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Applying Information Gap Decision Theory for Uncertainty Management in Building Lifecycle Assessment

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Abstract: This study applies Info-Gap Decision Theory (IGDT) to manage uncertainties in early-stage lifecycle assessment (LCA) in the building sector, focusing on carbon emissions and cost optimization. The building industry significantly contributes to global carbon emissions, making robust LCA models crucial for achieving environmental improvements. Traditional LCA methods often overlook deep uncertainties, leading to unreliable outcomes. To address this, this research integrates IGDT, providing a non-probabilistic approach that enhances decision-making under uncertainty. The study develops an optimization model that considers uncertainties in material choices, supplier selection, and transportation logistics, demonstrated through a case study of a Science and Technology Expo Pavilion in Chongqing, China. The results show that manufacturing processes are the main source of carbon emissions, with transportation having a smaller but notable impact. Significant emission reductions can be achieved by using alternative materials like fly ash and volcanic ash in cement production. Strategic supplier selection, based on the cost per ton of CO_2 reduction, balances environmental impact with economic feasibility. IGDT provides a robust framework for managing uncertainty, helping building projects to achieve sustainability targets even under deep uncertainty, thereby supporting the industry's efforts towards net-zero emissions.

Keywords: value engineering; carbon emissions; uncertainty; information gap decision theory (IGDT)

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1. Introduction

Addressing the challenges posed by climate change has emerged as a global imperative. At the COP26 conference, over 90% of the world's GDP committed to achieving net-zero emissions. Global Warming Potential (GWP) is the most widely utilized metric for assessing the impact of greenhouse gases on climate change [1]. These greenhouse gases vary in their potential to damage the atmosphere; however, for simplicity, they are generally quantified in terms of their 100-year carbon dioxide equivalents (CO_2e) [2]. The building industry is responsible for nearly 40% of the global carbon emissions [3]. Consequently, professionals within this sector bear a significant responsibility to reduce carbon emissions from buildings, making it a critical area for mitigating global climate change. Motivated by these considerations, this study aims to enhance the application and effectiveness of lifecycle assessment (LCA) during the early stages of the design process, thereby significantly improving environmental outcomes and addressing the challenge of managing uncertainties to increase the reliability and impact of LCA results in building projects.

Operational carbon, embodied carbon, and user carbon are collectively referred to as "Whole Life Carbon" (WLC). The carbon impacts of these components can be estimated using lifecycle assessment (LCA) methodologies. Teng developed a five-level embodied carbon analysis framework based on LCA that provides a foundation for future carbon reduction strategies in urban prefabricated buildings [4]. However, deterministic analysis is often only feasible after the completion of the building. Although applying LCA methods in the early design stages can significantly enhance the environmental performance of buildings, LCA is typically conducted in the later stages of the design process to obtain green building certification, with only about 20% of studies focusing on new designs and renovations [5]. Therefore, guiding early design decisions using LCA methods remains a substantial challenge.

Moreover, the application of LCA as a decision-support tool may be influenced by numerous uncertainties inherent in the calculations. Addressing these uncertainties is crucial for enhancing the reliability and credibility of LCA results [6]. Despite the requirements for uncertainty analysis outlined by the international standards ISO 14044 and ISO 21930 [7], a survey conducted by Feng et al. found that fewer than 10% of studies engaged in uncertainty research related to building LCA [8]. This finding underscores the importance of uncertainty analysis in building LCA and highlights the shortcomings of current practices. More transparent reporting of results, methods, and assumptions regarding uncertainties can enhance the reproducibility, readability, transparency, and interpretability of findings [7], thereby ensuring more scientific and rational decision-making.

To effectively address uncertainty, it is essential to first comprehend its sources. Walker categorizes uncertainty into three dimensions: location, level, and nature [9]. Among these dimensions, location has garnered the most attention [5]. Lloyd and Ries further subdivide location uncertainty into parameter, scenario, and model uncertainties [10]. In the context of building LCA, Warrier et al. [11] identify four principal types of uncertainties: early design decision uncertainties, input data uncertainties, future stage uncertainties, and LCA method-related uncertainties. Li et al. [5] propose a practical categorization based on stakeholders, which includes method-related uncertainties managed by LCA method providers, data-related uncertainties handled by third-party data providers, and design-related uncertainties managed by designers. Marsh et al. [7] focus on uncertainties present in various stages of the building lifecycle: early design stage uncertainties, material lifecycle assessment uncertainties, construction stage uncertainties, maintenance and refurbishment stage uncertainties, and end-of-life and climate change uncertainties. These classifications emphasize specific sources of uncertainty and lifecycle stages, while Li et al.'s classification underscores the roles and responsibilities of different stakeholders in managing uncertainty.

In addition to categorizing uncertainty by location, understanding the level of uncertainty can provide a new perspective on uncertainty in the field of building LCA. The level of uncertainty is linked to the information available for describing the quantity, model structure, or context [6]. Walker et al. [9] discuss the degree of uncertainty, which ranges from situations where statistical data can precisely quantify results or validate model structures to a state of total ignorance, where we are unaware of what we do not know. Methods for addressing these uncertainties, from low to high, include sensitivity analysis, probabilistic models, and scenario analysis [12]. For higher levels of uncertainty, Ben-Haim [13,14] developed the Info-Gap Decision Theory, a method for making decisions under deep uncertainty in the engineering field [15].

Info-Gap Decision Theory offers a non-probabilistic approach to decision-making under deep uncertainty, contrasting with traditional methods that rely on predefined probabilistic distributions. Traditional approaches often presuppose accurate probabilistic distributions based on data quality scores, which have been criticized for their reliability and subjectivity [7]. Moreover, using European data to represent global or other regional contexts, as well as the variability among suppliers, often leads to an underestimation of uncertainty [16]. The pedigree method characterizes uncertainty probabilistically and is employed in conjunction with Monte Carlo simulations for uncertainty propagation in lifecycle assessments (LCA). While Monte Carlo simulations are computationally intensive, they are a standard approach for addressing quantitative uncertainty analysis and typically do not fail to converge; rather, they may require a significant number of iterations to achieve stability in their results [6].

In contrast, the Info-Gap model is particularly effective in representing uncertainty regarding the shapes of functions, such as the stress–strain curves of metals and the demand–supply curves for new products, as well as uncertainty in parameters or vectors, and sometimes even in sets of such entities [12]. This model circumvents the pitfalls associated with reliance on unreliable data quality scores and inadequate probabilistic assumptions, providing a robust framework for decision-making where traditional probabilistic methods may falter.

The essence of Info-Gap Theory lies in its elucidation of the trade-off between "robustness" and "opportunity". This theory assists designers in identifying design solutions that can maintain their environmental performance standards under the most adverse conditions by assessing the robustness of decisions amidst extreme uncertainty, thereby rendering design decisions more resilient. This approach has been widely applied in various fields, including engineering decision-making and energy strategies. For instance, Kanno et al. [17] explored how structural design can enhance seismic resistance, providing insights crucial for the robust design of complex buildings under earthquake conditions. Ben-Haim [18] investigated robustness in energy conservation strategies under unknown future conditions. Additionally, a study by Ajenjo et al. [19] validated the utility of this theory in energy microgrid planning, demonstrating its effectiveness in addressing uncertainty in multi-objective resource allocation planning. In the context of building LCA, this means we can evaluate whether the environmental performance of a design decision continues to meet established LCA standards as the level of uncertainty increases.

This study aims to bridge existing gaps in the application of LCA by focusing on the timing of LCA application, effective integration during early design stages, handling uncertainties in LCA calculations, enhancing reporting and transparency, and exploring the potential of non-probabilistic approaches, such as Info-Gap Decision Theory, in managing uncertainty and making robust decisions under deep uncertainty within the building LCA context.

2. Methodology

2.1. Overview

This study employs a structured methodology to address uncertainties in the early lifecycle assessment (LCA) of building materials, focusing on carbon emissions and cost analysis. The key steps include the following:

System Boundary and Scope Definition: Concentrates on the A1–A4 stages of the embodied carbon lifecycle, covering raw material extraction, transportation to manufacturing sites, manufacturing processes, and transport of finished products to the construction site. The exclusion of construction activities (A5) reflects the study's emphasis on upstream impacts during the design phase.

Data Collection: Utilizes quantitative data from Environmental Product Declarations (EPDs), supplier interviews, and regional databases. Specific data sources and assumptions are explicitly documented to ensure transparency.

Uncertainty Modeling with IGDT: Integrates Info-Gap Decision Theory (IGDT) to model uncertainties, including variability in emission factors, material quantities, and transportation distances.

Optimization Framework: Develops an optimization model to evaluate material and supplier selection, balancing cost efficiency and carbon reduction under uncertainty.

Validation Through Case Study: Applies the methodology to a real-world project to demonstrate its practical relevance and effectiveness.

2.2. System Boundary and Study Scope

The scope of this study is concentrated on the early lifecycle impacts of building materials, specifically covering stages A1 through A4 of the embodied carbon lifecycle as defined by the WorldGBC. This includes the extraction and processing of raw materials (A1), transportation to the manufacturing site (A2), the manufacturing processes themselves (A3), and the transport of finished products to the construction site (A4). These stages are meticulously detailed in the framework provided by EN 15643:2021 [20] and are visually represented in Figure 1, which outlines the whole life carbon system boundary for these stages. The emphasis on these early stages aligns with findings showing that significant environmental impact reductions can be achieved during the initial planning and design phases of buildings, where crucial material and design decisions are made.

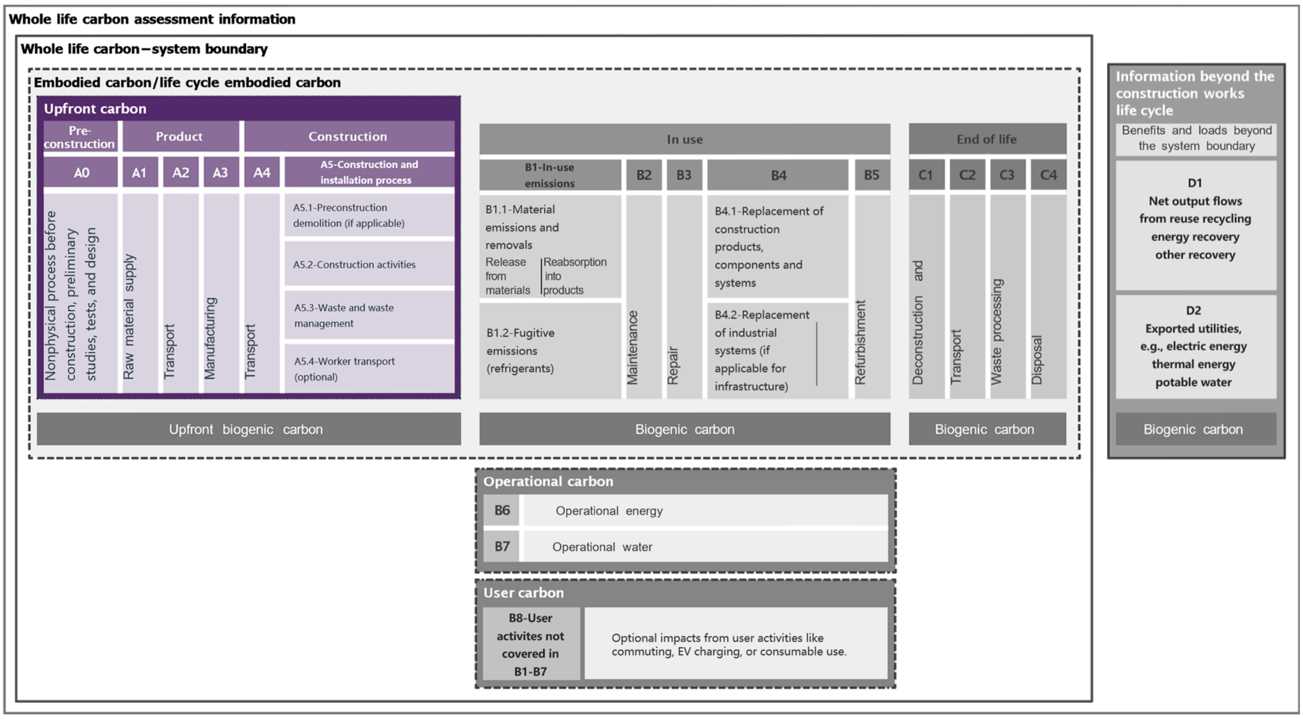

Figure 1. Whole life carbon system boundary for stages A1 to A4 (source: RICS, 2017).

The exclusion of on-site construction-related activities (A5) from this study is deliberate. It stems from the methodological focus on upfront embodied carbon, where the early design stages play a pivotal role in environmental impact. Research indicates that addressing the most influential parameters early on can lead to substantial reductions in overall environmental burdens. Moreover, the complexity and variability introduced by on-site activities often require details that are not yet finalized in the early stages of design, leading to significant uncertainties in lifecycle assessment (LCA) results. This strategic exclusion helps streamline the LCA process, focusing resources and analysis on stages with more controlled and predictable impact outcomes, thereby enhancing the accuracy and efficacy of the environmental assessment.

2.3. Cradle-to-Site Embodied Carbon and Cost Calculations

2.3.1. Cradle-to-Site Embodied Carbon Assessment

The carbon emissions created during the product stage are calculated by systematically assessing the extraction and supply of raw materials (A1), transportation to the manufacturing site (A2), and the final manufacturing processes (A3). These processes encompass the manufacturing of components and their subsequent transportation to another manufacturing plant for assembly into a complete system. To accurately evaluate the embodied carbon impact for each material included in the project, the following formula is applied:

$$EC_m = \sum Q_m \times e_m$$

In this equation, EC_m represents the total embodied carbon for materials and precast products, Q_m denotes the quantity of each material, and e_m is the embodied carbon factor per unit of material. All material quantities and their corresponding embodied carbon factors are measured using uniform metrics, such as per kilogram, per cubic meter, or per square meter. Appropriate conversion factors, such as density adjustments for converting mass to volume, are utilized when necessary. Additionally, when specific density information is unavailable, average data representative of the material type are used, with the sources of these data explicitly stated in the study, whether they come from Environmental Product Declarations (EPD) or technical documentation provided by suppliers.

The transportation impacts within this study are quantified by calculating the carbon emissions generated by moving materials and components from the factory gate to the project site and back. This assessment includes all transport stages required for delivering the materials to the site, incorporating any interim stops at storage depots or distribution centers. The carbon emissions for transportation are determined using the following formula:

$$EC_t = \sum Q_m \times D_{mt} \times e_{mt}$$

In the formula, Q_m denotes the quantity of each material, D_{mt} represents the distance that materials are transported in kilometers, and e_{mt} is the emission factor of the vehicles transporting the material. The emission factor e_{mt} is calculated as follows:

$$e_{mt} = c1 + (\text{empty running factor} \times c2)$$

Here, $c1$ is the outward carbon conversion factor appropriate for the journey delivering materials to the project site, and $c2$ is the return carbon conversion factor for an unladen vehicle. The empty running factor is included to account for the return journey of the vehicle without a load. In this study, the empty running factor is taken as 43%.

2.3.2. Cost Analysis

In this study, the cost analysis includes both the procurement and transportation costs associated with building materials. The procurement cost, denoted as C_p, is calculated by summing the costs of individual materials, and is expressed by the following formula:

$$C_p = \sum_{i=1}^{n} Q_{m_i} \times P_i$$

where Q_{m_i} represents the quantity of the i-th material and P_i is the price per unit of that material.

The transportation cost, denoted as C_t, is determined by accounting for the expenses incurred when moving each material from its source to the project site. The revised and more precise formula for calculating transportation costs is as follows:

$$C_t = \sum_{i=1}^{n} Q_{m_i} \times D_{mt_i} \times t$$

In this formula, Q_{m_i} is the quantity of the i-th material transported, D_{mt_i} represents the distance that each material is transported, and t is the transportation cost per unit weight per unit distance. This method ensures that the transportation costs are calculated based on a realistic pricing structure that considers both the weight and volume of the materials and the distance they are transported.

2.4. Optimization Model with Uncertainty of Source

The optimization of material type and supplier selection must account for uncertainties in carbon emission factors, material quantities, transportation distances, and material prices. Traditional deterministic models often assume fixed values for these parameters, ignoring real-world variability and leading to potential deviations. To address this issue, the Info-Gap Decision Theory (IGDT) framework is introduced, providing a robust approach to decision-making under deep uncertainty.

IGDT enhances reliability by explicitly modeling uncertainties, allowing for more realistic operational conditions in material and supplier selection. The following sections elaborate on the types of uncertainty in lifecycle assessments (LCA) and the application of IGDT techniques.

2.5. Information Gap Uncertainty in Early Stages of LCA

In the early stages of a building's lifecycle, significant information gaps and uncertainties arise from various sources. These uncertainties can be broadly categorized into several types:

Data Quality and Statistical Distribution: using data from Environmental Product Declarations (EPDs), different databases, or interviews introduces uncertainty when applied to different geographical locations or technologies where their validity may not be known or may be different. Database and Regional Variations: applying regional data from one geographical area (like European steel production characteristics) to another area where the environmental priorities or manufacturing technologies might differ.

The regional standards considered include China (GB 175-2023) [21], Europe (EN 197-1-2011) [22], and the USA (ASTM C595/C595M-23) [23]. Due to differences in the naming conventions and content requirements of cement standards across these regions, the analysis is based on the composition of Chinese cement types as per GB 175-2023. Corresponding cement types from other regions that closely match these compositions are then identified using data from EPD and ecoinvent 3.9.1, as shown in Tables 1 and 2.

Table 1. Correspondence of cement types across regions.

Chinese Standard	Corresponding European Standard	Corresponding US Standard
P.O	CEM II/A-S, CEM II/A-P, CEM II/A-V	Type I-PM, Type I-SM
P.C	CEM II/B-M, CEM V/A, CEM IV/B	Type IT
P.P	CEM II/B-P	Type IP/P

Table 2. Cement composition by standard (data for Type IT is not available in EPD and ecoinvent databases).

Cement Type	Clinker (%)	Blast Furnace Slag (%)	Fly Ash (%)	Pozzolana (%)	Other Additives (%)
P.O	80–94	6–20	-	-	0–5
CEM II/A-S	80–94	6–20	-	-	0–5
CEM II/A-P	80–94	-	-	6–20 (Natural)	0–5
CEM II/A-V	80–94	-	6–20	-	0–5
Type I-PM	-	-	0–15	-	0–5
Type I-SM	-	0–25	-	-	0–5
P.C	50–79	21–50	-	-	0–15
CEM II/B-M	65–79	-	-	21–35	0–5
CEM V/A	40–64	18–30	-	18–30	0–5
CEM IV/B	45–64	-	-	36–55	0–5
Type IT	60	20	-	20	-
P.P	60–79	-	-	21–40	0–5
CEM II/B-P	65–79	-	-	21–35	0–5
Type IP/P	-	-	15–40	-	-

The variability in lifecycle assessment (LCA) outcomes can often be traced back to multiple sources of uncertainty, including database updates, human behaviors, and unobserved socio-technical interactions. Database updates play a crucial role in influencing LCA results, as different versions of databases introduce variations. For instance, discrepancies between ecoinvent versions v3.5 (released in 2018) and v3.9.1 (released in 2023) show differences in key parameters such as cement grades and carbon emission factors, highlighting how database revisions can impact final assessments.

Human factors in construction processes also contribute to variability. Differences in on-site practices, worker efficiency, and errors in material estimation or quality assurance can lead to inconsistencies in the quantity and quality of materials used, affecting the LCA outcomes. Additionally, unobserved socio-technical interactions, such as transportation dynamics, can introduce further uncertainty. Variability in transportation routes, changes in the efficiency of transport modes over time, and assumptions about material reuse or recycling at the end of life add complexity to the system, influencing the overall assessment in ways that are not directly observable.

2.6. Info-Gap Decision Theory (IGDT) Technique

2.6.1. Conceptual Overview

IGDT models decide robustness by addressing uncertainty as deviations from nominal values. The main components include the following:

- $\widetilde{u}$: nominal value of the uncertain variable (e.g., carbon emission factor).
- q: decision variable representing a design choice (e.g., material or supplier selection).
- $R(q, u)$: performance function evaluating outcomes under uncertainty.
- r_c: critical performance level (e.g., cost or emissions threshold).

These elements are used to create the following:

- $\widehat{\alpha}(q, r_c)$, the info-gap robustness function. This function identifies the maximum level of uncertainty that a design option q can handle while still maintaining a performance level that is no worse than r_c.

The Info-Gap Decision Theory (IGDT) framework is composed of three key elements:

1. Deterministic model: establishes baseline performance metrics under nominal conditions.
2. Uncertainty parameters: models deviations from the nominal values of critical variables.
3. Performance criteria: defines thresholds (r_c) that decision options must meet or exceed [24].

In this paper, the deterministic modeling of carbon emissions and costs is detailed in earlier sections. IGDT adds value by managing uncertainties in these models, encapsulating deviations through interval-bounded representations.

When a variable u is uncertain and its exact value cannot be determined, IGDT employs the following interval-bounded model to express this uncertainty:

$$U(\alpha, \widetilde{u}) = \{u : |u - \widetilde{u}| \leq \alpha\}$$

Here, $\alpha \geq 0$ represents the uncertainty radius around the nominal value $\widetilde{u}$, forming an interval from $\widetilde{u} - \alpha$ to $\widetilde{u} + \alpha$. This interval clearly defines the possible range of u.

For a simplified expression, the uncertainty can be directly represented as follows:

$$\widetilde{u} - \alpha \leq u \leq \widetilde{u} + \alpha$$

To provide an intuitive understanding of variation, α can also be expressed as a fractional deviation from the nominal value $\widetilde{u}$, making it dimensionless:

$$U(\alpha, \widetilde{u}) = \left\{ u : \left| \frac{u - \widetilde{u}}{\widetilde{u}} \right| \leq \alpha \right\}$$

This can be equivalently expressed as follows:

$$(1-\alpha)\widetilde{u} \le u \le (1+\alpha)\widetilde{u}$$

This formulation interprets α as a percentage change relative to $\widetilde{u}$, enhancing its interpretability in decision-making contexts.

2.6.2. Performance Requirements

The performance function $R(q,u)$ evaluates the outcomes of decision variables q under uncertainties u. This function must reliably represent outcomes as a function of both q and u, ensuring that the outputs are quantifiable. The critical performance level r_c serves as a benchmark that decision outcomes must meet or exceed.

Depending on the context, performance requirements can be expressed as shown below.

Higher Performance Preferred:

$$R(q,u) \ge r_c$$

Lower Performance Preferred:

$$R(q,u) \le r_c$$

In building lifecycle assessments, performance requirements often depend on minimizing costs or emissions while ensuring robust results under variability.

2.6.3. Robustness and Opportuneness in IGDT

IGDT addresses uncertainty through two complementary principles: robustness and opportuneness.

1. Robustness: robustness measures the maximum uncertainty (α) that a decision option q can tolerate while ensuring the performance remains within acceptable limits (r_c):

$$\alpha(q,r_c) = max\left\{\alpha : \min_{u\in U(\alpha,\bar{u})} R(q,u) \le r_c\right\}$$

This function ensures that decision outcomes remain within predefined thresholds across a wide range of uncertain conditions. It offers a conservative approach, prioritizing resilience to worst-case scenarios.

2. Opportuneness: opportuneness identifies the lowest uncertainty (α) required for the performance of a decision option q to achieve or exceed a desired threshold (r_w):

$$\beta(q,r_w) = min\left\{\alpha : \max_{u\in U(\alpha,\widetilde{u})} R(q,u) \ge r_w\right\}$$

This function explores scenarios where uncertainty can create favorable conditions, maximizing rewards while managing risks.

Together, robustness and opportuneness provide a dual perspective on uncertainty, enabling decision-makers to balance resilience and opportunity across varying levels of uncertainty.

2.6.4. Practical Implications in LCA

In the early stages of lifecycle assessments, variations in data and assumptions significantly affect accuracy and performance. IGDT's robustness function identifies material suppliers and design choices that remain effective under high uncertainty, while the opportuneness function highlights scenarios where uncertainty enables favorable outcomes (e.g., cost savings or emission reductions).

By integrating robustness and opportuneness analyses, this study ensures that building lifecycle assessments account for variability, providing both stable and innovative solutions to sustainability challenges.

3. Case Study

This study applies the proposed optimization model to the selection of building materials and suppliers for a Science and Technology Expo Pavilion located in Dazu District, Chongqing, China. The pavilion, comprising three floors, spans a total area of 15,314.25 square meters. Situated in the southeastern part of the Sichuan Basin in western Chongqing, Dazu District has limited river navigability. However, its accessibility is enhanced by four major highways and arterial roads, facilitating the efficient procurement of materials from southeastern Sichuan and Chongqing.

3.1. Data Collection and Scope

Quantitative data were sourced through a detailed bill of quantities, along with product and pricing information from 31 cement companies in the specified regions. These companies, labeled C001 to C031, offer the cement types P.O, P.C, and P.P as defined by the GB 175-2023 standards. The base case used P.O cement from a supplier in Dazhou, Sichuan Province, serving as the reference point for comparisons.

3.2. Emission and Cost Calculations

The study accounted for both the manufacturing stage (A1–A3) and transportation stage (A4) carbon emissions:

1. Manufacturing Emissions (A1–A3):
   - Carbon emissions from the manufacturing process were calculated using local emission factors provided by the Donghe Building Carbon Emission Calculation and Analysis Software (V3.1).
   - These emissions represent the environmental impact associated with raw material extraction, processing, and cement production.
2. Transportation Emissions (A4):
   - Transportation emissions were estimated for bulk cement tankers with a 35-ton capacity, using emission factors for heavy-duty diesel trucks with a 46-ton load as specified by the GB/T 51366-2019 [25] standards.
   - The total emissions considered both loaded and return trips, with adjustments for the empty-running factor.
3. Cost Data:
   - Manufacturing costs were derived from the average daily price fluctuations of cement in the first half of 2024.
   - Transportation costs were calculated based on a rate of 0.375 yuan per ton per kilometer, covering fuel and toll fees. These rates were validated through interviews with fleet leaders managing cement tankers in Sichuan and Chongqing.

3.3. Transportation Distance and Geographic Distribution

Transportation distances from manufacturers to the construction site were determined using Baidu Maps, ensuring accurate routing. The geographic distribution of the 31 cement suppliers, along with their relative locations to the construction site, is shown in Figure 2.

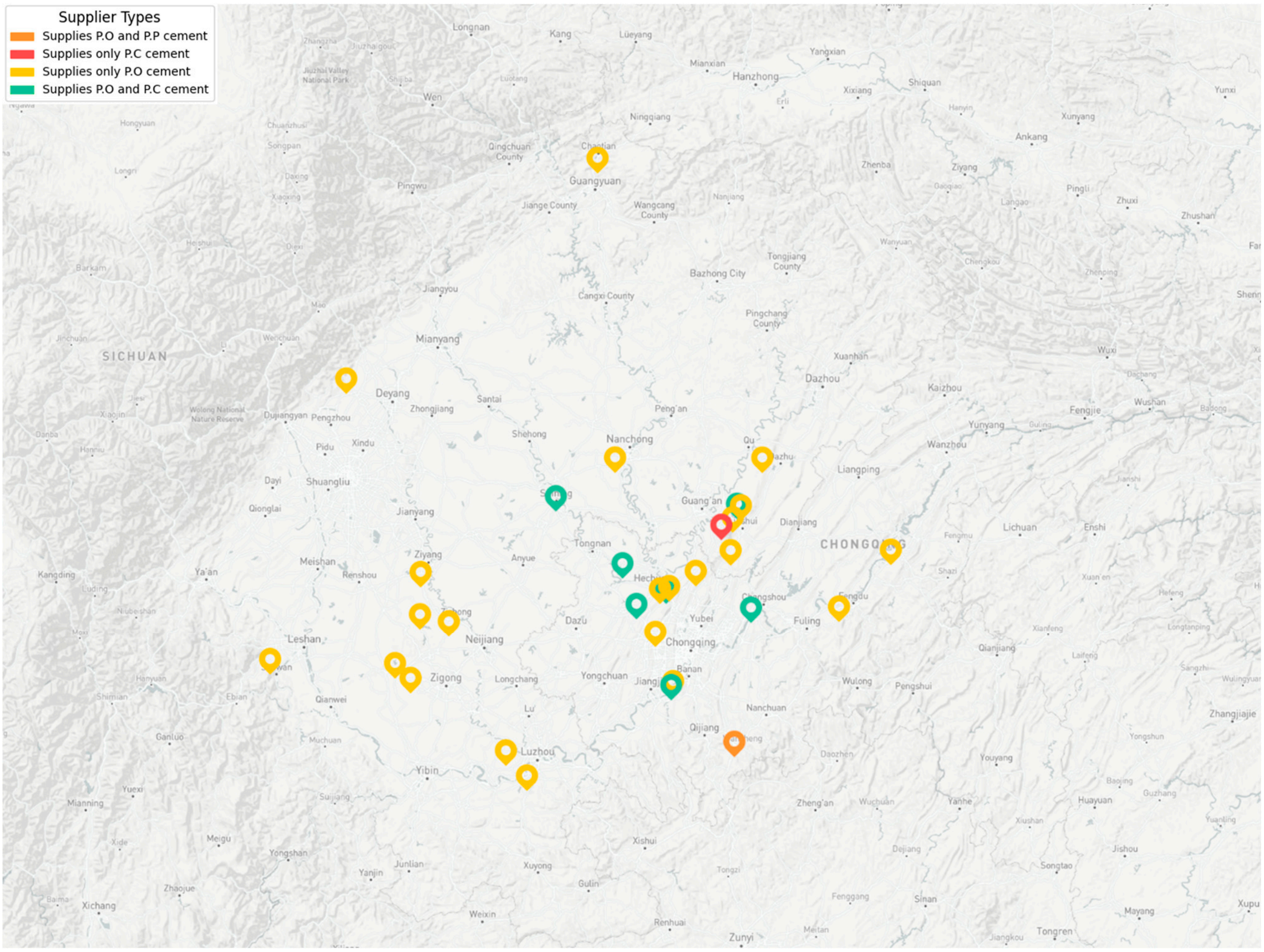

Figure 2. Geographic distribution of cement suppliers.

3.4. Assumptions and Simplifications

The model incorporated several assumptions and simplifications to streamline the decision-making framework:

- Simplifications: parameters were selected to reflect realistic scenarios, such as emission factors and cost estimates, while minimizing the complexity introduced by unverified field data.
- Focus on methodology: the analysis emphasized the decision-making process and the robustness of the analytical framework rather than the specific choice of cement type or manufacturer.

These assumptions ensured that the study maintained relevance and practicality, focusing on the utility of the optimization model rather than absolute accuracy in environmental or cost metrics.

4. Result and Discussion

4.1. Deterministic Embodied Carbon from Cradle to Site

The data analysis regarding cement suppliers reveals critical insights into the distribution of carbon emissions between the production and transportation stages. Manufacturing emissions dominate, with each supplier showing emissions of approximately 492,829.2 tCO_2-e, underscoring the significant environmental impact of the production process. Transportation emissions, although variable, contribute a smaller fraction to the total emissions. For instance, supplier C011O from Shapingba District, Chongqing, has transportation emissions of 1754.98 tCO_2-e, which constitutes only 0.34% of its total emissions.

This pattern is consistent across other suppliers, with transportation emissions ranging from 1350.82 tCO_2-e to 15,561.33 tCO_2-e, indicating that efforts to reduce the carbon footprint should primarily focus on the production process. However, optimizing transportation logistics remains important, particularly for suppliers located farther from the construction site, to further minimize overall emissions. For example, supplier C025O from Guangyuan City, Sichuan Province, has the highest transportation emissions at 15,561.33 tCO_2-e, constituting 3% of its total emissions, which highlights the potential benefits of logistical optimization. Figure 3 depicts the percentage distribution of carbon emissions between the production and transportation stages for both local and non-local operators.

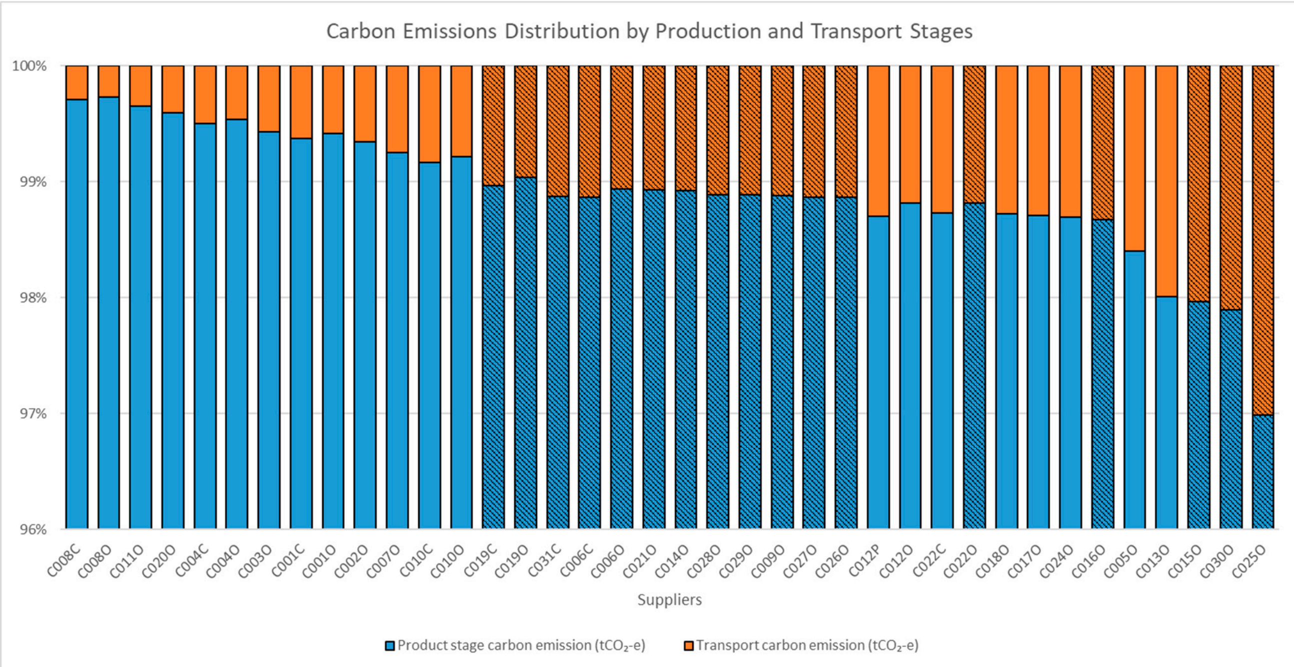

Figure 3. Carbon emissions distribution by production and transport stages.

Examining the impact of using alternative materials in cement production, such as fly ash and volcanic ash, reveals significant potential for reducing carbon emissions. Cement types P.C (Portland Composite) and P.P (Portland Pozzolanic) incorporate these materials to replace a portion of clinker, the primary source of emissions in cement. Suppliers using these types can achieve substantial emission reductions. For instance, supplier C012P, employing P.P, achieves total emissions of 461,047.42 tCO_2-e and a carbon saving of 48,307.91 tCO_2-e compared to the base scenario with P.O cement. Similarly, supplier C008C from Tongliang District, Chongqing, uses P.C and achieves total emissions of 469,018.58 tCO_2-e and a carbon saving of 40,336.75 tCO_2-e. These significant reductions underscore the environmental benefits of integrating more sustainable materials into cement production, which is crucial for projects targeting stringent sustainability standards. These data clearly support the case for wider adoption of the P.C and P.P cement types to achieve lower carbon footprints in construction projects.

Analyzing regional costs and carbon emissions highlights the benefits and trade-offs between local and non-local suppliers. Local suppliers in Chongqing benefit from reduced transportation distances, leading to lower transportation emissions and costs. For example, supplier C004O, a local supplier, incurs a transport cost of 15,327.6 RMB and a total cost of 269,599.9 RMB, reflecting significant savings compared to non-local suppliers. On the other hand, supplier C013O, also from Chongqing, has a slightly higher transport cost of 66,888.47 RMB but a higher total cost of 314,857.90 RMB, which is influenced by the manufacturing cost differences. However, non-local suppliers from Sichuan Province, despite higher transportation costs, may offer lower production costs or greater use of alternative materials, which can offset the increased transportation expenses. For instance, supplier C005O from Fengdu County, although incurring a high transport cost of 53,487.1 RMB, still competes on total cost at 298,305.2 RMB due to lower manufacturing costs. Therefore, non-local suppliers should not be dismissed outright, but rather considered based on a holistic view of their production practices and material efficiency. Figures 4 and 5 illustrate the spatial distribution of carbon emissions and costs among various cement suppliers. The comparison of the two maps shows that distant suppliers, marked in red on the carbon emissions map, have higher emissions due to long transportation distances. However, on the cost map, some of these suppliers do not necessarily have high costs, possibly due to factors like material costs or local production efficiency. This indicates that lower costs do not always align with lower carbon emissions, emphasizing the need to carefully balance environmental impact and cost considerations during decision-making.

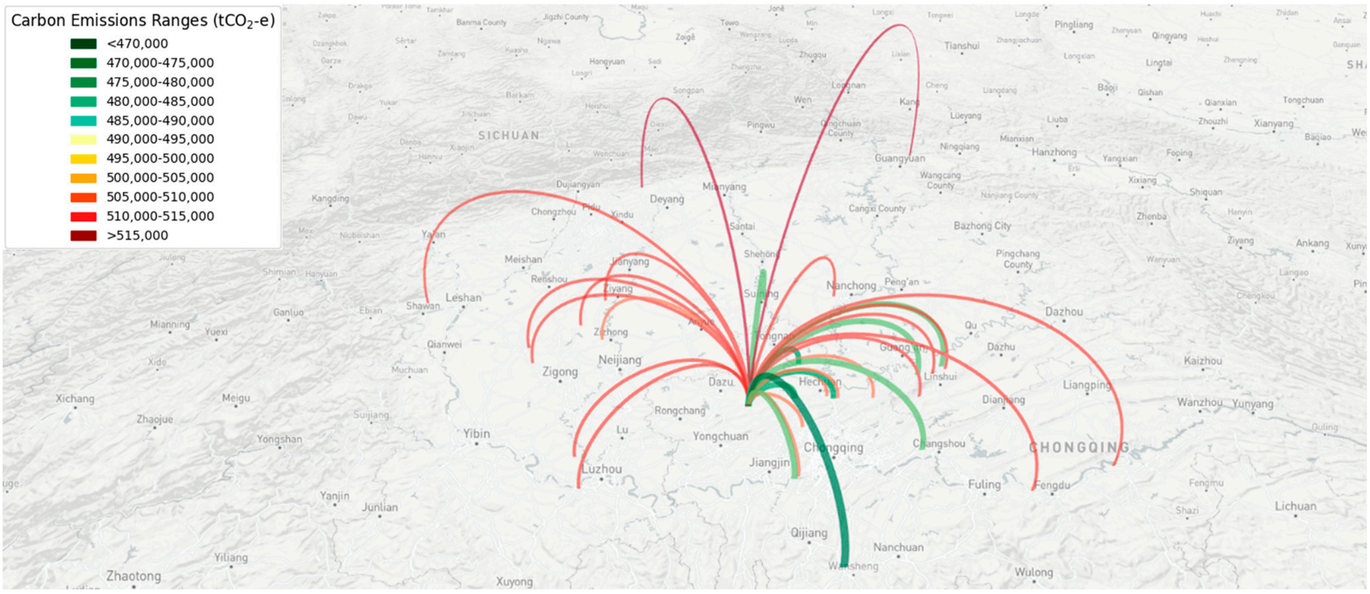

Figure 4. Spatial distribution of carbon emissions from cement suppliers.

Figure 5. Spatial distribution of costs from cement suppliers.

Balancing the reduction of carbon emissions and associated costs involves a strategic approach to supplier selection, focusing on the cost per ton of CO_2 reduction. Suppliers with lower or negative costs per tCO_2-e reduction, such as C027O with −12.13 RMB, offer the most cost-effective carbon management solutions. Similarly, supplier C031C shows a low cost per tCO_2-e reduction at 0.19 RMB, making it another cost-effective option. In contrast, suppliers with high costs per tCO_2-e reduction, such as C005O at 174.685 RMB, indicate that while they may achieve emissions reductions, they do so at a significantly higher cost.

As illustrated in Figure 6, the analysis of carbon savings versus cost efficiency by supplier reveals several key insights. The majority of suppliers have their carbon savings concentrated near zero or at higher ranges (the upper part of the vertical axis), with some achieving significant carbon savings, particularly the local suppliers. Some suppliers have negative costs, meaning they not only reduce carbon emissions, but also have lower overall costs during the reduction process (i.e., the cost per ton of CO_2 reduction is negative). This scenario is more common among non-local suppliers, possibly due to factors such as material costs or local production efficiency.

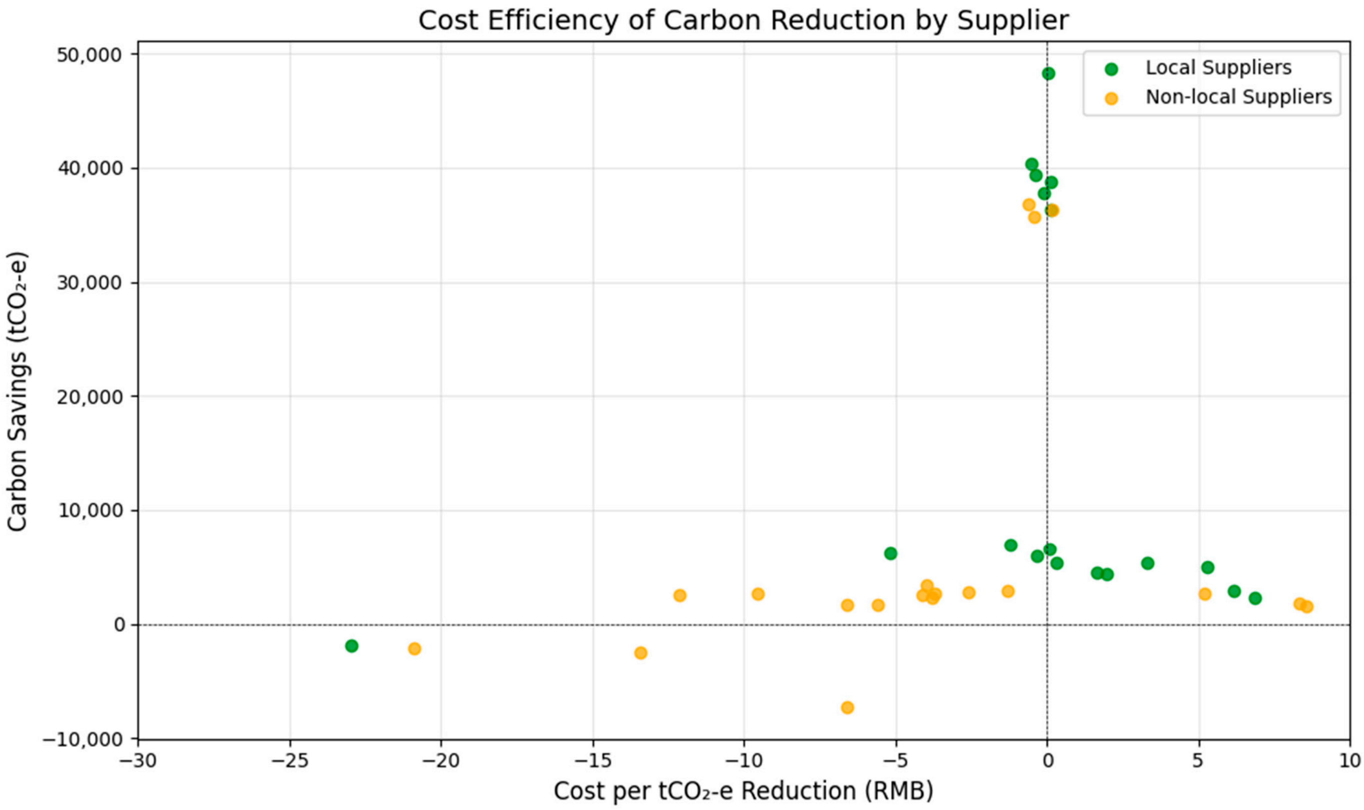

Figure 6. Cost efficiency and carbon savings analysis of cement suppliers.

The chart in Figure 6 can be divided into four quadrants to evaluate the recommendation level for each cement supplier based on their carbon savings and cost per ton of CO_2 reduction. The top-left quadrant (high carbon savings and negative costs) represents the most recommended suppliers, as they achieve significant carbon reductions while also reducing costs. The top-right quadrant (high carbon savings and positive costs) includes recommended suppliers, as they provide substantial environmental benefits despite incurring additional costs. The bottom-left quadrant (low carbon savings and negative costs) is not recommended, as these suppliers save costs but contribute minimally to carbon reduction. Finally, the bottom-right quadrant (low carbon savings and positive costs) is highly not recommended, as these suppliers fail to deliver both cost efficiency and meaningful carbon savings. This analysis helps in identifying the suppliers that best balance environmental impact and economic considerations.

This approach ensures that the project not only meets its environmental targets, but also remains economically viable. While local suppliers often provide immediate benefits in terms of lower transportation costs and emissions, non-local suppliers adopting sustainable practices and alternative materials can also play a crucial role. By focusing on the cost per ton of CO_2 reduction, decision-makers can make informed choices during supplier selection that support both economic and environmental goals, ensuring long-term sustainability and resilience. This balanced approach is essential for achieving both short-term project budgets and long-term environmental objectives.

4.2. Evaluating Cost Efficiency and Supplier Reliability Under Deep Uncertainty

This study employs a simulated deep uncertainty analysis to evaluate the cost efficiency of carbon reduction across various cement suppliers. By incorporating variations in regional standards, database versions, material price fluctuations, and transportation routes, the analysis encompasses a broad spectrum of potential real-world scenarios. Each simulation yields insights into CO_2 reduction costs, enabling robust estimations under uncertain conditions. The distribution of these costs, illustrated in Figure 7, highlights the central trend, providing an overview of typical CO_2 reduction expenses.

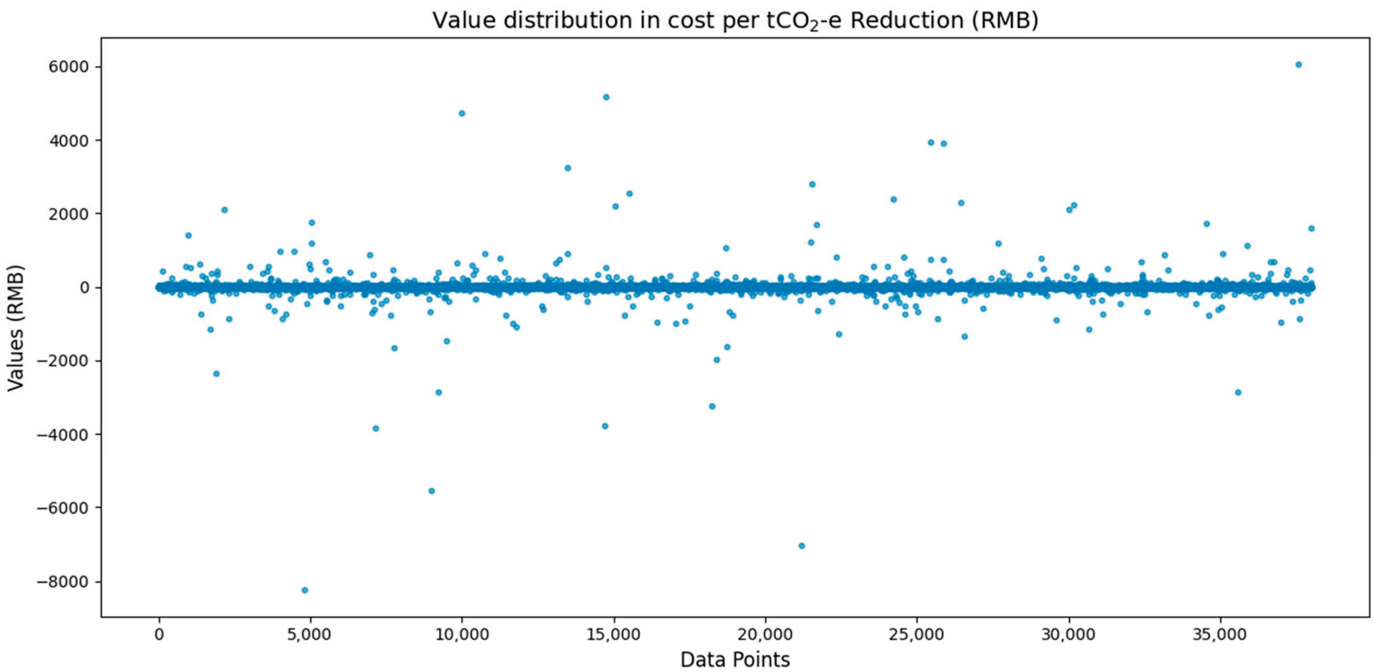

Figure 7. Distribution of CO_2 reduction costs under simulated deep uncertainty conditions.

To concentrate on the most probable outcomes and mitigate the influence of extreme values, only the central 90% of data points were retained, excluding the lowest and highest 5% of values. This filtering offers a clearer perspective on the typical cost range, which spans from −11.83 RMB to 12.98 RMB per ton of CO_2-equivalent reduction. By utilizing this refined dataset, decision-makers obtain a more stable estimate for CO_2 reduction costs, thereby facilitating the development of resilient and informed carbon reduction strategies.

Figure 8 illustrates the cost efficiency of carbon reduction across suppliers, categorizing them from "Most Recommended" to "Strongly Not Recommended" based on performance metrics. The upper left quadrant, populated by suppliers such as C025O, C013O, and C015O, showcases those achieving significant carbon reductions at low or negative costs, rendering them optimal choices for projects seeking a balance between cost savings and environmental impact. In the upper right quadrant, suppliers incur higher costs but achieve notable carbon savings, making them suitable when the priority is substantial carbon reduction despite increased expenses. The lower left quadrant includes suppliers with minimal carbon impact yet some cost savings, while the lower right quadrant comprises suppliers with both high costs and limited carbon savings, identifying them as the least favorable options.

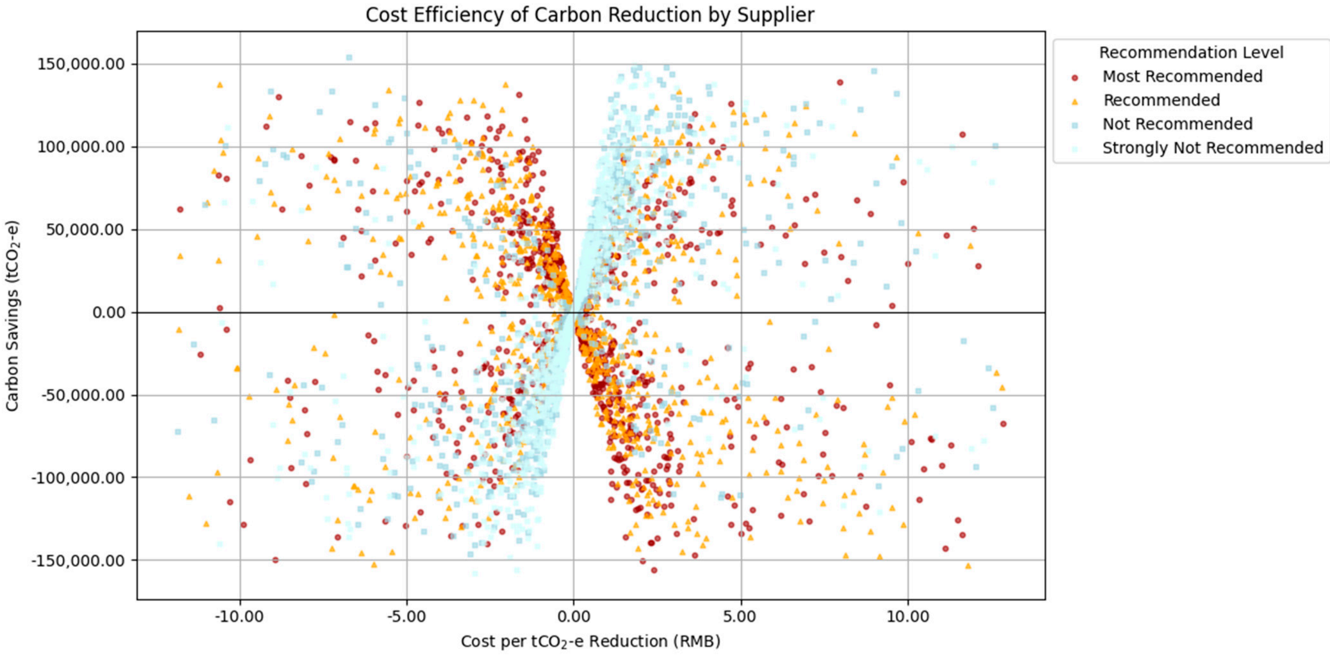

Figure 8. Cost efficiency of carbon reduction by supplier category.

However, traditional quadrant analysis can sometimes be inadequate in situations characterized by high variability, as suppliers like C025O may appear in both desirable and less favorable quadrants depending on specific scenarios. To address this limitation, Information Gap Decision Theory (IGDT) offers a more robust approach by focusing on supplier reliability across a spectrum of uncertain conditions. This method provides a stable assessment of suppliers, ensuring consistent carbon reduction results even in variable scenarios.

In Figure 9, C024O is presented as "Most Reliable" according to the IGDT framework. The data points for C024O cluster within the upper left quadrant, reflecting consistent carbon savings at low or negative costs, thereby demonstrating its robustness across various conditions. Conversely, Figure 10 highlights C002O, a generally recommended supplier with a wider spread of outcomes. While C002O often delivers favorable results, the broader distribution—especially in the upper right quadrant—suggests higher costs in certain instances, indicating moderate reliability.

The IGDT-based classification framework, therefore, provides decision-makers with a dependable system for selecting suppliers who meet both economic and environmental goals under uncertain conditions. By focusing on suppliers categorized as "Most Recommended" and "Recommended", projects can achieve consistent and resilient carbon reduction outcomes, aligning short-term budgetary needs with long-term sustainability objectives.

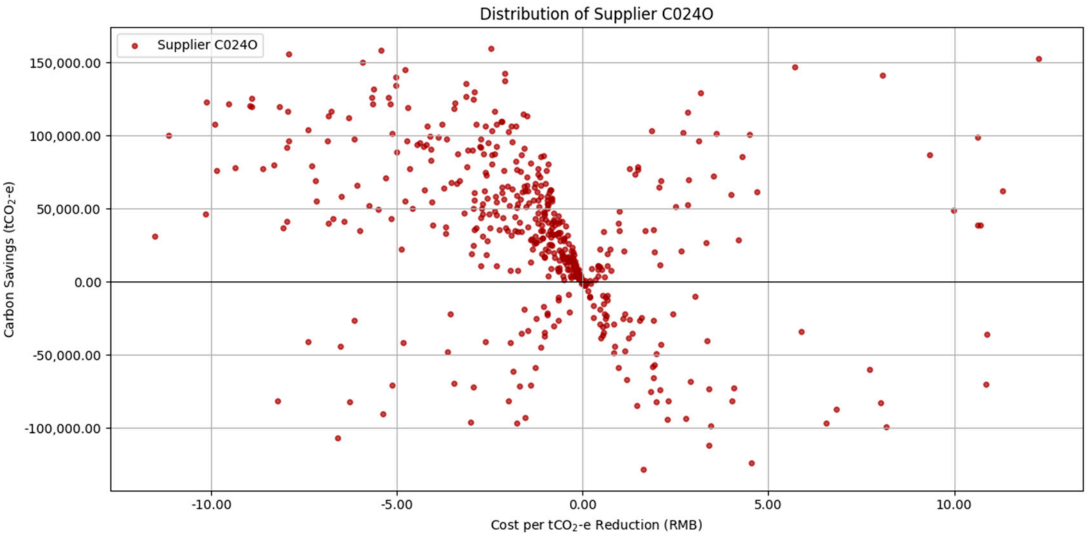

Figure 9. Performance consistency of supplier C024O in terms of cost and carbon savings under IGDT framework.

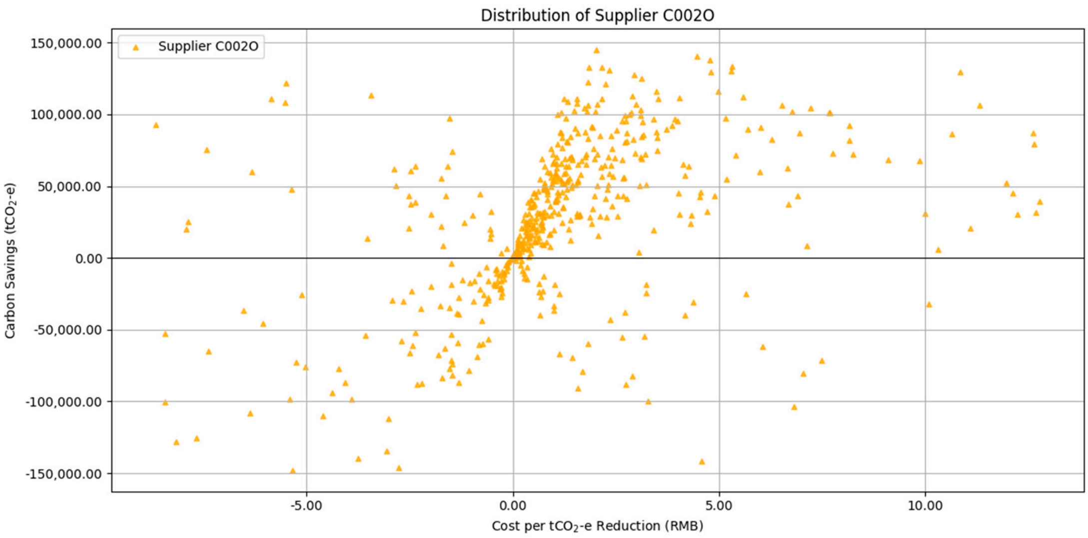

Figure 10. Performance variability of supplier C002O in terms of cost and carbon savings under IGDT framework.

4.3. Implications, Limitations, and Future Research Directions

This study's application of Information Gap Decision Theory (IGDT) to the lifecycle assessment of building materials presents a significant advancement in managing uncertainties within the building industry. For practitioners, this approach facilitates the integration of robust decision-making frameworks during early design stages, potentially revolutionizing environmental and cost optimizations. Given the pressing global imperative for carbon emission reduction, our findings suggest that policymakers should consider incentives for adopting advanced LCA techniques in building regulations. Specifically, policies could encourage the use of low-carbon materials and require uncertainty analysis in environmental assessments to ensure comprehensive sustainability evaluations. While the findings of this study are promising, several limitations warrant consideration. The primary data were geographically limited to Chongqing, China, possibly affecting the generalizability of the results to other regions with different environmental priorities or construction practices. Additionally, the IGDT model relies on certain assumptions regarding data quality and availability, which might not hold in varied contexts. These assumptions underline the importance of adapting the model based on regional and contextual specifics to maintain its efficacy and reliability.

Future research should aim to expand the application of the IGDT framework to different geographical locations and building types to verify and refine the model's effectiveness further. Integrating emerging technologies such as artificial intelligence (AI) and the Internet of Things (IoT) could enhance the precision of data inputs and thereby the decision-making capabilities of the IGDT model. Moreover, conducting longitudinal studies would be invaluable in understanding the long-term environmental and economic impacts of decisions influenced by this model, providing deeper insights into the sustainability of these practices. Additionally, exploring the interactions between different types of uncertainties and their cumulative impact on LCA outcomes could lead to more sophisticated models that accommodate a broader range of scenarios. This would not only improve the robustness of the decision-making process, but also cater to the increasingly complex nature of modern building projects.

5. Conclusions

This research explores the potential of Information Gap Decision Theory (IGDT) in addressing uncertainties within the early-stage lifecycle assessment (LCA) of building materials. By applying IGDT, the study provides a structured approach to managing deep uncertainties, particularly in early design stages where data limitations often undermine the reliability of traditional LCA methodologies. The results indicate that IGDT can support more informed decision-making by enabling robust material selection and supplier optimization that balance environmental impact with economic feasibility.

The case study of the Science and Technology Expo Pavilion in Chongqing, China, serves as a practical example, demonstrating how the IGDT framework can be applied to real-world scenarios. The findings suggest that integrating IGDT into LCA workflows may contribute to achieving carbon emission reductions even under significant uncertainty. However, the conclusions drawn from this study are limited by the specific regional data and assumptions used, which may not be directly applicable to all geographical contexts or building types.

While the application of IGDT shows promise, this study does not claim universal applicability. The reliance on localized data and predefined parameters necessitates cautious interpretation, especially when extending the framework to broader or more diverse settings. Future research should aim to validate the IGDT approach across varying regions and building scenarios. Additionally, integrating advanced data analytics and machine learning tools could further enhance the framework's ability to handle complex and dynamic design challenges.

In conclusion, this study provides a focused exploration of IGDT as a complementary tool for uncertainty management in LCA. While it highlights the potential benefits of applying IGDT, its conclusions are bounded by the study's scope and limitations. As such, the research primarily serves as a foundation for further investigation into robust decision-making frameworks in the context of sustainable building practices. The insights presented here can guide practitioners in developing adaptive and resilient strategies, contributing incrementally to the global pursuit of sustainable development goals.

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