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# CARBON EMISSION EVALUATION IN THE EMBODIED PHASE OF PREFABRICATED BUILDINGS USING SPHERICAL FUZZY AHP

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Abstract. *Prefabricated buildings, as a modern construction method, offer notable advantages such as high construction efficiency, superior thermal insulation, optimized spatial utilization, and enhanced energy and environmental performance. Compared with traditional cast-in-place techniques, the industrialized processes inherent in the embodied phase of prefabricated construction can significantly reduce carbon emissions. However, the modular nature of such systems introduces added complexity in managing emission reduction. To address uncertainties arising from subjective differences in expert judgments – due to varying professional backgrounds and knowledge structures – this study proposes a carbon emission evaluation model based on spherical fuzzy sets integrated with the Analytic Hierarchy Process (AHP). A comprehensive evaluation index system is established, encompassing seven key dimensions: project characteristics, material consumption, energy usage, transportation and storage, construction organization, ecological environment, and policy regulations. The Spherical Fuzzy Analytic Hierarchy Process (SF-AHP) is employed to develop a robust emission reduction efficiency model. The model is validated through application to a real-world prefabricated building project. Results demonstrate that the proposed approach enhances the objectivity and accuracy of carbon emission assessments in prefabricated construction, thereby supporting informed decision-making toward sustainable development goals.*

**Keywords:** Prefabricated building, Carbon emission assessment, Embodied phase, Spherical fuzzy sets

1. **Introduction.** Prefabricated buildings, as a new type of construction, have rapidly developed in recent years due to their advantages such as high construction efficiency, excellent thermal insulation, efficient space utilization, and energy conservation. According to statistics from 2021, the energy consumption of China's construction industry accounted for 44.7% of the country's total energy use, while carbon emissions from the construction sector made up 47.1% of energy-related carbon emissions nationwide [1]. These figures highlight the critical importance of reducing carbon emissions during the construction and operational phases of prefabricated buildings to achieve energy-saving and emission-reduction goals.

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The embodied phase of prefabricated buildings encompasses the entire process from the production of construction materials to the completion of the building. This phase primarily includes material manufacturing and processing, transportation, and on-site assembly. Although the carbon emissions during the embodied phase account for a smaller proportion compared to the operational phase, the emissions are relatively concentrated due to the short duration of this stage. As a result, the carbon intensity per unit time is high, posing a significant environmental impact. Consequently, the embodied phase has remained one of the key focuses in the field of building-related environmental research.

This approach aims to address the following key issues: 1) how to systematically identify and quantify the influencing factors of carbon emissions in the embodied phase; 2) how to effectively handle the uncertainty and vagueness inherent in expert evaluations; 3) how to establish a scientifically sound and rational carbon emission assessment framework to support decision-making in carbon reduction management for prefabricated buildings.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive literature review. Section 3 introduces the fundamental theory of spherical fuzzy sets. Section 4 details the construction of the proposed SF-AHP evaluation model. Section 5 presents case studies to validate the model, discusses the results, and proposes emission reduction recommendations. Finally, Section 6 concludes the paper by summarizing the key findings and outlining directions for future research.

## 2. **Literature Review.**

2.1. **Studies on carbon emissions in construction.** With increasing global concern about climate change and sustainability, the building sector has received growing attention due to its significant contribution to carbon emissions. In China, the construction industry accounts for approximately 30% of national $CO_2$ emissions, emphasizing its potential for low-carbon development strategies. Numerous studies have evaluated carbon emissions across the life cycle of buildings. Life Cycle Assessment (LCA) methods have been widely used to quantify embodied and operational carbon footprints in the built environment [2, 3, 4]. Huang et al. [5] provided a global review of construction sector emissions, identifying embodied carbon as a major contributor during the embodied phase. Prefabricated and modular construction techniques have emerged as promising solutions to reduce embodied carbon emissions. Compared to traditional cast-in-place construction, these methods offer advantages such as reduced material waste, optimized logistics, and enhanced resource efficiency [6, 7, 8]. Studies have shown that modular buildings significantly lower environmental impacts during both construction and operation phases [9, 10, 11].

Various analytical frameworks have been proposed to evaluate carbon performance in prefabricated construction. Building Information Modeling (BIM) combined with emission factor databases has enabled detailed carbon quantification [6, 12, 13]. Research has also explored policies and strategies for carbon reduction in prefabricated construction. Integration of digital technologies, offsite manufacturing, and government incentives are considered effective enablers for low-carbon outcomes [14, 15, 16]. Case studies have demonstrated measurable reductions in embodied emissions through improved material selection and modular system design [17, 18, 19].

2.2. **Fuzzy set extensions in carbon assessment.** Since the introduction of fuzzy set theory by Zadeh [20] in 1965, fuzzy sets have gained widespread application across nearly all scientific disciplines. Over the decades, various extensions of the classical fuzzy set model have been developed to better handle uncertainty and imprecision in complex systems. Atanassov introduced the Intuitionistic Fuzzy Set (IFS) to extend conventional fuzzy set theory by incorporating richer preference representations for decision-makers

[21]. In IFS, each element is characterized by a membership degree, a non-membership degree, and a hesitancy degree, with the fundamental constraint that the sum of these three degrees equals 1. This implies that the hesitancy degree is not independent, but instead determined by the membership and non-membership degrees. Building upon this framework, Smarandache [22] proposed the neutrosophic set, which generalizes IFS by allowing the truth, indeterminacy, and falsity degrees to be fully independent, with their total not constrained to 1 but ranging from 0 to 3.

To address uncertainty dynamics, Garibaldi and Ozen [23] introduced the concept of non-stationary fuzzy sets, which adapt over time. Hesitant fuzzy sets were subsequently developed to express multiple potential membership values for a single element, enabling a more nuanced representation of decision-makers' hesitation. Each of these fuzzy set extensions has been designed to manage ambiguity and improve the modeling of uncertainty in complex systems [24]. Among the most recent advancements, the Spherical Fuzzy Set (SFS), introduced by Gündoğdu and Kahraman [25], further extends the theory by allowing membership, non-membership, and hesitancy degrees to vary independently, while satisfying a spherical constraint to maintain logical consistency.

2.3. **Analytic hierarchy process in construction decision-making.** The AHP developed by Saaty [26], was designed to address complex decision-making problems involving multiple criteria [27]. AHP facilitates multi-criteria decision-making and enables prioritization of competing factors [28]. Decision-making in the field of construction is particularly characterized by complexity, ambiguity, and uncertainty [29]. Al-Harbi [30] further emphasized that construction-related decisions often involve a large number of interrelated factors with nonlinear interactions. Therefore, the ability to make sound and rational decisions is essential for the success of construction activities and operations. The AHP offers a robust methodological framework for supporting strategic and rational decision-making in construction [31]. It enables decision-makers to quantitatively evaluate multiple criteria and systematically compare alternative options in order to select the most appropriate solution. Conventional pairwise comparison algorithms typically rely on crisp real numbers. However, expert judgments in such comparisons are often subjective, imprecise, and prone to uncertainty [32]. To address this limitation, Kwong and Bai [33] proposed a fuzzy AHP approach based on extended analysis, which was employed to estimate the relative importance of customer requirements in the context of quality function deployment. Subsequent studies, such as those by Zheng et al. [34], further demonstrated the applicability of the integrated fuzzy AHP framework in expert selection for research and development project evaluation and safety assessment. Recently, the spherical fuzzy analytic hierarchy process has emerged as a newly developed extension of the traditional AHP, designed to better capture uncertainty and vagueness in expert judgments. Gündoğdu and Kahraman [35] introduced this novel method and applied it to the problem of renewable energy site selection. Subsequently, Dogan [36] employed an SF-AHP-based fuzzy multi-criteria decision-making approach to address process mining technology selection under uncertain and ambiguous conditions. These initial studies indicate that SF-AHP is gaining attention as a promising tool for complex decision-making under uncertainty.

The above literature review suggests that, although extensive research has explored carbon emissions in construction and developed various decision-making approaches, certain challenges remain. Current evaluation frameworks for prefabricated construction often rely on deterministic or conventional fuzzy methods, which may not adequately capture expert hesitation and uncertainty. While fuzzy set extensions have enhanced uncertainty modeling, their integration with structured decision-making tools such as AHP in carbon-emission assessment still requires further improvement. In addition, comprehensive indicator systems that simultaneously address material and organizational aspects of carbon emissions are still relatively limited.

To address these challenges, this study applies the SF-AHP to the embodied phase of prefabricated construction. Customized defuzzification and normalization operators are developed to improve the precision and adaptability of the method. By combining the hierarchical decision framework of AHP with the uncertainty-handling capability of spherical fuzzy sets, the proposed approach offers a more reliable and context-specific weighting mechanism, thereby facilitating more informed and effective low-carbon decision-making in the construction industry.

## 3. **Spherical Fuzzy Sets Theory.**

### 3.1. **Basic concepts and definitions.** Spherical Fuzzy Sets (SFS) extend classical fuzzy sets by introducing three independent parameters to describe uncertainty more comprehensively. Let $X$ be a finite set, a spherical fuzzy set $\tilde{A}_s$ on $X$ is defined as

$$\tilde{A}_s = \left\{ \left( x, \mu_{\tilde{A}_s}(x), \nu_{\tilde{A}_s}(x), \pi_{\tilde{A}_s}(x) \right) \middle| \, x \in X \right\} \tag{1}$$

where: $\mu_{\tilde{A}_s}(x) : X \to [0,1]$ denotes the membership degree; $\nu_{\tilde{A}_s}(x) : X \to [0,1]$ denotes the non-membership degree; $\pi_{\tilde{A}_s}(x) : X \to [0,1]$ denotes the hesitancy degree. These parameters must satisfy

$$0 \le \mu^2_{\tilde{A}_s}(x) + \nu^2_{\tilde{A}_s}(x) + \pi^2_{\tilde{A}_s}(x) \le 1, \quad \forall x \in X \tag{2}$$

### 3.2. **Fundamental operations.** Let $\tilde{A}_s$ and $\tilde{B}_s$ be two spherical fuzzy sets. Their basic operations are defined as

Union:

$$\begin{aligned}\tilde{A}_s \cup \tilde{B}_s = \Bigg( &\max\left\{\mu_{\tilde{A}_s}, \mu_{\tilde{B}_s}\right\}, \min\left\{\nu_{\tilde{A}_s}, \nu_{\tilde{B}_s}\right\}, \\ &\min\left\{ \sqrt{1 - \left( \max\left\{\mu_{\tilde{A}_s}, \mu_{\tilde{B}_s}\right\}^2 + \min\left\{\nu_{\tilde{A}_s}, \nu_{\tilde{B}_s}\right\}^2 \right)}, \max\left\{\pi_{\tilde{A}_s}, \pi_{\tilde{B}_s}\right\} \right\} \Bigg)\end{aligned} \tag{3}$$

Intersection:

$$\begin{aligned}\tilde{A}_s \cap \tilde{B}_s = \Bigg( &\min\left\{\mu_{\tilde{A}_s}, \mu_{\tilde{B}_s}\right\}, \max\left\{\nu_{\tilde{A}_s}, \nu_{\tilde{B}_s}\right\}, \\ &\max\left\{ \sqrt{1 - \left( \min\left\{\mu_{\tilde{A}_s}, \mu_{\tilde{B}_s}\right\}^2 + \max\left\{\nu_{\tilde{A}_s}, \nu_{\tilde{B}_s}\right\}^2 \right)}, \min\left\{\pi_{\tilde{A}_s}, \pi_{\tilde{B}_s}\right\} \right\} \Bigg)\end{aligned} \tag{4}$$

Addition:

$$\begin{aligned}&\tilde{A}_s \oplus \tilde{B}_s \\ &= \left( \sqrt{\mu^2_{\tilde{A}_s} + \mu^2_{\tilde{B}_s} - \mu^2_{\tilde{A}_s}\mu^2_{\tilde{B}_s}}, \nu_{\tilde{A}_s}\nu_{\tilde{B}_s}, \sqrt{\left(1 - \mu^2_{\tilde{B}_s}\right)\pi^2_{\tilde{A}_s} + \left(1 - \mu^2_{\tilde{A}_s}\right)\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}\pi^2_{\tilde{B}_s}} \right)\end{aligned} \tag{5}$$

Multiplication:

$$\begin{aligned}&\tilde{A}_s \otimes \tilde{B}_s \\ &= \left( \mu_{\tilde{A}_s}\mu_{\tilde{B}_s}, \sqrt{\nu^2_{\tilde{A}_s} + \nu^2_{\tilde{B}_s} - \nu^2_{\tilde{A}_s}\nu^2_{\tilde{B}_s}}, \sqrt{\left(1 - \nu^2_{\tilde{B}_s}\right)\pi^2_{\tilde{A}_s} + \left(1 - \nu^2_{\tilde{A}_s}\right)\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}\pi^2_{\tilde{B}_s}} \right)\end{aligned} \tag{6}$$

Scalar Multiplication: For $\lambda > 0$,

$$\lambda \cdot \tilde{A}_s = \left( \sqrt{1 - \left(1 - \mu^2_{\tilde{A}_s}\right)^{\lambda}}, \nu^{\lambda}_{\tilde{A}_s}, \sqrt{\left(1 - \mu^2_{\tilde{A}_s}\right)^{\lambda} - \left(1 - \mu^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s}\right)^{\lambda}} \right) \tag{7}$$

Scalar Power: For $\lambda > 0$,

$$\tilde{A}^{\lambda}_s = \left( (\mu_{A_s})^{\lambda}, \sqrt{1 - (1 - \nu^2_{A_s})^{\lambda}}, \sqrt{(1 - \nu^2_{A_s})^{\lambda} - (1 - \nu^2_{A_s} - \pi^2_{A_s})^{\lambda}} \right) \tag{8}$$

4. **SF-AHP Model Construction.** The SF-AHP is a hybrid evaluation approach that combines spherical fuzzy set theory with the classical AHP. Its core advantage lies in its enhanced capability to manage uncertainty and hesitation in expert judgments. The procedural framework of SF-AHP is illustrated in Figure 1. To facilitate understanding, the correspondence between the workflow and the manuscript structure is summarized as follows. Step 1, involving the establishment of the evaluation framework and the construction of the hierarchical structure, is detailed in Section 4.1. Steps 2 to 4, covering the pairwise comparison, the application of the SF-AHP method, and the aggregation and defuzzification of weights, are detailed in Sections 4.2 to 4.4. Finally, Step 5 corresponds to the analysis and interpretation of results, which is discussed in the result section.

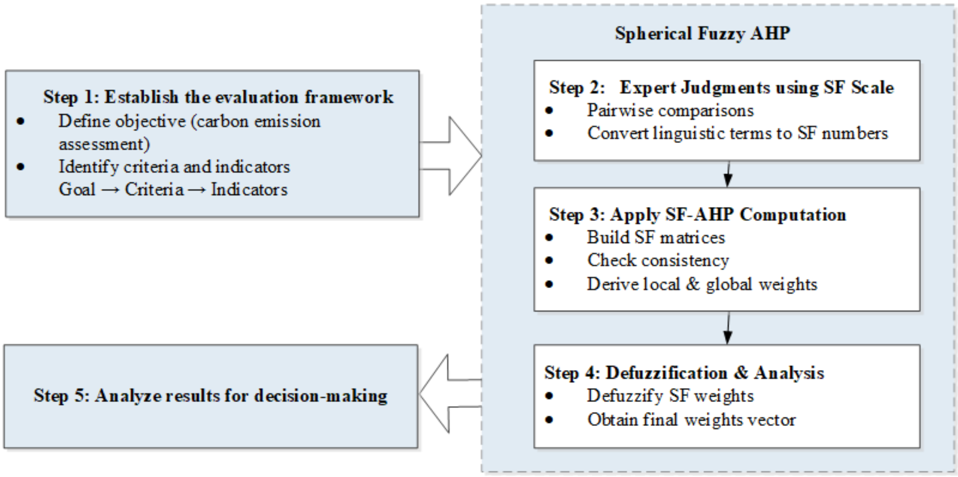


FIGURE 1. Workflow of the spherical fuzzy AHP method

4.1. **Description of the indicator system.** To develop the carbon-emission indicator system for the materialization phase of prefabricated construction, a comprehensive literature review was conducted using the Web of Science and CNKI databases, covering studies published over the past decade. Keyword analysis was employed to identify potential emission-related factors. In addition, relevant standards for prefabricated building evaluation were incorporated to ensure the completeness and applicability of the proposed system.

Subsequently, 18 experts with extensive experience in prefabricated construction (as listed in Table 1) were invited to review and validate the initially identified 21 indicators. Based on their feedback and consensus, the final set of indicators was established, as summarized in Table 2. Each criterion and its corresponding indicators are described as follows.

- ***$B_1$* Project Characteristics:** This criterion includes three indicators – building characteristics, investment scale, and low-carbon design and decision-making. These

TABLE 1. Background information of selected experts

| No. | Work experience | Position | Field of expertise |
|---|---|---|---|
| 1 | 18 years | Senior Architectural Engineer | Design and management of prefabricated residential and commercial building projects |
| 2 | 4 years | Construction Project Manager | Coordination and execution of large-scale prefabricated construction projects |
| 3 | 9 years | Structural Engineer | Structural design and analysis of prefabricated building systems |
| 4 | 2 years | Urban Planner | Integration of prefabricated construction projects into sustainable urban development planning |
| 5 | 5 years | Environmental Engineer | Environmental protection and emission control during construction and operation stages |
| 6 | 8 years | Engineering Management Scholar | Research and education on prefabricated construction management and technological innovation |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 18 | 11 years | Real Estate Developer | Development, investment, and promotion of prefabricated construction projects |

TABLE 2. Indicator system for embodied carbon assessment

| Criterion | Indicator | Description |
|---|---|---|
| $B_1$ Project Characteristics | $c_1$ Building Scale | Spatial layout, floor area, complexity |
| | $c_2$ Prefabrication Rate | Percentage of prefabricated volume |
| | $c_3$ Design Complexity | Number of unique connection types |
| $B_2$ Material Consumption | $c_4$ Concrete Usage | Volume per $m^2$ |
| | $c_5$ Steel Usage | Mass per $m^2$ |
| | $c_6$ Green Material Ratio | Proportion of certified low-carbon materials |
| $B_3$ Energy Consumption | $c_7$ Production Energy | kWh per $m^3$ of components |
| | $c_8$ Transportation Energy | MJ per km per ton |
| | $c_9$ Construction Energy | kWh per $m^2$ on site |
| $B_4$ Transport & Storage | $c_{10}$ Transport Distance | Average km |
| | $c_{11}$ Storage Duration | Days in warehouse |
| | $c_{12}$ Logistics Efficiency | Load factor percentage |
| $B_5$ Construction Organization | $c_{13}$ Technology | Use of digital/automated equipment |
| | $c_{14}$ Schedule Control | Deviation from planned duration |
| | $c_{15}$ Site Management | BIM integration level |
| $B_6$ Ecological Environment | $c_{16}$ Noise Control | dB(A) reduction measures |
| | $c_{17}$ Dust Emissions | $PM_{10}$ reduction techniques |
| | $c_{18}$ Waste Treatment | Recycling rate of construction waste |
| $B_7$ Policy & Regulation | $c_{19}$ Compliance | Adherence to standards |
| | $c_{20}$ Subsidies | Availability of financial incentives |
| | $c_{21}$ Carbon Trading | Participation in carbon markets |

indicators describe how project-specific attributes, such as design complexity, total investment, and low-carbon strategies, affect embodied carbon emissions.

- $\boldsymbol{B_2}$ **Material Consumption:** This criterion covers material quantity and selection, recycling rate, and green material ratio. It captures how the choice, usage, and recycling of construction materials influence the overall carbon footprint during the materialization phase.

- $\boldsymbol{B_3}$ **Energy Consumption:** This criterion includes clean energy utilization, renewable energy utilization, and energy structure configuration. It reflects the effect of energy composition and consumption patterns on carbon emissions in prefabricated construction.
- $\boldsymbol{B_4}$ **Transport and Storage:** This criterion consists of transportation schemes, warehouse location, and low-carbon warehouse management. It represents the impact of logistics planning, storage location, and operational management on transportation-related carbon emissions.
- $\boldsymbol{B_5}$ **Construction Organization:** This criterion comprises advanced machinery usage, construction management, and application of new technologies and processes. It focuses on the influence of construction methods, organizational efficiency, and technological innovation on carbon performance.
- $\boldsymbol{B_6}$ **Ecological Environment:** This criterion includes waste generation, waste recycling, and carbon sequestration from green systems. It evaluates how construction waste management and the surrounding ecological conditions contribute to overall emission levels.
- $\boldsymbol{B_7}$ **Policy and Regulation:** This criterion covers government regulation, land approval, and component standardization design. It reflects how policy instruments, land use decisions, and standardization practices affect the carbon-emission outcomes of prefabricated construction projects.

4.2. **Construction of the fuzzy pairwise comparison matrix.** A fuzzy pairwise comparison matrix for evaluating carbon emissions in prefabricated construction is established using spherical fuzzy linguistic variables, as shown in Table 3. Each linguistic variable corresponds to a triplet of spherical fuzzy numbers and a score index used for quantitative analysis.

$$SI = \sqrt{100 \times \left[ \left( \mu_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2 \right)^2 - \left( \nu_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2 \right)^2 \right]} \tag{9}$$

$$\frac{1}{SI} = \frac{1}{\sqrt{100 \times \left[ \left( \mu_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2 \right)^2 - \left( \nu_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2 \right)^2 \right]}} \tag{10}$$

where $\tilde{A}_s$ is a spherical fuzzy set, and $SI$ denotes the score index of $\tilde{A}_s$. $\mu_{\tilde{A}_s}$ is the membership degree, $\nu_{\tilde{A}_s}$ is the non-membership degree, and $\pi_{\tilde{A}_s}$ is the hesitancy degree of the spherical fuzzy set $\tilde{A}_s$.

TABLE 3. SF linguistic variables and their score indices

| **Linguistic variable** | $(\boldsymbol{\mu}, \boldsymbol{\nu}, \boldsymbol{\pi})$ | **Score index** |
|---|---|---|
| Absolutely High Impact | $(0.9, 0.1, 0.0)$ | 9 |
| Very High Impact | $(0.8, 0.2, 0.1)$ | 7 |
| High Impact | $(0.7, 0.3, 0.2)$ | 5 |
| Moderately High Impact | $(0.6, 0.4, 0.3)$ | 3 |
| Neutral Impact | $(0.5, 0.4, 0.4)$ | 1 |
| Moderately Low Impact | $(0.4, 0.6, 0.3)$ | 1/3 |
| Low Impact | $(0.3, 0.7, 0.2)$ | 1/5 |
| Very Low Impact | $(0.2, 0.8, 0.1)$ | 1/7 |
| Absolutely Low Impact | $(0.1, 0.9, 0.0)$ | 1/9 |

4.3. **Consistency verification.** A CR analysis is conducted to ensure the reliability of the expert evaluations. Before performing the consistency check, the linguistic pairwise comparison matrices are converted into appropriate SI. The consistency is then evaluated using Saaty's criterion [26]. If the calculated CR exceeds 0.1, the expert evaluations must be revised and re-evaluated until a satisfactory level of consistency is achieved. The calculation of the CI and CR is performed using Equations (11) and (12):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{11}$$

$$CR = \frac{CI}{RI} \tag{12}$$

where $CR$ is the consistency ratio, $CI$ is the consistency index, $n$ is the order of the judgment matrix, $\lambda_{\max}$ is the maximum eigenvalue of the matrix (which is guaranteed to exist and be unique when the matrix is positive and reciprocal), and $RI$ is the average random consistency index, the values of which are shown in Table 4.

TABLE 4. $RI$ values for matrices of $n$ order

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $RI$ | 0.00 | 0.00 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 | 1.51 |

4.4. **Defuzzification and normalization.** In this study, the spherical weighted average method is employed to extract the most representative values from fuzzy numbers, thereby reflecting the relative importance of evaluation criteria or alternatives. This process is critical in decision analysis, as it contributes to enhancing the scientific rigor and reliability of the evaluation.

The Spherical Weighted Geometric Mean (SWGM) operator for a set of $n$ spherical fuzzy numbers $\tilde{A}_i = (\mu_i, \nu_i, \pi_i)$ with corresponding weights $w_i$ ($i = 1, 2, \ldots, n$ and $\sum_{i=1}^{n} w_i = 1$) is defined in Equation (13):

$$\begin{aligned} &\mathrm{SWGM}_w\left(\tilde{A}_1, \ldots, \tilde{A}_n\right) \\ &= \left(\prod_{i=1}^{n} \mu_i^{w_i}, \sqrt{1 - \prod_{i=1}^{n} (1 - \nu_i^2)^{w_i}}, \sqrt{\prod_{i=1}^{n} (1 - \nu_i^2)^{w_i} - \prod_{i=1}^{n} (1 - \nu_i^2 - \pi_i^2)^{w_i}}\right) \end{aligned} \tag{13}$$

To incorporate conflict moderation among experts, we introduce a conflict adjustment factor $\xi_i$, which adjusts the influence of expert opinions based on their level of consensus with the group. Accordingly, we propose an improved SWGM operator called the Conflict-Resolved SWGM (CR-SWGM), which embeds the conflict factor into the weight redistribution process. Assume that the consistency level of expert $i$ is denoted as $c_i$. The conflict adjustment factor is redefined as

$$\xi_i = 1 + \frac{c_i - \bar{c}}{\sigma_c + \varepsilon}, \quad \varepsilon > 0 \tag{14}$$

where $\bar{c}$ is the mean consistency value across all experts, $\sigma_c$ is the standard deviation of expert consistency values, and $\varepsilon$ is a small positive constant (e.g., $10^{-6}$) introduced to prevent division by zero and ensure numerical stability when $\sigma_c$ is very small. This modification makes the model fault-tolerant: when $\sigma_c \approx 0$, all experts are treated nearly equally ($\xi_i \approx 1$), while for significant $\sigma_c$, the original behavior of the formula is preserved.

In order to account for expert consistency, the original weight $w_i$ assigned to each expert is adjusted by introducing a conflict adjustment factor $\xi_i$, resulting in an updated weight $w_i'$ computed as follows:

$$w_i' = \frac{w_i \cdot \xi_i}{\sum_{j=1}^{n} w_j \cdot \xi_j} \tag{14}$$

In this way, experts with higher consistency receive greater influence, while those with lower consistency are assigned less weight in the aggregation process. By substituting the adjusted weights $w_i'$ into the traditional SWGM operator, the conflict-resolved version is expressed as CR-SWGM operator in Equation (15):

$$\begin{aligned}&\text{CR-SWGM}\left(\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n\right)\\ &= \left(\prod_{i=1}^{n} \mu_i^{w_i'}, \sqrt{1 - \prod_{i=1}^{n}(1-\nu_i^2)^{w_i'}}, \sqrt{\left(1 - \prod_{i=1}^{n} \mu_i^{2w_i'}\right) - \left(1 - \prod_{i=1}^{n}(1-\nu_i^2)^{w_i'}\right)}\right)\end{aligned} \tag{15}$$

The score function is applied as defined in Equation (16), followed by normalization of the estimated values using Equation (17).

$$S\left(w_j'^s\right) = \sqrt{100 \times \left[\left(3\mu_{\tilde{A}_s} - \frac{\pi_{\tilde{A}_s}}{2}\right)^2 - \left(\frac{\nu_{\tilde{A}_s}}{2} - \pi_{\tilde{A}_s}\right)^2\right]} \tag{16}$$

$$w_j = \frac{S\left(w_j'^s\right)}{\sum_{j=1}^{n} S\left(w_j'^s\right)} \tag{17}$$

5. **Case Study.** In this section, several case studies are conducted to verify the applicability and robustness of the proposed SF-AHP-based evaluation framework. Both publicly available benchmark cases and an actual prefabricated construction project are analyzed and discussed. The benchmark cases are used to demonstrate methodological consistency and comparative performance, while the practical project case provides empirical validation and illustrates the model's effectiveness in real-world decision-making scenarios.

5.1. **Case study 1.** To highlight the advantages of the proposed SF-AHP method, we compare its results with those obtained from traditional AHP and Fuzzy AHP (FAHP) using a case study from a published study [37]. The case involves evaluating contractor performance under five attributes: cost (A1), quality (A2), schedule (A3), leadership (A4), and change management (A5). The pairwise comparison matrices are established using expert judgments, and then processed through the three decision-making methods.

In AHP, linguistic judgments are converted to a crisp Saaty 1-9 scale and a pairwise comparison matrix is constructed. The normalized principal eigenvector yields the criterion weights. For the case study, AHP results in a dominant weight for cost ($w_{A1} = 0.489$), while schedule, leadership, and change management receive very low importance as shown in Table 5. FAHP replaces crisp judgments with Triangular Fuzzy Numbers (TFNs), and applies extent analysis or fuzzy geometric mean to deriving fuzzy weights, which are then defuzzified to crisp values. The results show only a marginal adjustment compared to

Table 5. Results comparison of different methods

| **Method** | **A1** | **A2** | **A3** | **A4** | **A5** |
|---|---|---|---|---|---|
| AHP | 0.489 | 0.281 | 0.142 | 0.061 | 0.027 |
| FAHP | 0.476 | 0.277 | 0.141 | 0.070 | 0.036 |
| SF-AHP | 0.291 | 0.241 | 0.196 | 0.154 | 0.118 |

AHP ($w_{A1} = 0.476$), indicating that FAHP reduces numerical precision issues but does not significantly alter the dominance of cost.

In SF-AHP, expert judgments are mapped to spherical fuzzy sets $(\mu, \nu, \pi)$, capturing membership, non-membership, and hesitancy simultaneously. Aggregation is performed using the SWGM operator. The results show a substantial redistribution of importance: cost weight decreases to 0.291, while schedule, leadership, and change management increase significantly, reflecting more realistic expert hesitancy and uncertainty.

The comparison clearly demonstrates that AHP and FAHP emphasize cost excessively, leading to an imbalanced evaluation where managerial and organizational aspects (schedule, leadership, change management) are undervalued. By contrast, SF-AHP redistributes the weights more evenly, reducing cost dominance and giving higher importance to criteria that better capture the complexities of prefabricated building projects under uncertainty. This illustrates the superior ability of SF-AHP to incorporate expert hesitancy and non-membership information, making it a more realistic and reliable decision-support tool.

## 5.2. **Case study 2.**

5.2.1. *Project background.* To validate the proposed model, a modular residential building in China was selected as a case study. The building comprises 29 above-ground and 2 below-ground storeys, covers a site area of 229,500 m$^2$, and reaches a height of 90 m. The prefabrication rate is 65%. The project employs a steel modular system, wherein components are manufactured off-site and subsequently transported to the construction site for assembly.

5.2.2. *Carbon emission evaluation of the embodied phase in prefabricated buildings.* The criteria and indicator layers of the carbon emission evaluation system for prefabricated buildings were constructed through pairwise comparison analysis. Based on expert assessments, pairwise comparison matrices were established using the linguistic variables defined in Table 3.

To ensure the reliability of the constructed decision matrices, a consistency check was conducted by calculating the CR. The CR values obtained for each comparison matrix are presented in Tables 6 to 13, with results of 0.0681, 0.0158, 0.0279, 0.0810, 0.0158, 0.0696,

Table 6. Spherical fuzzy pairwise comparison matrix and weights for criterion layer

| **Criterion** | $B_1$ | $B_2$ | $B_3$ | $B_4$ | $B_5$ | $B_6$ | $B_7$ | $W$ |
|---|---|---|---|---|---|---|---|---|
| $B_1$ | (0.50, 0.40, 0.40) | (0.60, 0.40, 0.30) | (0.60, 0.40, 0.30) | (0.90, 0.10, 0.00) | (0.80, 0.20, 0.10) | (0.90, 0.10, 0.00) | (0.90, 0.10, 0.00) | 0.3354 |
| $B_2$ | (0.40, 0.60, 0.30) | (0.50, 0.40, 0.40) | (0.60, 0.40, 0.30) | (0.80, 0.20, 0.10) | (0.80, 0.20, 0.10) | (0.90, 0.10, 0.00) | (0.90, 0.10, 0.00) | 0.2492 |
| $B_3$ | (0.40, 0.60, 0.30) | (0.40, 0.60, 0.30) | (0.50, 0.40, 0.40) | (0.80, 0.20, 0.10) | (0.80, 0.20, 0.10) | (0.90, 0.10, 0.00) | (0.90, 0.10, 0.00) | 0.2044 |
| $B_4$ | (0.10, 0.90, 0.00) | (0.10, 0.90, 0.00) | (0.10, 0.90, 0.00) | (0.50, 0.40, 0.40) | (0.20, 0.80, 0.10) | (0.80, 0.20, 0.10) | (0.80, 0.20, 0.10) | 0.0567 |
| $B_5$ | (0.20, 0.80, 0.10) | (0.20, 0.80, 0.10) | (0.20, 0.80, 0.10) | (0.80, 0.20, 0.10) | (0.50, 0.40, 0.40) | (0.90, 0.10, 0.00) | (0.90, 0.10, 0.00) | 0.0994 |
| $B_6$ | (0.10, 0.90, 0.00) | (0.10, 0.90, 0.00) | (0.10, 0.90, 0.00) | (0.20, 0.80, 0.10) | (0.10, 0.90, 0.00) | (0.50, 0.40, 0.40) | (0.60, 0.40, 0.30) | 0.0316 |
| $B_7$ | (0.10, 0.90, 0.00) | (0.10, 0.90, 0.00) | (0.10, 0.90, 0.00) | (0.20, 0.80, 0.10) | (0.10, 0.90, 0.00) | (0.40, 0.60, 0.30) | (0.50, 0.40, 0.40) | 0.0233 |
| $CR = 0.0681$ | | | | | | | | |

Table 7. Weight calculation for project characteristics indicators ($B_1$)

| $B_1$ | $c_1$ | $c_2$ | $c_3$ | $W_1$ |
|---|---|---|---|---|
| $c_1$ | (0.50, 0.40, 0.40) | (0.80, 0.20, 0.10) | (0.70, 0.30, 0.20) | 0.6250 |
| $c_2$ | (0.20, 0.80, 0.10) | (0.50, 0.40, 0.40) | (0.40, 0.60, 0.30) | 0.1365 |
| $c_3$ | (0.30, 0.70, 0.20) | (0.70, 0.30, 0.20) | (0.50, 0.40, 0.40) | 0.2385 |
| $CR = 0.0158$ | | | | |

Table 8. Weight calculation for material consumption indicators ($B_2$)

| $B_2$ | $c_4$ | $c_5$ | $c_6$ | $W_2$ |
|---|---|---|---|---|
| $c_4$ | (0.50, 0.40, 0.40) | (0.70, 0.30, 0.20) | (0.90, 0.10, 0.00) | 0.6586 |
| $c_5$ | (0.30, 0.70, 0.20) | (0.50, 0.40, 0.40) | (0.80, 0.20, 0.10) | 0.2628 |
| $c_6$ | (0.20, 0.80, 0.10) | (0.20, 0.80, 0.10) | (0.50, 0.40, 0.40) | 0.0786 |
| $CR = 0.0279$ | | | | |

Table 9. Weight calculation for energy consumption indicators ($B_3$)

| $B_3$ | $c_7$ | $c_8$ | $c_9$ | $W_3$ |
|---|---|---|---|---|
| $c_7$ | $(0.50, 0.40, 0.40)$ | $(0.70, 0.30, 0.20)$ | $(0.40, 0.60, 0.30)$ | 0.1865 |
| $c_8$ | $(0.40, 0.60, 0.30)$ | $(0.50, 0.40, 0.40)$ | $(0.30, 0.70, 0.20)$ | 0.1265 |
| $c_9$ | $(0.90, 0.10, 0.00)$ | $(0.80, 0.20, 0.10)$ | $(0.50, 0.40, 0.40)$ | 0.6870 |
| $CR = 0.0810$ | | | | |

Table 10. Weight calculation for transport & storage indicators ($B_4$)

| $B_4$ | $c_{10}$ | $c_{11}$ | $c_{12}$ | $W_4$ |
|---|---|---|---|---|
| $c_{10}$ | $(0.50, 0.40, 0.40)$ | $(0.70, 0.30, 0.20)$ | $(0.80, 0.20, 0.10)$ | 0.6548 |
| $c_{11}$ | $(0.40, 0.60, 0.30)$ | $(0.50, 0.40, 0.40)$ | $(0.70, 0.30, 0.20)$ | 0.2503 |
| $c_{12}$ | $(0.30, 0.70, 0.20)$ | $(0.40, 0.60, 0.30)$ | $(0.50, 0.40, 0.40)$ | 0.0950 |
| $CR = 0.0158$ | | | | |

Table 11. Weight calculation for construction organization indicators ($B_5$)

| $B_5$ | $c_{13}$ | $c_{14}$ | $c_{15}$ | $W_5$ |
|---|---|---|---|---|
| $c_{13}$ | $(0.50, 0.40, 0.40)$ | $(0.20, 0.80, 0.10)$ | $(0.30, 0.70, 0.20)$ | 0.1428 |
| $c_{14}$ | $(0.90, 0.10, 0.00)$ | $(0.50, 0.40, 0.40)$ | $(0.60, 0.40, 0.30)$ | 0.6273 |
| $c_{15}$ | $(0.80, 0.20, 0.10)$ | $(0.40, 0.60, 0.30)$ | $(0.50, 0.40, 0.40)$ | 0.2299 |
| $CR = 0.0696$ | | | | |

Table 12. Weight calculation for ecological environment indicators ($B_6$)

| $B_6$ | $c_{16}$ | $c_{17}$ | $c_{18}$ | $W_6$ |
|---|---|---|---|---|
| $c_{16}$ | $(0.50, 0.40, 0.40)$ | $(0.60, 0.40, 0.30)$ | $(0.70, 0.30, 0.20)$ | 0.6833 |
| $c_{17}$ | $(0.40, 0.60, 0.30)$ | $(0.50, 0.40, 0.40)$ | $(0.60, 0.40, 0.30)$ | 0.1998 |
| $c_{18}$ | $(0.30, 0.70, 0.20)$ | $(0.40, 0.60, 0.30)$ | $(0.50, 0.40, 0.40)$ | 0.1168 |
| $CR = 0.0079$ | | | | |

Table 13. Weight calculation for external support indicators ($B_7$)

| $B_7$ | $c_{19}$ | $c_{20}$ | $c_{21}$ | $W_7$ |
|---|---|---|---|---|
| $c_{19}$ | $(0.50, 0.40, 0.40)$ | $(0.30, 0.70, 0.20)$ | $(0.20, 0.80, 0.10)$ | 0.0812 |
| $c_{20}$ | $(0.80, 0.20, 0.10)$ | $(0.50, 0.40, 0.40)$ | $(0.60, 0.40, 0.30)$ | 0.2035 |
| $c_{21}$ | $(0.90, 0.10, 0.00)$ | $(0.70, 0.30, 0.20)$ | $(0.50, 0.40, 0.40)$ | 0.7153 |
| $CR = 0.0212$ | | | | |

0.0079 and 0.0212, respectively. All values fall below the commonly accepted threshold of 0.10, indicating good consistency of the judgment matrices and enhancing the credibility of the evaluation results.

5.2.3. *Evaluation results.* The computed weights reflect the relative importance of influencing factors in the embodied phase of prefabricated construction, thereby indicating their potential impact on carbon emissions. This provides a scientific basis for prioritizing the management of highly correlated elements. As shown in Table 6, among all the criterion layers, project characteristics ($B_1$) holds the highest weight at 33.54%, making it the dominant factor in carbon emissions. Notably, the indicator building characteristics ($c_1$) accounts for 20.9%, which is significantly higher than the other sub-criteria, indicating that structural attributes such as floor area, building mass, and number of modules directly determine the carbon emission intensity. Material consumption ($B_2$) is the second most important criterion, indicating its considerable influence on carbon emissions. This highlights that materials – particularly their type and utilization efficiency – are critical in determining carbon emissions during the industrialized phase of modular construction. Among its sub-indicators, green material utilization and selection of prefabricated materials are the most influential, underscoring the core role of low-carbon material adoption and rational material selection in emission reduction efforts. The relative importance of the remaining criterion and indicator layers is detailed in Tables 7 to 13. Through systematic evaluation, the final weights for both the criteria and indicator layers were determined, as illustrated in Figures 2 and 3. Based on these weights, the influencing factors were ranked in ascending order of their contribution to carbon emissions as follows:

$$B_1 \succ B_2 \succ B_3 \succ B_5 \succ B_4 \succ B_6 \succ B_7$$

$$c_1 \succ c_3 \succ c_2$$

$$c_4 \succ c_5 \succ c_6$$

$$c_9 \succ c_7 \succ c_8$$

$$c_{10} \succ c_{11} \succ c_{12}$$
$$c_{14} \succ c_{15} \succ c_{13}$$
$$c_{16} \succ c_{17} \succ c_{18}$$
$$c_{21} \succ c_{20} \succ c_{19}$$

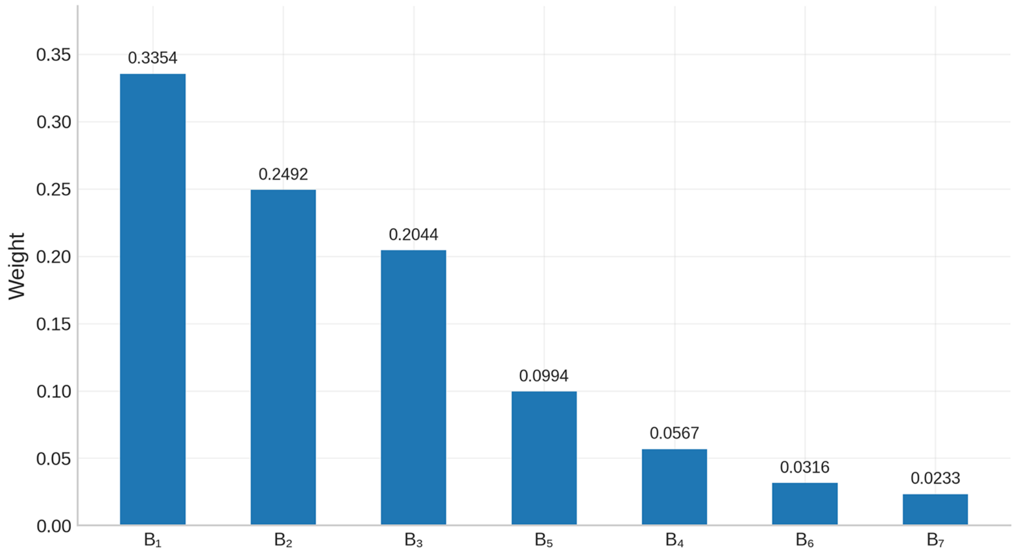


FIGURE 2. Final weights of criterion layers

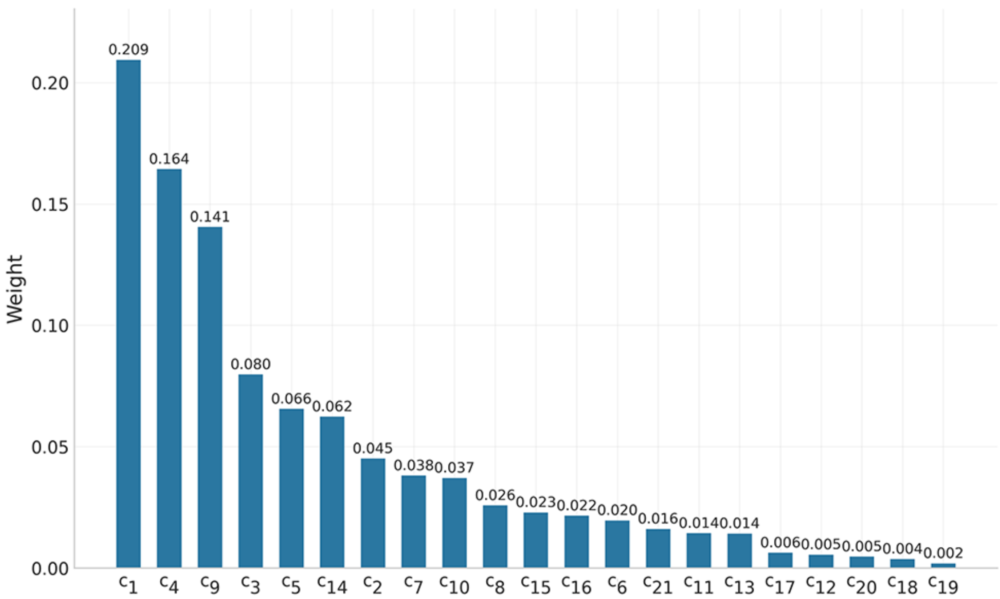


FIGURE 3. Final weights of index layers

### 5.3. **Emission reduction recommendations.**

5.3.1. *Enhancing low-carbon design and planning in modular construction.* Compared with cast-in-place and traditional prefabricated buildings, modular construction exhibits environmentally friendly features. Strengthening low-carbon design and planning allows for zero on-site module stacking, avoiding secondary transportation and associated emissions, as well as emissions from module storage and maintenance. Moreover, it contributes to a more orderly assembly process and reduces emissions related to construction management inefficiencies.

5.3.2. *Selection of low-carbon modular prefabricated materials.* Material consumption holds the highest weight in the evaluation of emission reduction efficiency during the embodied phase of modular construction. This indicates that it is the largest contributor to carbon emissions and the most critical factor for mitigation. Therefore, selecting low-carbon modular prefabricated materials is essential. Building Information Modeling (BIM) technology, which has matured in supporting material selection, can assist in improving the use of green materials. Promoting BIM integration with modular construction enhances the application rate of environmentally friendly materials and reduces emissions at the source.

5.3.3. *Optimizing the energy structure in prefabricated building construction.* Optimizing the energy structure is another essential pathway for reducing emissions during the embodied phase. This includes promoting the use of renewable energy sources – such as wind and solar power – during the construction process, as well as optimizing the overall energy mix by reducing dependence on coal-based electricity and increasing the adoption of hydropower and nuclear energy. These measures contribute to improved energy efficiency and a reduction in $CO_2$ emissions.

5.3.4. *Promoting the application of new technologies and construction methods.* Within this category, the use of new technologies and construction methods is a key factor. By applying advanced techniques – such as production-assistive equipment for precise module alignment – modular assembly can be accelerated, mechanical operation time reduced, and carbon emissions minimized.

6. **Conclusion and Future Work.** This study presents a carbon emission evaluation model based on the spherical fuzzy analytic hierarchy process, which effectively addresses the uncertainty inherent in expert judgments and offers a more realistic representation of complex decision-making scenarios than traditional AHP methods. The results of the case study demonstrate the model's feasibility and alignment with practical engineering conditions. The analysis reveals that project characteristics, material consumption, and construction organization emerged as the key influencing factors, collectively accounting for 78.90% of the total weight.

To guide carbon reduction strategies, a targeted mitigation framework is proposed along four key dimensions: materials, energy, logistics, and technology. Notably, the integration of building information modeling is highlighted as an effective approach to enable precise control and real-time optimization of carbon emissions throughout the prefabricated construction process. Future work will focus on refining the spherical fuzzy AHP by developing more robust scoring and aggregation operators and integrating adaptive weight-learning mechanisms to reduce sensitivity to expert bias. In parallel, alternative multi-attribute decision-making models will be explored to capture interdependencies among criteria and to enable comparative validation. Benchmark case studies and domain-specific databases will further support the practical application and scalability of embodied carbon assessment frameworks in modular and industrialized building systems.

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