Research Article

Application of ATS-GWIFBM Operator Based on Improved Time Entropy in Green Building Projects

Rongxin Zhang, Lvjiang Yin, Jing Jia, and Yuanxing Yin

School of Economics and Management, Hubei University of Automotive Technology, 167 Checheng West Road, Shiyan City, Hubei, China

Correspondence should be addressed to Lvjiang Yin; yinlvjiang@126.com

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For decision-making on the attributes and time weights existing in a dynamic intuitionistic fuzzy environment, a new ATS-generalized weighted intuitionistic fuzzy Bonferroni mean operator MADM model based on dynamic comprehensive time entropy and an ATS-generalized weighted intuitionistic fuzzy Bonferroni mean operator was established by taking into consideration the intrinsic correlations between attributes. An intuitionistic fuzzy decision matrix with the same time sequence was integrated into the model. According to the idea of “laying more stress on the present than on the past,” a time sequence weight considering both the subjective preferences and the objective information of samples was obtained to overcome the irrationality of subjective value assignment on existing time sequence weight and ideal time weighting. Based on dynamic comprehensive time entropy, the model not only reflects the degree of importance attached to the latest data but also gives consideration to the subjective preferences of decision-makers in order to set a new vector for time sequence weight. The dynamic intuitionistic fuzzy weighted operator was used to conduct aggregation to obtain a dynamic intuitionistic fuzzy comprehensive value, and the obtained results are sorted by the sorting function of intuitionistic fuzzy sets. The best alternative was selected and applied to a case study on green building project selection. The results indicate that the proposed method is comprehensive, scientific, and feasible.

1. Introduction

Because of the limitations of people’s ways of thinking, as well as the complexity, fuzziness, and uncertainty of things themselves, which affect the scientificity of decisions, decision-makers often fail to obtain accurate results when making specific decisions. In 1965, to improve people’s ability to deal with complex problems, Zadeh proposed the concept of fuzzy sets and used membership to describe fuzziness [1]. However, the concept of fuzzy sets involves only one membership and can only reflect two aspects of information, which are “yes” and “no.” For this reason, considering three aspects of information comprehensively, membership, nonmembership, and hesitancy degree, Atanassov extended the theory of fuzzy sets and proposed the theory of intuitionistic fuzzy sets [2]. Compared with a traditional fuzzy set, an intuitionistic fuzzy set can describe and depict the essence of the fuzziness of the objective world more delicately, so this theory attracted the attention of scholars in the field of decision-making at home and abroad [3, 4]. Xu and Yager systematically studied the integration mode of the intuitionistic fuzzy attribute information and proposed a series of aggregation operators, such as the intuitionistic fuzzy weighted average, intuitionistic fuzzy weighted geometric average, regional intuitionistic fuzzy ordered weighted average, and interval-valued intuitionistic fuzzy mixed geometric operators, for intuitionistic fuzzy information [5–7]. Considering the relationship between decision-makers’ attitudes and intuitionistic fuzzy numbers, he established intuitionistic fuzzy weighted neutral and average operators [8]. The I-IIFHA and I-IIFHG operators proposed by Wu and Su have widened the research into intuitionistic fuzzy operators [9]. The intuitionistic fuzzy information aggregation operators mentioned above neglect the intrinsic correlations between attributes in decision-making issues. Some scholars, such as Yager [10] and Xu and
Yager [11], considered the intrinsic relationship between attributes synthetically, discussed the intuitionistic fuzzy information aggregation operators interrelated in attributes and established an intuitionistic fuzzy Bonferroni mean operator and an intuitionistic fuzzy weighted Bonferroni average operator. More importantly, Wan et al. [12] has established some new generalized aggregation operators and intuitionistic fuzzy weighted Bonferroni average operator for triangular intuitionistic fuzzy numbers and application to multiattribute group decision-making, further enriching the theory of intuitionistic fuzzy sets. However, as to the decision-making method of intuitionistic fuzzy multiple attributes, the study was only limited to the focus on the static information in a single period and few studies have been conducted on dynamic multiattribute decision-making issues in multiple periods. In actual situations, most decisions need to integrate the decision information of different time periods. Even though some scholars, such as Park et al. [13] and Shi and Baizhou [14], have established multiattribute dynamic intuitionistic fuzzy decision models based on the time dimension, the establishment of time weights is based on random direct value assignment with subjective ideas, rendering the results of decision-making unreasonable and lacking in scientificity. Although Yang and Huang [15], by “laying more stress on the present than on the past,” introduced the law of time and used the ideal time weight vector to obtain the time sequence weight, the determination of the time weight did not take actual situations, which possessed subjectivity, into account. Finally, the time weight suffered interference with zero, causing the decision-making result to be very unreasonable and seriously affecting the universality and applicability of Yang’s research. In addition to, Xu et al. [16] have accomplished heterogeneous multiattribute group decision-making by some novel methods, bringing a good thinking for our research.

In this study, the intrinsic correlations between attributes in multiattribute decision-making were taken into consideration at first. The attribute weight was determined according to the existing decision information and intuitionistic fuzzy entropy equation. The intuitionistic fuzzy decision matrix with the same time sequence is integrated by using an intuitionistic fuzzy Bonferroni mean operator based on ATS-generalized weighting. Then, by “laying more stress on the present than on the past,” the time sequence weight giving consideration to both the subjective preferences, and the objective information of samples is obtained while the irrationality of subjective assignments on the existing time sequence weight and ideal time weighting is overcome. Based on dynamic comprehensive time entropy, it not only reflects the degree of importance attached to the latest data but also considers the subjective preferences of decision-makers in order to set a new vector for time sequence weights. Finally, a dynamic intuitionistic fuzzy weighted operator was used for aggregation to obtain dynamic intuitionistic fuzzy comprehensive values, and the obtained results were sorted by the sorting function of intuitionistic fuzzy sets. The best alternative was selected and applied to a green supply chain [17]. The results indicate that the proposed method is comprehensive, scientific, and feasible.

2. Related Concepts

2.1. Intuitionistic Fuzzy Sets

Definition 1 [6, 7]. Suppose that \( X \) is a nonempty set, then \( A = \{ (x, u_A(x), v_A(x)) \mid x \in X \} \) is defined as an intuitionistic fuzzy set, where \( u_A(x) \) and \( v_A(x) \) are membership and nonmembership, respectively:

\[
\begin{align*}
    u_A(x) : X &\rightarrow [0, 1], \quad x \in X \rightarrow u_A(x) \in [0, 1], \\
    v_A(x) : X &\rightarrow [0, 1], \quad x \in X \rightarrow v_A(x) \in [0, 1].
\end{align*}
\]

(1)

The following condition is satisfied:

\[
0 \leq u_A(x) + v_A(x) \leq 1, \quad x \in X.
\]

(2)

Moreover,

\[
\pi_A(x) = 1 - u_A(x) - v_A(x), \quad x \in X.
\]

(3)

It indicates the degree of hesitancy or uncertainty that the element \( x \) in \( X \) belongs to \( A \).

Definition 2 [18]. Suppose that \( \alpha_1 = (u_{\alpha_1}, v_{\alpha_1}) \) and \( \alpha_2 = (u_{\alpha_2}, v_{\alpha_2}) \) denote the intuitionistic fuzzy number, then \( s(\alpha_1) = u_{\alpha_1} - v_{\alpha_1} \) and \( s(\alpha_2) = u_{\alpha_2} - v_{\alpha_2} \) denote the scores for \( \alpha_1 \) and \( \alpha_2 \), respectively, while \( h(\alpha_1) = u_{\alpha_1} + v_{\alpha_1} \) and \( h(\alpha_2) = u_{\alpha_2} + v_{\alpha_2} \) denote the accuracies of \( \alpha_1 \) and \( \alpha_2 \), respectively. The following can be concluded.

If \( s(\alpha_1) < s(\alpha_2) \), then \( \alpha_1 \) is less than \( \alpha_2 \), denoted by \( \alpha_1 < \alpha_2 \).

If \( s(\alpha_1) = s(\alpha_2) \),

\[
\begin{align*}
    (1) & \text{ If } h(\alpha_1) = h(\alpha_2), \quad \alpha_1 \text{ is equal to } \alpha_2, \text{ denoted by } \alpha_1 = \alpha_2; \\
    (2) & \text{ If } h(\alpha_1) < h(\alpha_2), \quad \alpha_1 \text{ is less than } \alpha_2, \text{ denoted by } \alpha_1 < \alpha_2; \\
    (3) & \text{ If } h(\alpha_1) > h(\alpha_2), \quad \alpha_1 \text{ is greater than } \alpha_2, \text{ denoted by } \alpha_1 > \alpha_2.
\end{align*}
\]

2.2. Archimedean Norm

Definition 3 [19–22]. If the two-variable function \( T : [0, 1] \times [0, 1] \rightarrow [0, 1] \) satisfies the following four conditions, then function \( T(x, y) \) is called \( T^- \) norm:

\[
(1) \text{ As to } \forall x \in [0, 1], \ T(x, 1) = x; \\
(2) \text{ As to } \forall x, y \in [0, 1], \ T(x, y) = T(y, x); \\
(3) \text{ As to } \forall x, y, z \in [0, 1], \ T(x, T(y, z)) = T(T(x, y), z); \\
(4) \text{ As to } x \leq x' \text{ and } y \leq y', \text{ then } T(x, y) \leq T(x', y').
\]

If the two-variable function \( S : [0, 1] \times [0, 1] \rightarrow [0, 1] \) satisfies the following four conditions, then function \( S(x, y) \) is called \( S^- \) norm:

\[
(1) \text{ As to } \forall x \in [0, 1], \ S(x, 0) = x; \\
(2) \text{ As to } \forall x, y \in [0, 1], \ S(x, y) = S(y, x); \\
(3) \text{ As to } \forall x, y, z \in [0, 1], \ S(x, S(y, z)) = S(S(x, y), z);
\]
(4) If \( x \leq x' \) and \( y \leq y' \), then \( S(x, y) \leq S(x', y') \).

In fact, \( T^- \) norm and \( S^- \) norm are mutually dual. If \( T^- \) norm \( T(\cdot, \cdot) \) is continuous on \([0, 1] \times [0, 1] \) and \( T(\cdot, \cdot) < x, \forall x \in [0, 1] \); then \( T(\cdot, \cdot) \) is called Archimedean \( T^- \) norm. If \( S^- \) norm \( S(\cdot, \cdot) \) is continuous on \([0, 1] \times [0, 1] \) and \( S(\cdot, \cdot) > x, \forall x \in [0, 1] \); then \( S(\cdot, \cdot) \) is called Archimedean \( S^- \) norm.

Definition 4 [22]. Let \( \alpha = (u, v) \), \( \alpha_i = (u_i, v_i) \), and \( \alpha_j = (u_j, v_j) \) be three IFNs. The following can be concluded:

1. \( \alpha_i \oplus \alpha_j = (S(u_i, u_j), T(v_i, v_j)) = (h^{-1}(u_i) + h(u_j)), g^{-1}(v_i) + g(v_j)) \);
2. \( \alpha_j \ominus \alpha_j = (T(u_i, u_j), S(v_i, v_j)) = (g^{-1}(g(u_i) - g(u_j)), h^{-1}(v_i) - h(v_j)) \);
3. \( \lambda \alpha = (h^{-1}(\lambda h(u_i)), g^{-1}(\lambda g(v_i))) \), \( \lambda > 0 \);
4. \( \alpha_i \ominus \lambda \alpha_j = (g^{-1}(\lambda g(u_i)), h^{-1}(\lambda h(v_i))) \), \( \lambda > 0 \).

2.3. ATS-Generalized Weighted Intuitionistic Fuzzy Bonferroni Mean Operator Based on Dynamic Time Entropy

Definition 5 [22]. If \( \alpha_i = (u_i, v_i)(i = 1, 2, \ldots, n) \) is a list of IFN and the parameters \( p, q > 0 \), then the ATS-generalized intuitionistic fuzzy Bonferroni mean operator is expressed by

\[
\text{ATS - GIFBM}^{p,q}(\alpha_1, \alpha_2, \ldots, \alpha_n) = \left( \frac{1}{n(n-1)} \sum_{i,j=1}^{n} \left( w_i \alpha_i^p \ominus (w_j \alpha_j)^q \right)^{1/(p+q)} \right).
\]

\[
= \left( 1 - \prod_{i,j=1}^{n} \left( 1 - \left( 1 - u_{\alpha_i} \right)^w \right)^p \left( 1 - \left( 1 - v_{\alpha_i} \right)^w \right)^q \right)^{1/(n(n-1))} \left( 1 - \prod_{i,j=1}^{n} \left( 1 - \left( 1 - u_{\alpha_i} \right)^w \right)^p \left( 1 - \left( 1 - v_{\alpha_i} \right)^w \right)^q \right)^{1/(n(n-1))} \right)^{1/(p+q)},
\]

which is called the dynamic intuitionistic fuzzy weighted geometric operator.

3. Time Sequence and Target Attribute
Weight Vectors Based on Time Entropy

3.1. Determination of Time Weight. By analogy of traditional intuitionistic fuzzy multiple-attribute decision-making, dynamic multiattribute intuitionistic fuzzy decision-making based on time entropy should not only consider the importance of attributes but also consider the influence of time factors. Therefore, the determination of time weight is an important issue in an intuitionistic fuzzy model. "Laying more stress on the present than on the past" proposed by Meiimei Xia attached more importance to the most current and timeliness of information [23]. Under the condition that the time scale \( \lambda \) is given, Cao determined the time weight \( \eta(t_k) (k = 1, 2, \ldots, p) \) according to the criterion of
When the decision-maker’s preference information is subjective, he will prefer the time weight based on subjective information. When λ gets closer to 0, decision-maker attaches more preference to recent information of time series; when λ gets closer to 1, decision maker attaches more preference to forward information of time series.

According to “laying more stress on the present than on the past,” Zhang et al. searched for a set of time weight coefficients to maximize their closeness under the condition that the time scale was available ahead of time and established a time-scale optimization model with a positive time weight vector and a negative ideal time weight vector [25]:

\[
\max \quad c(\eta(t_k), \eta(t_{\bar{k}})) = \frac{\sqrt{(1 - \eta(t_1))^2 + \sum_{k=2}^{P} \eta(t_k)^2}}{\sqrt{(1 - \eta(t_1))^2 + \sum_{k=2}^{P-1} \eta(t_k)^2 + \sqrt{\sum_{k=1}^{P-1} \eta(t_k)^2 + (1 - \eta(t_1))^2}}}
\]

\[
\text{s.t.} \quad \lambda = \frac{P - k}{p - 1} \eta(t_k), \quad \sum_{k=1}^{P} \eta(t_k) = 1, \eta(t_k) \in [0, 1), k = 1, 2, \ldots, P.
\]

By solving this model, the time weight vector of the time-sequence multiattribute decision-making issue can be obtained. This study established a new comprehensive dynamic time weight model that attaches importance not only to the timeliness but also to the objectivity and validity of information. The new optimization model is as follows:

\[
\max \quad R = l \frac{\sqrt{(1 - \eta(t_1))^2 + \sum_{k=2}^{P} \eta(t_k)^2}}{\sqrt{(1 - \eta(t_1))^2 + \sum_{k=2}^{P-1} \eta(t_k)^2 + \sqrt{\sum_{k=1}^{P-1} \eta(t_k)^2 + (1 - \eta(t_1))^2}} + (1 - l) \left( - \sum_{k=1}^{P} \eta(t_k) \ln \eta(t_k) \right),
\]

\[
\text{s.t.} \quad \lambda = \frac{P - k}{p - 1} \eta(t_k), \quad \sum_{k=1}^{P} \eta(t_k) = 1, \eta(t_k) \in [0, 1), k = 1, 2, \ldots, P.
\]

where \( l \) denotes the adjustment parameter and \( l \in [0, 1] \).

When \( l \) is close to 0, the decision-makers prefer the time weight based on objective information. When \( l \) is close to 1, the decision-makers prefer the time weight based on subjective preference information. The solution to the time weight vector was obtained by means of the Lingo 11 software package.

### 3.2. Determination of Target Attribute Weight

At different times, people pay attention to different attributes of decision-making objectives. Therefore, in actual decision-making, attribute weight should be adjusted according to different time sequence stages so as to achieve the decision-making objectives of different periods.

The dynamic intuitionistic fuzzy decision matrix is denoted by \( C(t_k) = (C_{ij}(t_k))_{m \times n} \), where \( C_{ij}(t_k) = (u_{ij}(t_k), v_{ij}(t_k)) \), where \( u_{ij}(t_k) \) denotes the membership of the \( i \)th scheme in the \( j \)th attribute during the time period \( t_k \), and \( v_{ij}(t_k) \) denotes the nonmembership of the \( i \)th scheme in the \( j \)th attribute during the time period \( t_k \). At this time, the hesitancy degree is \( \pi_{ij}(t_k) = 1 - u_{ij}(t_k) - v_{ij}(t_k) \). Therefore, the target attribute weight during the time period of \( t_k \) is represented by

\[
E_j(t_k) = \frac{1}{m} \sum_{i=1}^{m} \left( 1 - \sqrt{(1 - \pi_{ij}(t_k))^2 - u_{ij}(t_k) v_{ij}(t_k)} \right)
\]

\[
\text{min} \quad \sum_{j=1}^{n} w_j(t_k)^2 E_j(t_k),
\]

\[\text{s.t.} \quad \sum_{j=1}^{n} w_j(t_k) = 1.\]

According to the above model, a Lagrangian function is established as follows:

\[
L(w_j(t_k), \lambda) = \sum_{j=1}^{n} w_j(t_k)^2 E_j(t_k) + 2\lambda \left( \sum_{j=1}^{n} w_j(t_k) - 1 \right).
\]

Partial derivatives are conducted on \( w_j(t_k) \) and \( \lambda \) and then set to 0:
4. MADM Method for ATS-GWIFBM Operator Based on Dynamic Time Entropy

This study uses an ATS-GWIFBM operator based on dynamic time entropy for intuitionistic fuzzy multiple-attribute decision-making with attributes and time weight, as well as proposes a dynamic comprehensive decision-making method that considers the interrelations between the attributes and time entropy. \(Y = \{Y_1, Y_2, \ldots, Y_m\}\) is an alternative option set and \(C \equiv \{C_1, C_2, \ldots, C_n\}\) is an attribute index set. When making specific decisions, decision-makers need to consider not only the intrinsic relationship between attributes in a static environment but also the changes in the relationship between attributes in a dynamic environment over time. The alternative option scheme \(Y_j\) provided by decision-makers is denoted by an intuitionistic fuzzy number (IFN) under the preference information of attribute index \(C_j\), where \(a_{ij} = (u_{ij}, v_{ij})(i = 1, 2, \ldots, m, j = 1, 2, \ldots, n)\). \(u_{ij}\) and \(v_{ij}\) denote the satisfaction and dissatisfaction, respectively, of decision-makers with the scheme \(Y_j\) under attribute index \(C_j\) that satisfies \(0 \leq u_{ij} \leq 1, 0 \leq v_{ij} \leq 1\) and \(0 \leq u_{ij} + v_{ij} \leq 1\). The decision preference information of alternative option scheme \(Y_j\) under attribute index \(C_j\) constitutes an intuitionistic fuzzy decision matrix \(D = (a_{ij})_{m \times n}\).

The specific steps are as follows:

Step 1. The decision-makers use the decision matrix \(D^k = (a_{ij}^k)_{m \times n} = ((u_{ij}(t_k), v_{ij}(t_k)))\) during the \(t_k\)th \((k = 1, 2, \ldots, p)\) time period.

Step 2. Use equations (10)–(14) to determine the entropy weight \(w_j\) of the \(j\)th attribute \(C_j\).

Step 3. Use equations (4) and (5) to obtain the comprehensive intuitionistic fuzzy attribute value \(a_{ij}^k\) between attributes in every alternative option scheme during the \(t_k\)th time period.

Step 4. Select a different \(l\) according to the requirements of decision-makers and the opinions of relevant experts, then solve equation (9) to obtain the time weight \(\eta(t_k)\).

Step 5. Use equation (6) to aggregate multiple periods to obtain the dynamic intuitionistic fuzzy comprehensive decision matrix \(D^l = (a_{ij}^l)_{m \times n}\).

Step 6. Calculate the scoring function and precision function for the dynamic intuitionistic fuzzy comprehensive value, then sort the obtained results according to Definition 2 to choose the best scheme.

5. Case Study

5.1. A Green Suppliers Selection Example and the Analysis Process. Company H is a construction enterprise with specific qualifications. The company’s business scope covers the fields of general contracting in building construction engineering, infrastructure construction, investment in real estate, engineering design, etc., and its business covers China, Africa, South Asia, Southeast Asia, and many other regions [26].

Taking product innovation and providing green building products as the development goals, Company H will be dedicated to the development and practice of green residential technology. Reducing carbon emissions from construction projects and enhancing green competitiveness is one of the important subjects faced by project builders. Under this circumstance, Company H must choose green suppliers from a wide range of suppliers. The company has accumulated some experience in selecting suppliers, but still faces the challenge of choosing the best green supplier [27]. On the one hand, the company has established a standard, but this standard is not suitable for selecting green suppliers, as it does not set characteristic standards for green supplier selection for construction projects. On the other hand, Company H has experience in supplier selection and a better understanding of information fuzziness. However, even if the selection of suppliers is considered during multiple periods, it can still cause subjectivity and objectivity of time weight.

At present, Company H is buying a batch of reinforcement bars for green buildings under construction. After the preliminary selection of the iron and steel enterprises, five enterprises enter the final selection, and the company must select its steel suppliers from five major green suppliers. Fifteen managers and professionals in Company H, together with experts in related fields, conduct a fuzzy evaluation on index attributes according to the standards.

The five alternative green suppliers are \(Y_1, Y_2, Y_3, Y_4,\) and \(Y_5\), denoted by \(Y = \{Y_1, Y_2, Y_3, Y_4, Y_5\}\), and are evaluated according to three attribute indicators—building material information \((C_1)\), green technology degree of materials \((C_2)\), and potential for sustainable cooperation \((C_3)\)—which are denoted by the attribute set \(C = \{C_1, C_2, C_3\}\). All the indicators of each alternative green supplier in three different periods are evaluated to construct an intuitionistic fuzzy decision matrix \(D^i = (a_{ij}^i)_{3 \times 3}\), as shown in Table 1.

Step 1. Determine the weight of the \(j\)th attribute \(C_j\) during the \(t_k\)th time period according to equations (8)–(12), as shown in Table 2.

Step 2. Use the ATS-GWIFBM operator, and without the loss of generality, let \(p = q = 1\). The comprehensive intuitionistic fuzzy attribute value \(a_{ij}^l\) between attributes of every alternative option scheme during the \(t_k\)th time period is obtained by equations (4) and (5), as shown in Table 3.
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Table 1: Intuitionistic fuzzy matrix in different periods.

<table>
<thead>
<tr>
<th>t_k</th>
<th>C_1</th>
<th>C_2</th>
<th>C_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y_1</td>
<td>(0.5, 0.4)</td>
<td>(0.7, 0.2)</td>
<td>(0.4, 0.3)</td>
</tr>
<tr>
<td>Y_2</td>
<td>(0.4, 0.3)</td>
<td>(0.8, 0.1)</td>
<td>(0.5, 0.2)</td>
</tr>
<tr>
<td>Y_3</td>
<td>(0.5, 0.2)</td>
<td>(0.2, 0.5)</td>
<td>(0.6, 0.1)</td>
</tr>
<tr>
<td>Y_4</td>
<td>(0.4, 0.2)</td>
<td>(0.5, 0.3)</td>
<td>(0.3, 0.6)</td>
</tr>
<tr>
<td>Y_5</td>
<td>(0.6, 0.3)</td>
<td>(0.5, 0.2)</td>
<td>(0.8, 0.1)</td>
</tr>
<tr>
<td>t_2</td>
<td>C_1</td>
<td>C_2</td>
<td>C_3</td>
</tr>
<tr>
<td>Y_1</td>
<td>(0.6, 0.3)</td>
<td>(0.3, 0.4)</td>
<td>(0.7, 0.1)</td>
</tr>
<tr>
<td>Y_2</td>
<td>(0.8, 0.1)</td>
<td>(0.3, 0.5)</td>
<td>(0.6, 0.2)</td>
</tr>
<tr>
<td>Y_3</td>
<td>(0.2, 0.6)</td>
<td>(0.4, 0.5)</td>
<td>(0.3, 0.1)</td>
</tr>
<tr>
<td>Y_4</td>
<td>(0.7, 0.2)</td>
<td>(0.5, 0.3)</td>
<td>(0.6, 0.1)</td>
</tr>
<tr>
<td>Y_5</td>
<td>(0.4, 0.2)</td>
<td>(0.7, 0.1)</td>
<td>(0.4, 0.3)</td>
</tr>
<tr>
<td>t_3</td>
<td>C_1</td>
<td>C_2</td>
<td>C_3</td>
</tr>
<tr>
<td>Y_1</td>
<td>(0.3, 0.4)</td>
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<td>(0.5, 0.3)</td>
</tr>
<tr>
<td>Y_2</td>
<td>(0.5, 0.2)</td>
<td>(0.4, 0.1)</td>
<td>(0.6, 0.1)</td>
</tr>
<tr>
<td>Y_3</td>
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<td>(0.7, 0.2)</td>
<td>(0.4, 0.4)</td>
</tr>
<tr>
<td>Y_4</td>
<td>(0.2, 0.6)</td>
<td>(0.8, 0.1)</td>
<td>(0.3, 0.2)</td>
</tr>
<tr>
<td>Y_5</td>
<td>(0.5, 0.1)</td>
<td>(0.6, 0.3)</td>
<td>(0.2, 0.5)</td>
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</table>

Table 2: Attribute weights.

<table>
<thead>
<tr>
<th>t</th>
<th>w_{1}(t_i)</th>
<th>w_{2}(t_i)</th>
<th>w_{3}(t_i)</th>
</tr>
</thead>
<tbody>
<tr>
<td>t_1</td>
<td>0.281</td>
<td>0.364</td>
<td>0.355</td>
</tr>
<tr>
<td>t_2</td>
<td>0.370</td>
<td>0.336</td>
<td>0.294</td>
</tr>
<tr>
<td>t_3</td>
<td>0.332</td>
<td>0.357</td>
<td>0.311</td>
</tr>
</tbody>
</table>

5.2. Comparison Analysis with Different Decision-Making Methods. For further comparison of the comprehensiveness and rationality of algorithm in this paper, an evaluation of the alternative solutions is conducted by combining with the data in Tables 4 and 5, and by using the improved TOPSIS method [28], grey correlation analysis method [29] and evaluation results are shown in Table 6 (we have used the method of Yang et al. in Table 6) [30].

Table 6 is reproduced from Yang et al.[30] (under the Creative Commons Attribution License/public domain).

See from Table 6, improved TOPSIS method is an improvement on traditional TOPSIS method; the ranking results is S_2 > S_5 > S_3 > S_4, which is inconsistent with the method proposed in this paper, but the solution is S_2. The ordering result of grey correlation analysis is S_2 > S_3 > S_4 > S_5, and we also can obtain the optimal solution S_2. Although the total order result is inconsistent with this paper, the optimal solution is always S_2, which does not affect the final decision-making results.

Compared with the similar dynamic multicriterion decision-making method for green supplier selection, our method takes into account the interactions among the criteria under the condition of time sequence. The method proposed in this paper can help construction personnel to identify the targets and reduce the time cost of green supplier selection in construction projects. To summarize,

Step 3. Determine time weight. According to the opinions of experts in the field of supply chain management, combine subjective and objective thoughts with emphasis on “laying more stress on the present than on the past.” Let \( l = 0, 0.2, 0.5, 0.8, 1 \), solve the nonlinear programming model (10) and obtain the time weight for the most recent three years as follows:

\[
\begin{align*}
0 & \Rightarrow \eta_{t_i} = (0.154, 0.292, 0.554)^T, \\
0.2 & \Rightarrow \eta_{t_i} = (0.562, 0.276, 0.162)^T, \\
0.5 & \Rightarrow \eta_{t_i} = (0.582, 0.236, 0.182)^T, \\
0.8 & \Rightarrow \eta_{t_i} = (0.627, 0.147, 0.226)^T, \\
1 & \Rightarrow \eta_{t_i} = (0.09, 0.245, 0.665)^T.
\end{align*}
\]

Multiple periods are aggregated according to equation (6) and the comprehensive values for the dynamic ATS-GWIFBM operator are obtained, as shown in Table 4.

Step 4. Solve the scoring function according to the comprehensive values for the dynamic ATS-GWIFBM operator. The results are shown in Table 5.

Table 5 shows that different values of \( l \) lead to different evaluation results. By comparing the evaluation and selection results of the different values for \( l \), it is found that when \( l = 1 \), the evaluation value is the largest. At this time, the selection result is still S_2.

Step 5. Sort the five alternative green suppliers according to the scoring function of the comprehensive values for the dynamic ATS-GWIFBM operator.

6. Conclusion

Based on the idea of an intuitionistic fuzzy model's depicting dynamic change and fuzziness in detail and on dynamic time entropy, an ATS-generalized weighted intuitionistic fuzzy Bonferroni mean operator MADM was established. The following conclusions can be drawn:

(1) On the basis of existing decision information, the intrinsic correlation between attributes is considered and an ATS-generalized weighted intuitionistic fuzzy Bonferroni mean operator is used to integrate a fuzzy decision matrix with the same time sequence.

(2) Yang and Huang [15] used the guideline of “laying more stress on the present than on the past” to determine the time weight vector \( v = (0.2282, 0.1077, 0.6641) \). One of the time weights is 0, which is not consistent with the actual situation. In this
paper, the time sequence weights of both the subjective preferences and the objective information on samples are taken into account, and the irrationality of the subjective value assignment on the existing time sequence weight and ideal time weighting is overcome. On the basis of the fact that dynamic time entropy reflects the importance attached to the latest data, a new time sequence weight vector is set.

(3) The existing studies, which are not dynamic, emphasize on decision-making in a fixed period of time. In this paper, on the basis of time scale and variations in the attribute weight during multiple periods, an ATS-GWIFBM operator based on dynamic time entropy was established to conduct decision analysis.

(4) In empirical research, with the selection of green suppliers in green building projects taken as an example, an analysis was conducted according to the three dimensions of building material information, green technology level of materials, and the potential of sustainable cooperation. The problem of green supplier selection for green building projects was transformed into a fuzzy multiattribute group decision problem. It not only can simplify calculations and overcome the disadvantages of subjective weight but also realize dynamic evaluation, provide a new method for selecting green suppliers in green building projects, and expand the applications of dynamic intuitionistic fuzzy decision theory.

**Data Availability**

The data used to support the findings of this study are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**Authors’ Contributions**

L. Y. designed the model and did the paper write-up. J. J. assisted with the data collection and the results during the performance analysis. Y. Y. and B. H. conceived the overall idea of improved time entropy.

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