the foundational role of digital platforms for transparency and precision in carbon management, as highlighted by initiatives like the WEF's Global Lighthouse Network.。
C21	The proportion of enterprises that have conducted zero-carbon production audits or in-depth energy conservation diagnostics. Formula: C21 = (*Number of enterprises conducting audits / Total number of enterprises*) × 100%。	Such audits are a standardized starting point for deep decarbonization at the enterprise level, promoted by organizations like the World Resources Institute (WRI) under frameworks for carbon footprint accounting and reduction planning.