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Comprehensive Assessment and Empirical Research on Green and Low-Carbon Technologies in the Steel Industry

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Abstract: The iron and steel industry is the leading industry supporting China's industrial sector. Currently, there is less assessment work on green and low-carbon technologies for the iron and steel industry. This study clarifies the overall strategy of technology assessment by researching the relevant theories and methods of technology assessment. The study further establishes a scientific and reasonable comprehensive assessment index system of green and low-carbon technologies for the iron and steel industry from the aspects of technology index, economy and promotion, and application, including factors such as 11 indexes, the amount of energy saving, carbon dioxide emission reduction, and the resource recovery rate by utilising analytical and comprehensive methods and combining with the characteristics of the technologies. By analysing and comparing the advantages and disadvantages of the commonly used assessment methods, the entropy weighting method, grey correlation analysis method, and TOPSIS (technique for order preference by similarity to an ideal solution) method are combined and optimised to construct a comprehensive assessment model. The Latin hypercube sampling method is also introduced to analyse the technical parameters in combination with the evaluation model. Finally, fourteen iron and steel green and low-carbon technologies were selected for case assessment and uncertainty analysis of technical parameters, and it was found that the comprehensive assessment result of gas combined cycle power generation technology was optimal. After determining the weights of each assessment indicator through the entropy weighting method, it is concluded that the technical performance indicator > economic indicator > promotional indicator. A comparative analysis of the results under the three preference decisions concludes that technical performance is the main obstacle to improving the comprehensive assessment score of the technology, followed by the economics of the technology. Finally, the uncertainty analysis of the technical parameters shows that the fluctuation of the technical parameters not only affects the performance of the technology, but also affects the weights of the indicators and the comprehensive evaluation results of the technology.

Keywords: energy-saving technologies for the steel industry; Latin hypercube sampling; indicator system assessment; entropy weight method-grey correlation analysis-TOPSIS method

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1. Introduction

In response to the continued rise in global greenhouse gas emissions, China has set a strategic goal of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 [1,2]. The iron and steel industry is energy-intensive and also an important area for green and low-carbon development. The steel industry accounts for about 15 per cent of the country's total carbon emissions. To achieve the 2060 carbon neutrality target, low-carbon steelmaking is a challenge that Chinese steel companies must meet. Currently, China's steel industry is at the beginning of a zero-carbon transition. The primary raw material for steelmaking in China is coal, and the steelmaking process is dominated by long-process steel; the steel production system is shown in Figure 1. A large amount of energy consumption and pollutant emissions accompany the high output of China's iron and steel industry. To promote green and low carbon, China's iron and steel industry is actively promoting the three major iron and steel projects, namely, capacity replacement, ultra-low emission, and extreme energy efficiency [3]. According to a report on the economic operation of China's iron and steel industry, China's crude steel output will be 1.013 billion tonnes in 2022, accounting for 55.3 per cent of the global share [4,5]. Vigorously developing green and low-carbon technologies in the iron and steel industry and promoting the application of green and low-carbon technologies is an effective way to realise the energy-saving and low-carbon development of the iron and steel industry and ensure green and sustainable development [6].

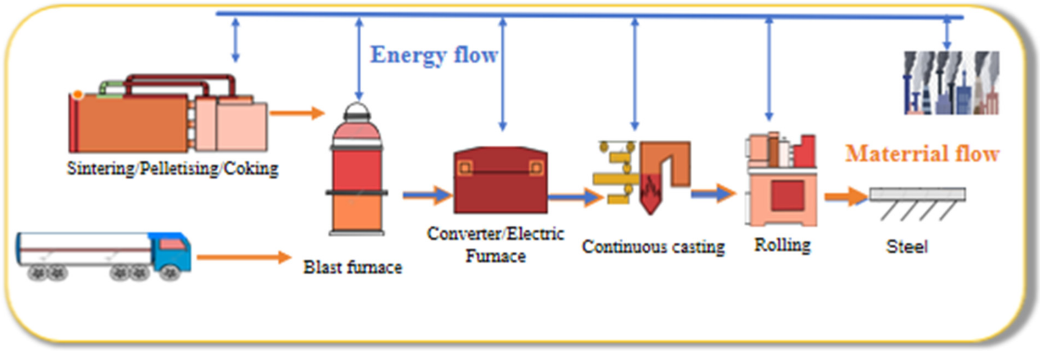

Figure 1. Steel production process.

The iron and steel industry is in urgent need of technological upgrading for greening and carbon reduction. The green emission reduction pathway can be summarised as green management, green structure, and green technology [7]. Among them, the management of the green emission reduction path focuses on improving the productivity of the primary production technology and avoiding unnecessary production waste behaviour; structural green emission reduction focuses on structural adjustment to achieve the transformation of enterprise production, reduce production energy consumption, and achieve the comprehensive energy consumption and emissions reduction; technological green emission reduction focuses on the application of advanced green emission reduction technology to improve the overall level of enterprise technology and energy efficiency, so as to achieve the green emission reduction of enterprises. As the Chinese government attaches importance to the promotion and application of green emission reduction technologies, specific measures such as legal responsibilities, administrative penalties, government subsidies, and tax regulations are also being gradually implemented and strengthened to provide constraints and incentives for the promotion and application of green emission reduction technologies [8]. To strictly implement green and low-carbon development policies and related standards and ensure that major high-carbon emission projects achieve low-carbon emission or carbon-reducing technologies to meet the standards, conducting green and low-carbon evaluation has become an urgent need for sustainable development and environmental protection. Green energy saving and low carbon in the iron and steel industry have always been a hot issue of concern in social development. However, there are fewer studies on the comprehensive assessment of energy-saving and low-carbon technologies in the iron and steel industry. A green and low-carbon evaluation of the steel industry can prompt steel enterprises to adopt more environmentally friendly and efficient production technologies to reduce the negative impact on the environment and, at the same time, promote the adoption of more energy-saving and efficient production methods to improve the efficiency of resource utilisation, reduce the waste of resources, and lower the risks, so as to better adapt to the future development trend of sustainable development [9].

Since the end of the twentieth century, many scholars have applied life cycle assessment (LCA) to the field of technology evaluation. Adisa Azapagic et al. [10] selected indicators such as investment costs, operating costs, floor space, and energy consumption to evaluate wastewater treatment systems from both economic and environmental perspectives using the LCA methodology, which proved the validity and flexibility of the overall methodology for project evaluation, although the specific conclusions reached depended to a certain extent on the economic assumptions made. Deng Julong et al. [11] proposed grey system theory for the first time, including factors such as grey situation analysis and grey coupling evaluation. It transforms a linear time-varying system stability determination problem into a constant symmetric matrix, whether a negative definite determination problem, through the generating number to find out the law from the cluttered data, opening up a new way for the research of the abstract system in various fields which is simple to apply and more convenient than the existing method of determining the stability of the linear time-varying system. Yang Yuan et al. [12] constructed an evaluation index system including three criteria of technology, economy, and environment on the basis of research, determined the weights through the expert consultation method and entropy weighting method, and finally synthesised it using fuzzy integration methods. The best wastewater treatment technology applicable to small towns and cities was screened out, as is the optimal technology by applying this index system under the precondition of perfecting the research of indexes' qualitative and quantitative. Cheng Rui et al. [13] constructed a comprehensive soil quality evaluation index system and assessment method applicable to the whole life cycle of mines in five aspects. They improved the effectiveness of the assessment work with a reasonable assessment process. The comprehensive judgement results were in line with the actual situation, which proved that the two-level fuzzy comprehensive judgement method could make objective and accurate evaluations. Yang Zhongya et al. [14] selected the Yangtze River Delta region as a case study, where the application of China's energy-saving technologies has broader prospects. They incorporated the synergistic benefits into the calculation of technological energy-saving costs. They carried out single-factor sensitivity analyses and systematic uncertainty analyses in response to the results, which further extended the significance and accuracy of the technology assessment. The popularisation of the technology was found to be conducive to promoting energy conservation and emission reduction in the iron and steel industry. Yan Haochun et al. [15] addressed the building materials industry's green, low-carbon development through the relevant recommendations. The completion of the evaluation and rating of technology was based on the score and rating to complete the evaluation of green low-carbon technology report, a clear evaluation of the situation of the evaluation indicators and evaluation of the comprehensive situation and the evaluation of green low-carbon technology to regulate the evaluation process.

The assessment of green and low-carbon technologies in the steel industry should take into account technical, economic, and environmental factors. At present, most of the evaluation of green energy-saving and low-carbon technologies is based on empirical judgment and qualitative analysis. There is a large subjectivity, lack of corresponding reference basis and judgment standards, and there are no effective comprehensive evaluation index system or comprehensive and quantitative evaluation methods to comprehensively evaluate the actual energy-saving and carbon-reduction effects and potential impacts of energy-saving and low-carbon technologies. This has resulted in enterprises or energy-saving service companies in the process of implementing energy-saving and low-carbon technology transformation or updating, and there is a certain blindness in the selection of energy-saving and low-carbon technologies, which affects the comprehensive benefits of project implementation. This makes it necessary to establish a comprehensive evaluation index system and a quantitative comprehensive evaluation tool to comprehensively evaluate energy-saving and low-carbon technologies. Second, few studies have considered the uncertainty of technical parameters and their impact on the evaluation results. There are various uncertainties in technical performance, such as measurement deviations, changes in the application environment, and fluctuations in the technical performance itself. Because these uncertainties have an impact at the same time, they can lead to a large number of possible scenarios and lead to results that are not in line with practice. This study constructs a comprehensive assessment methodology system for energy-saving and low-carbon technologies in the iron and steel industry, combined with the characteristics of the iron and steel industry. It selects some of the technologies for assessment. Firstly, the index system is constructed following the steps of the index system to build a comprehensive assessment index system for energy-saving and low-carbon technologies in the iron and steel industry. Secondly, we compare and analyse the advantages and disadvantages of different assessment methods, select a technology assessment method that meets the characteristics of the comprehensive assessment of green energy-saving and low-carbon technologies in the iron and steel industry and the purpose of this paper, and combine the entropy weighting method and the grey correlation analysis–TOPSIS assessment method to construct a comprehensive assessment model. Finally, a number of energy-saving and low-carbon technologies in the iron and steel industry are selected for the case study, and the evaluation index system and assessment model are constructed and applied to the comprehensive assessment of a number of selected energy-saving and low-carbon technologies. Different technological solutions are selected for different decision-making preferences. At the same time, uncertainty analysis is carried out for the uncertainty of technical parameters. In this study, technical performance factors, economic factors, environmental factors, and the promotion and application of the technology are taken into account. The TOPSIS method and grey correlation analysis method are combined and improved to establish a comprehensive assessment model, which overcomes the shortcomings of the assessment methods and the gaps in the assessment of technologies in the iron and steel industry. The multifaceted structure, multidisciplinary underlying knowledge support, and quantitative and comprehensive assessment results provided by the comprehensive assessment model of iron and steel industry technologies are not only difficult to replace with other research methods but also contribute to the implementation of green, energy-saving, and low-carbon work in China's iron and steel industry. They provide scientific and reasonable bases and references for the release and updating of advanced green, energy-saving, and low-carbon technologies and the phasing out and updating of energy-saving and low-carbon technologies in each iron and steel enterprise. They can also provide a scientific and reasonable basis and reference.

2. Establishment of an Evaluation System

2.1. Assessment of Green and Low-Carbon Technologies in the Steel Industry

A comprehensive assessment of technology first requires the establishment of an assessment indicator system, and whether the assessment process is scientific and feasible, as well as the accuracy of the final assessment results, largely depend on whether the selection of technology assessment indicators is reasonable. This study will elaborate on the subject and object of assessment, assessment objectives and content, principles for establishing the indicator system, the basis for establishing the indicators, and the establishment of the indicator system. The technology assessment in this study takes into account the needs of different subjects. From the perspective of comprehensive and all-round development of the industry, the relevant subjects in the selection of green and low-carbon technologies are mainly included in the processes of technology assessment and selection. In addition to the need for coordination of the purposes and interests between different assessment subjects, it is also necessary to realise the coordination of the final purposes or interests between assessment subjects of different levels to achieve a comprehensive balance of purposes or interests of the country and society, the industry and region, and enterprises, so as to achieve a comprehensive balance of purposes or interests of the technology selection issue. In addition to the coordination of purposes and interests between different assessment bodies, coordination of purposes or interests between different levels of assessment bodies is also necessary to achieve a comprehensive balance between the purposes or interests of the state and society, the industry and region, and the enterprises in the selection of technologies. Regarding green, energy-saving, and low-carbon technologies in the iron and steel industry, this study screens out a set of comprehensive assessment indicators and undertakes technology assessment and corresponding validation analyses, with the specific research route shown in Figure 2.

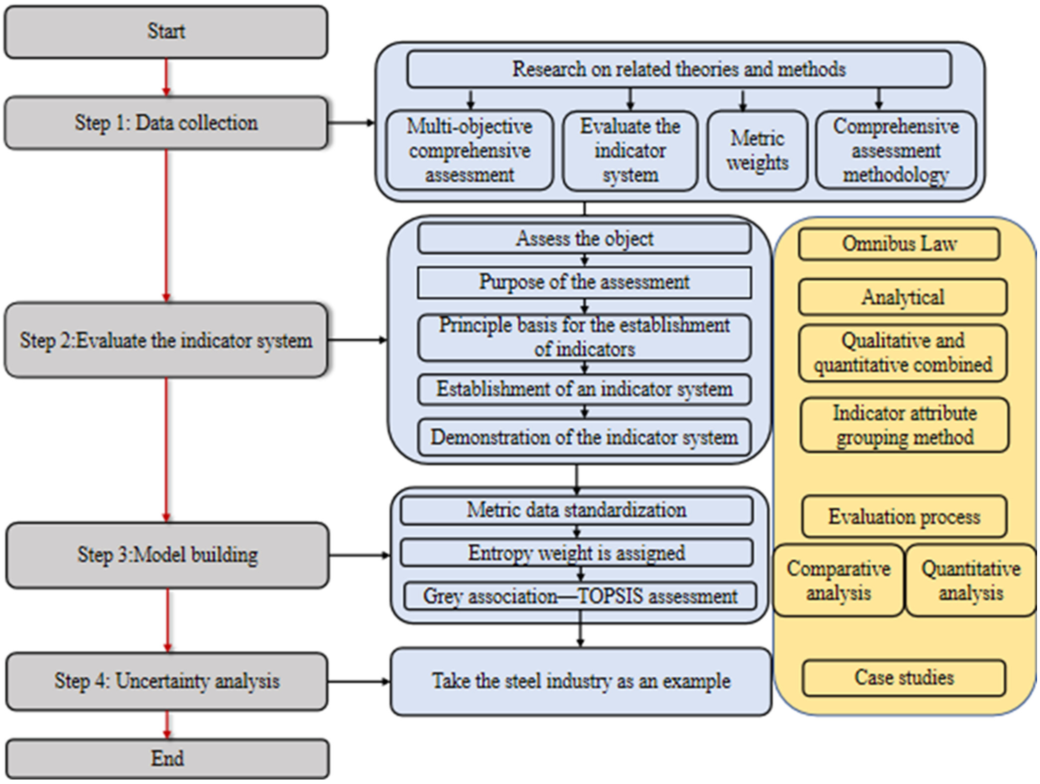

Figure 2. Line of research.

2.2. The Basis and Influencing Factors of Technical Evaluation

The technology assessment index system of the iron and steel industry includes the three criteria of technology, economy, and environment [16]. Referring to the technology assessment index system of other industries, most of them also include the three criteria layers of technical performance, economic cost, and environmental impact, and, due to different focuses, others also involve social impact, operation and management, pollution control, and other indicators. The indicator layer is a specific refinement on the basis of the guideline layer indicators, and the technical guideline layer mainly includes the advanced nature of the technology, the effect of technology application, technology maturity, technology stability, and other indicators [17,18]. The economic guideline layer mainly includes the cost of investment in fixed assets, the cost of operation and maintenance, the land area, the economic return, and other indicators. The environmental impact of the guideline layer mainly includes the control of pollutant emissions, secondary pollution, the consumption of energy and resources, noise, and other indicators. When selecting evaluation indexes, we should consider national laws and regulations, industrial policies, technologies, environmental protection standards, and other relevant regulations and documents related to the iron and steel industry. Table 1 presents a summary study of existing assessment indicators for the steel industry.

The factors affecting the comprehensive assessment of green and low-carbon technologies in the iron and steel industry include 1. the impact of the technology itself, 2. the economic level, 3. the environmental benefits and the social benefits. The comprehensive assessment of green and low-carbon technologies in the iron and steel industry is based on a multifaceted assessment. The comprehensive assessment indicator system for green and low-carbon technologies in the iron and steel industry consists of three layers: the target layer is used to reflect the results of the comprehensive assessment of each assessed technology, the normative layer is used to comprehensively reflect the status of all aspects of the assessed technologies, and the indicator layer is used to reflect the effect of the implementation of each technology from the single characteristic of particular aspects of the technology.

Table 1. Study of existing assessment indicators in the steel industry.

Target Layer	Normative Layer	Indicator Layer
A comprehensive evaluation of flue gas desulphurisation technology in the iron and steel industry [17]	Technical indicator	System upgrade performance, adverse impact, system operational stability, technology maturity
	Economic indicator	Infrastructure investment, unit desulphurisation cost, floor space
	Environmental indicator	Recovery performance of by products, secondary pollution, desulphurisation efficiency
Assessment of symbiotic technologies in the steel industry [18]		Energy saving CO_2 emission reduction By product recovery rate fixed-asset investment Technology payback period Technology penetration

3. Comprehensive Assessment Model of Green and Low-Carbon Technologies in the Steel Industry

3.1. Selection of Assessment Methodology

Comprehensive assessment of green and low-carbon technologies in the iron and steel industry, as a complex problem with many influencing factors, mutual influence between factors, and difficulty in determining the relationship between the influencing factors, is most suitable for adopting the multi-objective comprehensive assessment method. Based on the introduction of comprehensive assessment methods, it can be seen that each method is widely used and has its unique advantages, but also has its disadvantages, which are analysed in Table 2 below.

Table 2. Analytical table of commonly used multi-objective integrated assessment methods.

Method	Advantage	Disadvantage
Expert scoring method	Simple methodology; Intuitive; Can be assessed even in the absence of informative data.	Highly subjective; Accuracy depends on expert perception and lacks objectivity.
Hierarchical analysis [19]	Simple and practical; Rigorous structure; Few quantitative information needs; Highly operational.	Too many qualitative components, too subjective; Difficult to calculate when assessing more indicators; Unable to judge elements that think differently.
TOPSIS method [20]	Low sample requirements; Raw data are well utilised, close to the actual situation, strong objectivity.	Prone to reverse sequencing; Some situations cannot be judged and are not very sensitive; Programmes cannot be classified and managed.
Data envelopment analysis [21,22]	Stronger objectivity; Indicators do not need to be weighted; Data do not need to be dimensionless.	High demand for the number of decision-making units; Inability to reflect the actual situation of decision-making units; Inability to distinguish between levels of technical efficiency.

Table 2. *Cont.*

Method	Advantage	Disadvantage
Grey correlation analysis [23]	Lower workload; Reduced losses from information asymmetry; Low data requirements.	Deficiencies in the overall assessment of the programme; Poor analysis of qualitative indicators; Sorting from curve shape similarity only; Inability to address similarity of indicator information.
Fuzzy integrated assessment method [24]	Simple and easy to grasp; Fuzzy problems quantified; Strong applicability; Ability to solve complex problems.	Indicator relevance is difficult to address; Excessive subjectivity; Inadequate assessment methodology.

3.2. Standardisation of Evaluation Indicators

There are m technologies to be assessed, n assessment indicators, to determine the specific quantitative value of each technology under each indicator. Thus, m technologies to be assessed and n assessment indicators constitute the matrix $V = \left(x_{ij}\right)_{m\times n}$ (Equation (1)), which is called the decision matrix [25]. x_{ij} denotes the value of the j-th indicator for the i-th technology, where $i = 1, 2, 3, \cdots, m$, $j = 1, 2, 3, \cdots, n$.

$$V = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{1}$$

In the assessment process, the outline and order of magnitude of each assessment indicator are usually different, so it is not possible to directly compare the calculation. In order to ensure the accuracy of the final assessment results, the parameters of the assessment indicators need to be dimensionless [26]. For the above matrix, the standardised treatment is calculated as follows:

The treatment of benefit-based indicators is as in Equation (2).

$$x'_{ij} = \frac{x_{ij} - \min\left(x_{ij}\right)}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)},\ i = 1,\ 2,\ \ldots,\ m,\ j = 1,\ 2,\ \ldots,\ n \tag{2}$$

For cost-based indicators, the treatment is as in Equation (3).

$$x'_{ij} = \frac{max\left(x_{ij}\right) - x_{ij}}{max\left(x_{ij}\right) - min\left(x_{ij}\right)},\ i = 1,\ 2,\ \ldots,\ m,\ j = 1,\ 2,\ \ldots,\ n \tag{3}$$

In the above two equations, $max\left(x_{ij}\right)$, $min\left(x_{ij}\right)$ are the maximum value of the indicator and the minimum value of the indicator in different technologies under the same assessment indicator, respectively. Find the maximum and minimum values of the indicator among all technologies assessed, with the maximum value being 1 and the minimum value being 0. The number of intermediate indicators between the maximum and minimum values is calculated by linear interpolation.

3.3. Determination of Indicator Weights

As for the weighting of factors affecting technical performance, technical economy, and technology diffusion in the process of technology assessment, if it is decided through experts' empirical judgement and artificial assignment of values, it will inevitably result in a certain degree of subjectivity and one-sidedness. In this study, in the process of determining the weights of the comprehensive assessment indicators of green and low-carbon technologies in the iron and steel industry, the entropy weight method is used to assign values to the weights of the indicators. Entropy represents the degree of chaos of a system in physics [27]. In information data, entropy is the amount of information and uncertainty that reflects the system. The greater the amount of information that can be accessed, the less chaotic the system is, so the lower the uncertainty and the lower the entropy [28]. When the data gap is larger, and the distribution of each assessment technique on a particular assessment indicator is more dispersed, the smaller its entropy value, the greater the impact of the indicator on the assessment results, then the greater the weight of the indicator [29]. The calculation steps are as follows:

Firstly, the decision matrix $V = \left(x_{ij}\right)_{m\times n}$ is normalised to obtain the normalised decision matrix as $V' = \left(x_{ij}{}'\right)_{m\times n}$ (Equation (4)). $x_{ij}{}'$ is the standardised value of the j-th indicator for the i-th objective, where $i = 1, 2, 3, \cdots, m$; $j = 1, 2, 3, \cdots, n$. Secondly, according to the definition of entropy itself, the entropy value of the j-th indicator is calculated according to Equations (5)–(7):

$$V' = \begin{pmatrix} x_{11}{}' & \cdots & x_{1n}{}' \\ \vdots & \ddots & \vdots \\ x_{m1}{}' & \cdots & x_{mn}{}' \end{pmatrix} \quad (4)$$

$$e_j = -k\sum_{i=1}^{m} p_{ij}\ln\left(p_{ij}\right), e_j \geq 0 \quad (5)$$

$$k = \frac{1}{In(m)} \quad (6)$$

$$P_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}}, i = 1,2,\ldots m, j = 1,2,\ldots n \quad (7)$$

where m denotes the number of technologies and P_{ij} denotes the probability of a specific state in which the system is located ($0 \leq \mathrm{P} \leq 1$, $\sum\mathrm{P} = 1$). To make sense of $\ln\left(p_{ij}\right)$, when $p_{ij} = 0$, $\ln\left(p_{ij}\right)$ is considered to be a larger value based on the practical significance of the assessment. The result of multiplication with p_{ij} tends to 0 and can be considered as $p_{ij}\ln\left(p_{ij}\right) = 0$. Finally, the entropy weight W of the assessment indicators is calculated (Equation (8)), where w_j denotes the entropy weight of the j-th assessment indicator, n is the number of assessment indicators, and $Ee = \sum_{j=1}^{n} e_j, 0 \leq w_j \leq 1, \sum_{j=1}^{n} w_j = 1$.

$$W = \begin{pmatrix} w_1 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & w_n \end{pmatrix} \quad (8)$$

$$w_j = \frac{1 - e_j}{n - Ee} \quad (9)$$

3.4. Integrated Assessment Method Based on Grey Correlation Analysis-TOPSIS Improvement

Based on the traditional TOPSIS method, the combination of TOPSIS and grey correlation analysis is improved to establish a comprehensive assessment model [30]. The improved TOPSIS model based on grey correlation analysis is a comprehensive assessment method that ranks the strengths and weaknesses of assessment objects based on positive and negative ideal solutions to the problem and the correlation coefficients [31]. The entropy weight objective assignment method was used to assign weights to the indicators of the assessment system, while grey correlation analysis was used to improve the basic idea of the TOPSIS method [32]. Constructing the grey correlation TOPSIS model based on entropy assignment to rank the advantages and disadvantages of green and low-carbon technologies in the iron and steel industry is a good way to make up for the shortcomings of TOPSIS and grey correlation analysis and synthesise the advantages of both [33].

Construct and standardise a matrix of assessment indicators based on m technologies and n assessment indicators, calculate the weights W of each assessment indicator, and calculate the weighted standardised decision matrix Z. Calculate the positive ideal solution J^+ and the negative ideal solution J^- for the technology to be evaluated, and calculate the Euclidean distances D_i^++ and D_i^- from technology i to the positive and negative ideal solutions. Calculate the grey correlation R_i^++ and R_i^- between technology i and the positive and negative ideal solutions, the dimensionless distance D_i^+ and D_i^- from technology i to the positive and negative ideal solutions, and the grey correlation R_i^+ and R_i^- to the positive and negative ideal solutions. Calculate the proximity of technique i to the positive ideal point S_i^+ and the proximity of the negative ideal solution S_i^-, then calculate the relative closeness of technique i to be evaluated to the ideal solution CS_i and rank them. A large number of simulations from random samples is necessary to avoid the possibility that uncertainty in the parameters of the technique may lead to significant deviations between theoretical results and reality. Therefore, the Latin hypercubic sampling method is introduced in conjunction with an evaluation model to analyse the uncertainty in the parameters of the technology to be evaluated.

Firstly, the standardised decision proof $V' = \left(x_{ij}'\right)_{m\times n}$ and the entropy weights of evaluation indexes $W = \left(w_j\right)_{m\times n}$ will be obtained, and the standardised decision matrix V' will be multiplied by the corresponding indexes' weights W, which leads to the weighted standardised decision matrix Z (Equation (10)). Next, calculate the positive and negative ideal solutions under each assessment metric (Equations (11) and (12)).

$$Z = V' \times W = \begin{pmatrix} x_{11}' & \cdots & x_{1n}' \\ \vdots & \ddots & \vdots \\ x_{m1}' & \cdots & x_{mn}' \end{pmatrix} \times \begin{pmatrix} w_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & w_n \end{pmatrix} \tag{10}$$

$$z_j^+ = \begin{cases} \max\left(z_{ij}\right), j \in + \\ \min\left(z_{ij}\right), j \in - \end{cases} j = 1, 2, \dots n \tag{11}$$

$$z_j^- = \begin{cases} \min\left(z_{ij}\right), j \in + \\ \max\left(z_{ij}\right), j \in - \end{cases} j = 1, 2, \dots n \tag{12}$$

where: z_j^+ indicates that the assessment technique is positively desirable under indicator j, z_j^- indicates that the assessment technique is negatively desirable under indicator j, $+$ indicates that indicator j is a benefit-based indicator, and $-$ indicates that indicator j is a cost-based indicator. The positive ideal solution J^+ (Equation (13)) and the negative ideal solution J^- (Equation (14)) of the weighted decision matrix are obtained via the above. Then, the Euclidean distance between the values of each technical indicator and the ideal value is calculated [34]. Let D_i^+ be the Euclidean distance from technology i to the positive ideal solution and D_i^- be the Euclidean distance from technology i to the negative ideal solution, then the Euclidean distance formula is shown in Equations (15) and (16):

$$J^+ = \left(z_1^+, z_2^+, z_3^+, \cdots, z_j^+\right) \tag{13}$$

$$J^- = \left(z_1^-, z_2^-, z_3^-, \cdots, z_j^-\right) \tag{14}$$

$$D_i^+ = \left(\sum_{j=1}^{j=n}\left(z_{ij} - z_j^+\right)^2\right)^{\frac{1}{2}}, i = 1, 2, \dots, m \tag{15}$$

$$D_i^- = \left(\sum_{j=1}^{j=n}\left(z_{ij} - z_j^-\right)^2\right)^{\frac{1}{2}}, i = 1, 2, \dots n \tag{16}$$

The grey correlation coefficients between the parameters of each assessed technology and the positive and negative ideal solutions are calculated [35,36]. Based on the weighted normalisation matrix Z, the grey correlation coefficient between the parameters of the

i-th technology under the j-th index and the positive ideal solution is r_{ij}^{+}, and the grey correlation coefficient with the negative ideal solution is r_{ij}^{-}, respectively. The specific calculation formulas are shown in Equations (17) and (18).

$$r_{ij}^{+} = \frac{\min_i \min_j \left| z_j^{+} - z_{ij} \right| + \rho \max_i \max_j \left| z_j^{+} - z_{ij} \right|}{\left| z_j^{+} - z_{ij} \right| + \rho \underset{i}{max} \underset{j}{max} \left| z_j^{+} - z_{ij} \right|} \tag{17}$$

$$r_{ij}^{-} = \frac{\min_i \min_j \left| z_j^{-} - z_{ij} \right| + \rho \max_i \max_j \left| z_j^{-} - z_{ij} \right|}{\left| z_j^{-} - z_{ij} \right| + \rho \underset{i}{max} \underset{j}{max} \left| z_j^{-} - z_{ij} \right|} \tag{18}$$

where ρ is the discrimination coefficient, which serves to increase the significance of the difference between the correlation coefficients. ρ is generally between 0 and 1, usually taken as 0.5, and in this study, it is taken as 0.5. Let the grey correlation of each indicator parameter of the ith assessment technique with the positive ideal solution be R_i^{+}, and the grey correlation with the negative ideal solution be R_i^{-}. The specific calculations are shown in Equations (19) and (20). Calculate the proximity of the evaluation technique to the positive and negative ideal solutions, the dimensionless treatment of D_i^{+} and D_i^{-} with R_i^{+} and R_i^{-}, respectively, as shown in Equation (21):

$$R_i^{+} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{+}, i = 1, 2, \cdots, m \tag{19}$$

$$R_i^{-} = \frac{1}{n} \sum_{j=1}^{n} r_{ij}^{-}, i = 1, 2, \cdots, m \tag{20}$$

$$M_i^{*} = \frac{M_i}{\underset{1 \leqslant i \leqslant m}{max} (M_i)} \tag{21}$$

where M_i^{*} represents the corresponding D_i^{+}, D_i^{-}, R_i^{+}, R_i^{-}, respectively, let S_i^{+} be the proximity of the evaluation technique to the positive ideal solution under the combination of the two methods, S_i^{-} as the closeness of the assessment technique to the negative ideal solution under the combination of the two methods. The larger the values of D_i^{-} and R_i^{+}, and the larger the value of S_i^{+}, the closer the assessment technique is to the positive ideal technique. The larger the values of D_i^{+} and R_i^{-} and the larger the value of S_i^{-}, the closer the assessment technique is to the negative ideal technique. S_i^{+} and S_i^{-} are calculated as shown in Equations (22) and (23).

$$S_i^{+} = \lambda D_i^{-} + (1 - \lambda) R_i^{+}, i = 1, 2, \cdots, m \tag{22}$$

$$S_i^{-} = \lambda D_i^{+} + (1 - \lambda) R_i^{-}, i = 1, 2, \cdots, m \tag{23}$$

where λ is the assessor's preference coefficient for the two methods, which is generally taken as 0.5. When λ = 0, it is the grey correlation analysis method only that is used to determine the proximity of the assessed technology to the positive and negative ideal solutions. When λ = 1, it is the TOPSIS method only that is used to determine the proximity of the assessed technology to the positive and negative ideal solutions. Since the two methods evaluate the technology from different perspectives, when the evaluator's preference for the similarity of location and shape between the technology parameter curves and the ideal solution varies (the degree of the evaluator's preference for Euclidean distance and grey correlation), the evaluation results made for the technology will also be different [37]. The evaluator can choose the appropriate preference coefficients to obtain the best evaluation results in line with his/her preferences. Finally, the comprehensive relative closeness CS_i of the assessment technology is calculated, the size of the relative closeness is the comprehensive score of the technology, and the comprehensive effect of the technology is judged according to the size of the score; the larger the closeness is, the better the comprehensive performance of the assessment technology is, and, vice versa, the worse the comprehensive performance is.

$$CS_i = \frac{S_i^+}{S_i^- + S_i^+}, i = 1, 2, \ldots m \tag{24}$$

4. Assessment of Examples of Green and Low-Carbon Technologies in the Steel Industry

4.1. Technology Selection and Parameter Acquisition

Compared with other industries, the iron and steel industry is characterised by a long industrial chain, complex internal processes, many emission points of air pollutants, and a large amount of pollutant generation. In order to conduct a comprehensive assessment of green and low-carbon technologies, this paper takes the iron and steel industry as an example to verify the feasibility of the model. This paper selects energy-saving and low-carbon technologies for the iron and steel industry from a total of 35 low-carbon technologies in 6 categories according to the Catalogue of Low-Carbon Technologies to be Promoted by the State (the Fourth Batch) and other documents (Table 3), which describes in detail the technological principles, conditions of applicability, economics, and effects of the actual application of the technologies, but lacks a comprehensive assessment of the technologies and a comparative analysis of the technologies. In this paper, each of the processes involved in the iron and steel production process is taken as an assessment object. The model is validated, and a comprehensive score for each technology is derived.

Table 3. List of assessment techniques.

Serial Number	Technical Name	Thrust
T1	High-temperature and high-pressure dry coke quenching	Coke production is carried out under high-temperature and high-pressure conditions, The volatiles in the coal are rapidly evaporated and burned in a short period of time.
T2	CO_2 cycle device	The coke oven gas reacts with recycled CO_2 separated from CO_2-rich exhaust gas to produce syngas for synthetic natural gas production.
T3	Sintering flue gas sensible heat recovery	The waste heat of the cooler is recovered by using the existing technology, which is mainly focused on the recovery of the waste heat flue gas of the cooler.
T4	Sintering waste heat turbine	The waste heat of the flue gas generated by sintering is used to make the steam generated by the waste heat boiler output useful work of the steam turbine.
T5	Sinter ore apparent heat utilisation by SCR of sinter ore flue gas	The waste heat of the sintering flue gas is purified.
T6	Washable blast furnace slag sensible heat exchange	Recovery of sensible heat from blast furnace slag.
T7	Blast furnace slag sensible heat coal gasification	High-value-added products are produced using slag and sensible heat.
T8	Blast furnace gas residual pressure turbine power generation	The by product of blast furnace smelting is used to make the gas work through the turboexpander, which is converted into mechanical energy, which in turn is converted into electrical energy.

Table 3. *Cont.*

Serial Number	Technical Name	Thrust
T9	Fan power recovery turbine	A device that converts the kinetic energy of the wind into electrical energy.
T10	Gas-fired combined cycle power generation	A combined cycle in which the exhaust gas from a gas turbine is used as a heating source circulating by a steam turbine unit.
T11	Blast furnace gas boiler power generation	Low sulphur content and low dust concentration.
T12	Methanol from coke oven and blast furnace gas	In the transformation of the circular industrial chain of the coking industry, coke oven gas is used as raw material to produce methanol.
T13	Cement made from blast furnace slag	Hydration of clinker minerals, chemical reaction of slag powder with calcium hydroxide and calcium sulfate.
T14	Steel slag to cement	The hydraulic cementitious material made of open-hearth furnace and converter steel slag is the main component, and granulated blast furnace slag and gypsum are added.

This indicator is categorised by distinguishing between qualitative and quantitative indicators. Qualitative indicators include the maturity of the technology, its advancement, and its stability. When such data are counted, they are directly classified into a number of grades, and appropriate judgements are given with assessment rules according to the actual situation of the technology and personal experience. Quantitative indicators include energy saving, carbon dioxide emission reduction, resource recovery rate, fixed investment cost, operating cost, economic efficiency, static payback period, and technology promotion potential. The statistics of such technologies directly utilise the characteristic parameters of the technology. For quantitative indicators, there are two types of indicators: benefit-type indicators and cost-type indicators [38]. The parameters of the generalizability indicators are obtained through the experts' professional understanding of the technical indicators, and the corresponding evaluation is given, as shown in Table 4. Among them are benefit-type indicators, i.e., the larger the indicator data, the better the performance of the technology, such as energy saving; and cost-type indicators, i.e., the smaller the indicator data, the better the performance of the technology, such as fixed investment costs, operating costs, and payback period. The indicator data for each technology are shown in Table 5.

Table 4. Detailed rules for the evaluation of qualitative indicators of green energy-saving and low-carbon technologies in the iron and steel industry.

Index	Evaluation Details
Technology maturity	Score 9: Matured; Score 7: More mature; Score 5: Ordinary; Score 3: Not mature enough; Score 1: Immature
Technological advancement	Score 9: International advanced; Score 7: Domestic advanced; Score 5: Domestic average; Score 3: Backward in the country; Score 1: Domestic elimination
Technical stability	Score 9: Very stable; Score 7: Relatively stable; Score 5: Ordinary; Score 3: Poor; Score 1: Very unstable

Table 5. Statistics related to technical indicators [21,39,40].

Normative / Technical	Energy Saving (Kgce/t Products)	Carbon Reduction (kg/t Products)	Resource Recovery Rate %	Fixed Investment Costs (t Products)	Running Cost (t Products·a)	Economic Gain/ (t Products·a)	Static Payback Period (a)	Technology Maturity	Technological Superiority	Technical Stability	Potential for Outreach %
T1	12.65	64	36.2	130	18.89	34.64	9.25	9	7	9	80
T2	19.31	168.81	79	15	30.84	39.46	2.74	5	3	5	10
T3	8.07	20	72.97	12.23	6.93	9.18	6.44	9	5	9	40
T4	4.61	10.43	41.78	12.5	6.36	13.5	2.75	9	5	5	10
T5	11.27	108.4	32.39	1	2.43	3.45	1.98	7	5	5	10
T6	7.12	18.83	21.06	13	1.29	3.02	8.51	7	5	7	10
T7	17.02	101.2	92.2	122.9	122.74	135.14	10.91	5	5	3	1
T8	5.53	36.72	39	16.37	4.16	6.51	7.97	9	7	9	75
T9	6.35	52.16	44.8	23.08	12.37	25.85	2.71	9	7	7	50
T10	76.75	509.62	51	164.45	93.25	189.92	2.7	9	7	7	30
T11	18.25	46.72	28	18.44	8.27	59.38	1.36	9	7	9	50
T12	94.62	45.5	10.86	22.42	63.72	120.84	1.39	5	7	3	20
T13	43.3	54	95	162.56	104.42	150	4.57	9	7	9	60
T14	8.35	144	80	24.62	19.57	27.93	3.94	9	7	9	50
Type of indicator	efficiency-based	efficiency-based	efficiency-based	cost-based	cost-based	efficiency-based	cost-based	efficiency-based	efficiency-based	efficiency-based	efficiency-based

4.2. Analysis of the Assessment Process and Results

Construct a decision matrix $V = (x_{ij})_{14\times 11}$. x_{ij} denotes the value of the j-th indicator of the i-th technology, where i = 1, 2, 3, $\cdots$, 14, j = 1, 2, 3, $\cdots$, 11. The decision matrix is standardised to obtain the standardised decision matrix $V' = (x_{ij}')_{m\times n}$, and x_{ij}' is the standardised value of the jth indicator of the i-th technology, as in Equation (25). Knowing the standardised decision matrix V', $k = \frac{1}{In(14)} = 0.379$, the indicator entropy value e can be calculated, and the result is shown in Figure 3.

$$V = \begin{pmatrix} 12.65 & 64 & 36.2 & 130 & 18.89 & 34.64 & 9.25 & 9 & 7 & 9 & 80 \\ 19.31 & 168.81 & 79 & 15 & 30.84 & 39.46 & 2.74 & 5 & 3 & 5 & 10 \\ 8.07 & 20 & 72.97 & 12.23 & 6.93 & 9.18 & 6.44 & 9 & 5 & 9 & 40 \\ 4.61 & 10.43 & 41.78 & 12.5 & 6.36 & 13.5 & 2.75 & 9 & 5 & 5 & 10 \\ 11.27 & 108.4 & 32.39 & 1 & 2.43 & 3.45 & 1.98 & 7 & 5 & 5 & 10 \\ 7.12 & 18.83 & 21.06 & 13 & 1.29 & 3.02 & 8.51 & 7 & 5 & 7 & 10 \\ 17.02 & 101.2 & 92.2 & 122.9 & 122.74 & 135.14 & 10.91 & 5 & 5 & 3 & 1 \\ 5.53 & 36.72 & 39 & 16.37 & 4.16 & 6.51 & 7.97 & 9 & 7 & 9 & 75 \\ 6.35 & 52.16 & 44.8 & 23.08 & 12.37 & 25.85 & 2.71 & 9 & 7 & 7 & 50 \\ 76.75 & 509.62 & 51 & 164.45 & 93.25 & 189.92 & 2.7 & 9 & 7 & 7 & 30 \\ 18.25 & 46.72 & 28 & 18.44 & 8.27 & 59.38 & 1.36 & 9 & 7 & 9 & 50 \\ 94.62 & 45.5 & 10.86 & 22.42 & 63.72 & 120.84 & 1.39 & 5 & 7 & 3 & 20 \\ 43.3 & 54 & 95 & 162.56 & 104.42 & 150 & 4.57 & 9 & 7 & 9 & 60 \\ 8.35 & 144 & 80 & 24.62 & 19.57 & 27.93 & 3.94 & 9 & 7 & 9 & 50 \end{pmatrix} \quad (25)$$

$$V' = \begin{pmatrix} 0.089 & 0.107 & 0.301 & 0.211 & 0.855 & 0.169 & 0.174 & 1 & 1 & 1 & 1 \\ 0.163 & 0.317 & 0.810 & 0.914 & 0.757 & 0.195 & 0.855 & 0 & 0 & 0.333 & 0.114 \\ 0.038 & 0.019 & 0.738 & 0.931 & 0.954 & 0.033 & 0.468 & 1 & 0.5 & 1 & 0.494 \\ 0 & 0 & 0.367 & 0.930 & 0.958 & 0.056 & 0.854 & 1 & 0.5 & 0.333 & 0.114 \\ 0.074 & 0.196 & 0.256 & 1 & 0.991 & 0.002 & 0.935 & 0.5 & 0.5 & 0.333 & 0.114 \\ 0.028 & 0.017 & 0.121 & 0.927 & 1 & 0 & 0.251 & 0.5 & 0.5 & 0.667 & 0.114 \\ 0.138 & 0.182 & 0.967 & 0.254 & 0 & 0.706 & 0 & 0 & 0.5 & 0 & 0 \\ 0.010 & 0.053 & 0.334 & 0.906 & 0.976 & 0.019 & 0.307 & 1 & 1 & 1 & 0.937 \\ 0.019 & 0.084 & 0.403 & 0.865 & 0.909 & 0.122 & 0.859 & 1 & 1 & 0.667 & 0.620 \\ 0.801 & 1 & 0.477 & 0 & 0.243 & 1 & 0.860 & 1 & 1 & 0.667 & 0.367 \\ 0.152 & 0.073 & 0.204 & 0.893 & 0.943 & 0.302 & 1 & 1 & 1 & 1 & 0.620 \\ 1 & 0.070 & 0 & 0.869 & 0.486 & 0.630 & 0.997 & 0 & 1 & 0 & 0.241 \\ 0.430 & 0.087 & 1 & 0.012 & 0.151 & 0.786 & 0.664 & 1 & 1 & 1 & 0.747 \\ 0.042 & 0.268 & 0.822 & 0.855 & 0.850 & 0.133 & 0.730 & 1 & 1 & 1 & 0.620 \end{pmatrix} \quad (26)$$

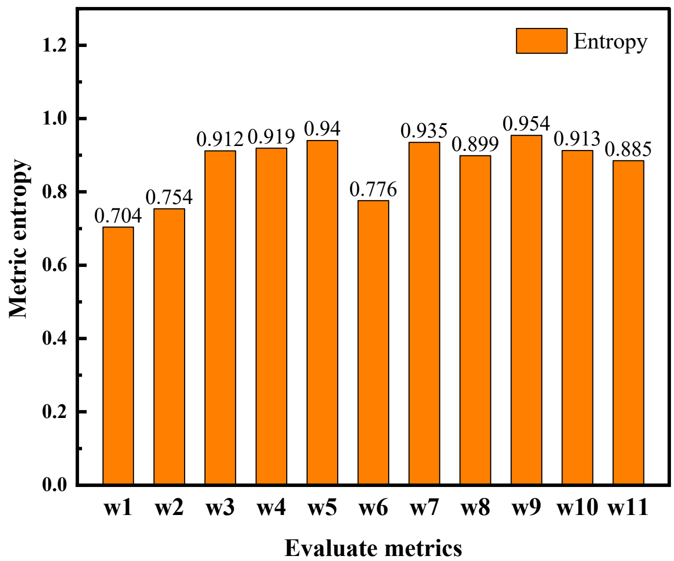

Figure 3. Entropy value of each indicator.

As can be seen from Figure 4, technical performance indicators > economic indicators > diffusion indicators. The larger the weight the value represents, the greater its influence on the comprehensive assessment results, and the smaller the weight, the smaller the influence, then the technical performance indicators have the highest proportion of influence on the assessment results when assessing the technologies selected for this study, followed by the economy, and the promotability has the smallest proportion. As can be seen from the Figure 5, the indicators of each index layer are ranked in order of weight:

$$\begin{aligned} &w_1(\text{Energy conservation}) > w_2(CO_2 \text{ emission reductions}) > w_6(\text{Economic gain}) \\ &> w_{11}(\text{Potential for technology diffusion}) > w_8(\text{Technology maturity}) \\ &> w_3(\text{Resource recovery rate}) > w_{10}(\text{Technical stability}) > w_4(\text{Fixed investment costs}) \\ &> w_7(\text{Static payback period}) > w_5(\text{Running cost}) > w_9(\text{technological superiority}) \end{aligned}$$

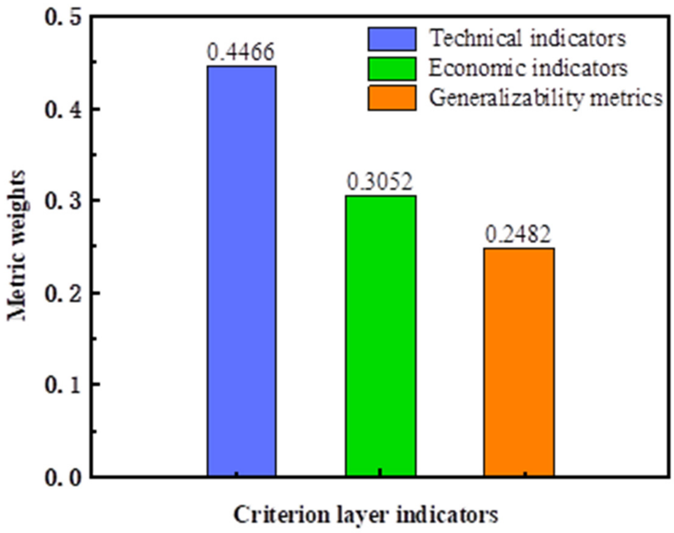

Figure 4. Comparison of the weights of indicators at the criterion layer.

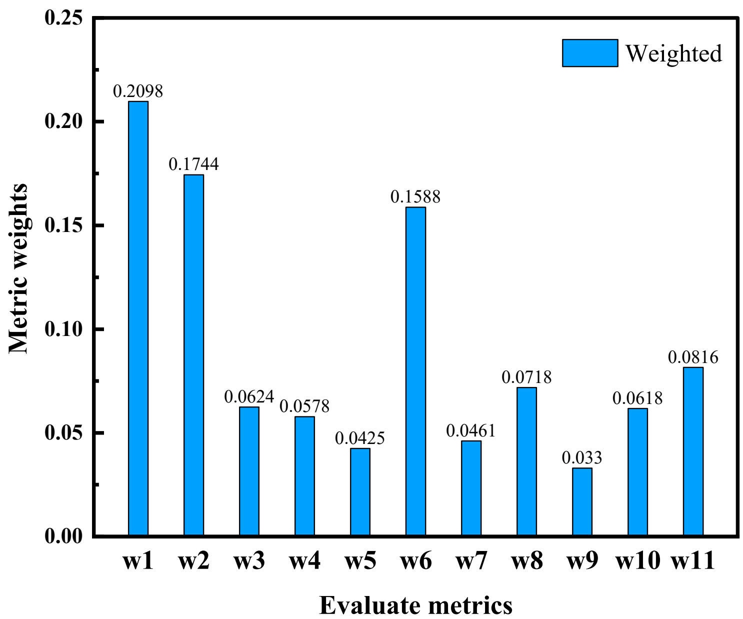

Figure 5. Comparison of indicator weights at the indicator layer.

The energy-saving indicator w_1 occupies the largest proportion, indicating that energy saving has the largest impact share in the integrated assessment of technologies. Next, the CO_2 emission reduction indicator w_2 and the economic return indicator w_6 ranked second and third, respectively. On the other hand, the technological advancement indicator

w_9, the operating cost indicator w_5, and the static payback period indicator w_7 accounted for smaller proportions, indicating that the influence of these three indicators accounted for a smaller proportion in the comprehensive assessment. The relevant data of each technology on the three indicators of energy saving, carbon dioxide emission reduction, and economic return are more different. Hence, the uncertainty of the data under these three indicators is more considerable, resulting in a smaller information entropy value. Its weight value is larger, indicating that the indicator can provide more helpful assessment information to the assessor. While differences in the data related to each technology on the three indicators of technological advancement indicator, operating cost indicator and static payback period are small, the uncertainty of the data under their indicator is small, so the information entropy value is more considerable. Its weighting value is smaller, which indicates that the indicator provides less useful assessment information to the assessor. When the parameters of the technology under an indicator are the same, the data under the indicator are customised, there is no uncertainty, the information entropy value reaches the maximum, and its weight value is zero, indicating that the indicator cannot provide the assessor with useful assessment information, i.e., under the indicator, there is no difference in the assessment technology for the assessor among all the assessment techniques, and removal of the indicator can be considered. The calculation results are consistent with the fundamental data analysis and also indicate the correctness of the calculation results.

4.3. Integrated Assessment

Multiplying the standardised evidence for decision making with the corresponding indicator weights results in a weighted standardised decision matrix $Z = V' \times W$ (Equation (27)). The positive ideal solution J^+ and negative ideal solution J^- of the weighted normalised decision matrix are shown in Table 6. As can be seen from the scores of the positive and negative ideal solutions, due to the values in the standardised decision matrix, with a maximum of 1 and a minimum of 0, after assigning values to them, the positive ideal solution for the benefit-type indicators is essentially the value of the weights of the indicators, while the negative ideal solution is 0. The opposite is true for the cost-type indicators. After obtaining the positive and negative ideal solutions of the weighted normalised decision matrix, the Euclidean distances D_i^+ and D_i^- are calculated for each technology distance from the positive and negative ideal solutions, and the results are shown in Table 7. After that, the grey correlations R_i^+ and R_i^- of each index parameter of the assessment technique with the positive and negative ideal solutions are calculated, and the results are shown in Table 8. The Euclidean distances D_i^+ and D_i^- and the grey correlations R_i^+ and R_i^- are, respectively, dimensionless, and the results are shown in Table 9. Finally, the proximity of the technique to the positive and negative ideal solutions, S_i^+ and S_i^-, are calculated by taking $\lambda = 0, \lambda = 0.5, \lambda = 1$, respectively, and the relative closeness CS_i is calculated; the results are shown in Table 10.

$$Z = \begin{pmatrix} 0.019 & 0.019 & 0.019 & 0.012 & 0.036 & 0.027 & 0.008 & 0.072 & 0.033 & 0.062 & 0.082 \\ 0.034 & 0.055 & 0.051 & 0.053 & 0.032 & 0.031 & 0.039 & 0 & 0 & 0.021 & 0.009 \\ 0.008 & 0.003 & 0.047 & 0.054 & 0.041 & 0.005 & 0.022 & 0.072 & 0.017 & 0.062 & 0.040 \\ 0 & 0 & 0.023 & 0.054 & 0.041 & 0.009 & 0.039 & 0.072 & 0.017 & 0.021 & 0.009 \\ 0.016 & 0.034 & 0.016 & 0.058 & 0.042 & 0.0004 & 0.043 & 0.036 & 0.017 & 0.021 & 0.009 \\ 0.006 & 0.003 & 0.008 & 0.054 & 0.043 & 0 & 0.012 & 0.036 & 0.017 & 0.041 & 0.009 \\ 0.029 & 0.032 & 0.060 & 0.015 & 0 & 0.112 & 0 & 0 & 0.017 & 0 & 0 \\ 0.002 & 0.009 & 0.021 & 0.052 & 0.042 & 0.003 & 0.014 & 0.072 & 0.033 & 0.062 & 0.076 \\ 0.004 & 0.015 & 0.025 & 0.050 & 0.039 & 0.019 & 0.040 & 0.072 & 0.033 & 0.041 & 0.051 \\ 0.168 & 0.174 & 0.030 & 0 & 0.010 & 0.159 & 0.040 & 0.072 & 0.033 & 0.041 & 0.030 \\ 0.032 & 0.013 & 0.012 & 0.052 & 0.040 & 0.048 & 0.046 & 0.072 & 0.033 & 0.062 & 0.051 \\ 0.210 & 0.012 & 0 & 0.050 & 0.021 & 0.100 & 0.046 & 0 & 0.033 & 0 & 0.020 \\ 0.090 & 0.015 & 0.062 & 0.001 & 0.006 & 0.125 & 0.031 & 0.072 & 0.033 & 0.062 & 0.061 \\ 0.009 & 0.047 & 0.051 & 0.049 & 0.036 & 0.021 & 0.034 & 0.072 & 0.033 & 0.062 & 0.051 \end{pmatrix} \quad (27)$$

Table 6. Positive and negative ideal solutions.

Indicator	Energy Saving w1	Carbon Dioxide Emission Reduction w2	Resource Recovery Rate w3	Fixed Investment Cost w4	Operating Cost w5	Economic Return w6
z^+	0.210	0.174	0.062	0	0	0.159
z^-	0	0	0	0.058	0.043	0
Indicator	**Static payback period w7**	**Technology maturity w8**	**Technology advancement w9**	**Technology stability w10**	**Technology promotion potential w11**	
z^+	0	0.072	0.033	0.062	0.082	
z^-	0.046	0	0	0	0	

Table 7. Euclidean distances.

Technical	T1	T2	T3	T4	T5	T6	T7	T8
D_i^+	0.286	0.283	0.317	0.334	0.316	0.334	0.267	0.318
D_i^-	0.149	0.092	0.117	0.081	0.061	0.068	0.155	0.132
Technical	**T9**	**T10**	**T11**	**T12**	**T13**	**T14**		
D_i^+	0.309	0.087	0.283	0.227	0.205	0.286		
D_i^-	0.109	0.313	0.128	0.237	0.215	0.135		

Table 8. Grey correlation.

Technical	T1	T2	T3	T4	T5	T6	T7
R_i^+	0.286	0.283	0.317	0.334	0.316	0.334	0.267
R_i^-	0.149	0.092	0.117	0.081	0.061	0.068	0.155
Technical	**T8**	**T9**	**T10**	**T11**	**T12**	**T13**	**T14**
R_i^+	0.318	0.309	0.087	0.283	0.227	0.205	0.286
R_i^-	0.132	0.109	0.313	0.128	0.237	0.215	0.135

Table 9. Dimensionless quantification.

Technical	${D_i^+}^*$	${D_i^-}^*$	${R_i^+}^*$	${R_i^-}^*$
T1	0.854	0.474	0.881	0.840
T2	0.846	0.293	0.729	0.957
T3	0.950	0.374	0.809	0.926
T4	1	0.260	0.741	1
T5	0.946	0.196	0.713	0.998
T6	0.998	0.218	0.736	0.997
T7	0.799	0.496	0.831	0.879
T8	0.951	0.422	0.838	0.912
T9	0.925	0.348	0.794	0.922
T10	0.260	1	1	0.725
T11	0.846	0.408	0.810	0.896
T12	0.679	0.757	0.w802	0.925
T13	0.615	0.688	0.953	0.749
T14	0.855	0.431	0.840	0.868

Table 10. Comparison of assessment result.

Preference Factor	λ=0			λ=0.5			λ=1		
technical	S_i^+	S_i^-	CS_i	S_i^+	S_i^-	CS_i	S_i^+	S_i^-	CS_i
T1	0.881	0.840	0.512	0.678	0.847	0.444	0.474	0.854	0.357
T2	0.729	0.957	0.432	0.511	0.902	0.362	0.293	0.846	0.257
T3	0.809	0.926	0.466	0.592	0.938	0.387	0.374	0.950	0.283
T4	0.741	1	0.426	0.500	1	0.334	0.260	1	0.206
T5	0.713	0.999	0.417	0.454	0.972	0.318	0.196	0.947	0.171
T6	0.736	0.998	0.425	0.477	0.997	0.324	0.218	0.998	0.179
T7	0.831	0.879	0.486	0.663	0.839	0.442	0.496	0.799	0.383
T8	0.838	0.912	0.479	0.630	0.932	0.403	0.422	0.951	0.307
T9	0.795	0.922	0.463	0.571	0.924	0.382	0.348	0.925	0.273
T10	1	0.725	0.580	1	0.493	0.670	1	0.260	0.794
T11	0.810	0.896	0.475	0.609	0.871	0.411	0.408	0.846	0.325
T12	0.802	0.925	0.465	0.780	0.802	0.493	0.757	0.679	0.527
T13	0.953	0.749	0.560	0.820	0.682	0.546	0.688	0.615	0.528
T14	0.840	0.868	0.492	0.636	0.861	0.425	0.431	0.855	0.335
sorted	T10 > T13 > T1 > T14 > T7 > T8 > T11 > T3 > T12 > T9 > T2 > T4 > T6 > T5			T10 > T13 > T12 > T1 > T7 > T14 > T11 > T8 > T3 > T9 > T2 > T4 > T6 > T5			T10 > T13 > T12 > T7 > T1 > T14 > T11 > T8 > T3 > T9 > T2 > T4 > T6 > T5		

When λ = 0, this is when only grey correlation analysis is considered to evaluate the technology. When λ = 1, this is when only TOPSIS is considered to evaluate the technologies, and when λ = 0.5, a combination of the two evaluation methods is combined. The value of λ depends on the evaluator's preference in terms of the similarity of the location and shape of the technological parameter curves in terms of their relation to the positive and negative ideal solutions (how much preference the evaluator has for the Euclidean distance and the grey correlation). It can be concluded from Figure 6 that, regardless of the value of λ, the combined assessment of technologies 10 and 13 outperforms the other technologies. Although there are some technologies whose evaluation results vary with the value of λ, the evaluation results of the combination of the two methods are basically the same as the ranking of the traditional TOPSIS and grey correlation methods. However, it solves the shortcomings of the grey correlation method's unidirectional evaluation and the problem of not being able to efficiently rank the two evaluated objects due to the same relative proximity of the two evaluated objects as they appear in the TOPSIS method.

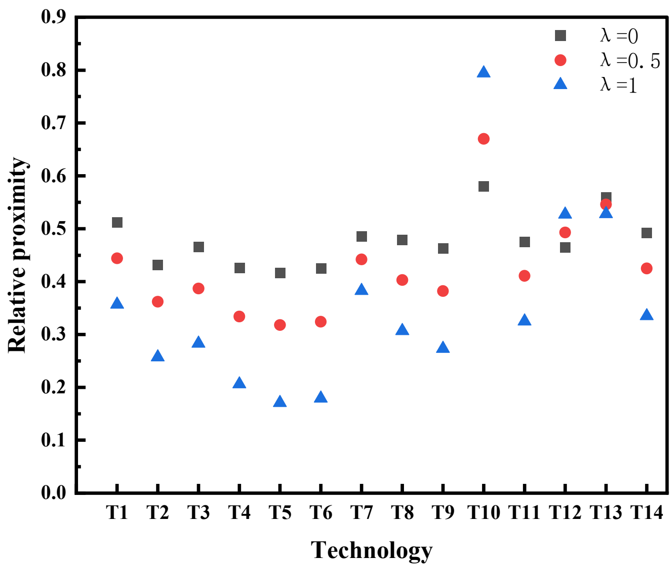

Figure 6. Comparison of relative closeness of each technology with different preference.

4.4. Technology Preference Assessment

When assessing technologies, it is also essential to consider the results of the assessment under different preference types. In this study, three types of technology preferences are considered: corporate preference, environmental preference, and diffusion and application preference, and their preferences are assessed.

(1) Enterprise preference

When the assessment subject is an enterprise user, the enterprise user focuses more on the technical economy when conducting technology assessment and selection. When assessing enterprise preference, the four indicators of fixed investment cost, operation cost, economic return, and static payback period are selected as assessment indicators. The results of the enterprise preference assessment are shown below.

As can be seen from Figure 7, when assessing the firm preference decision, the assessment results of each technique in order of magnitude are T10 > T7 > T13 > T12 > T1 > T11 > T2 > T6 > T14 > T8 > T3 > T9 > T4 > T5. Technique 10 is closest to the positive ideal solution, furthest from the negative ideal solution, and has the highest correlation with the most optimal solution and the highest relative closeness, i.e., Technique 10 is optimal among the evaluated technologies. Although Technology 10 does not perform as well as the other technologies in the two indicators of fixed investment cost and operation cost, its performance in the two indicators of economic return and static payback period, which account for a large proportion of the weight, is much better than that of the other technologies. Its final evaluation result is optimal and ranks first.

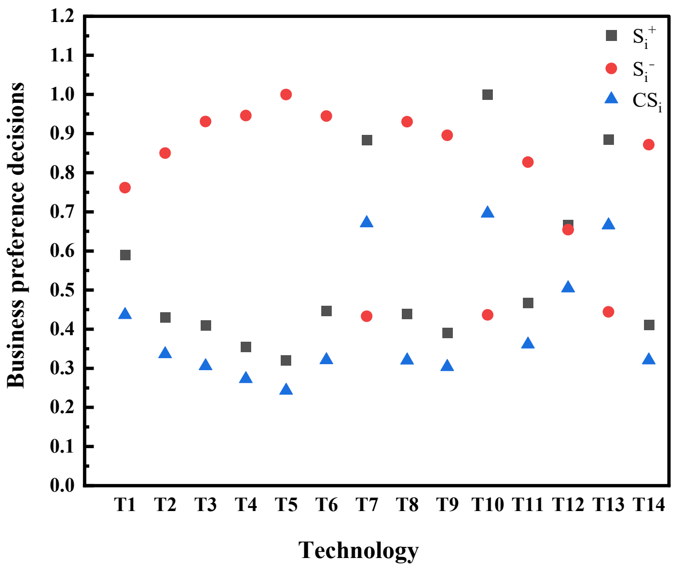

Figure 7. Results of the assessment of firms' preference decisions.

(2) Environmental preference

When the subject of evaluation is environmental preference, the evaluation at this point focuses more on environmental protection and technical performance is the focus of the evaluation.When the subject of evaluation is the environmental preference, more emphasis is placed on environmental protection and the technical performance of the technology is the focus of the evaluation. In the evaluation of environmental preference decision making, the three indicators of energy saving, CO_2 emission reduction, and resource recovery rate were selected as evaluation indicators. The results of the environmental preference assessment are shown below.

As can be seen from Figure 8, when the environmental preference decision making is evaluated, the evaluation results of each technique in order of magnitude are T10 > T12 > T13 > T2 > T7 > T14 > T3 > T5 > T11 > T1 > T9 > T8 > T4 > T6. Technique 10 is the closest to the positive ideal solution, and the furthest from the negative ideal solution. It has the highest correlation with the most optimal solution, and the highest relative closeness, i.e., Technique 10 in the environmental preference decision making is optimal among the evaluated techniques. Technology 10 outperforms the other technologies in both energy saving and CO_2 emission reduction, two indicators with considerable weighting.

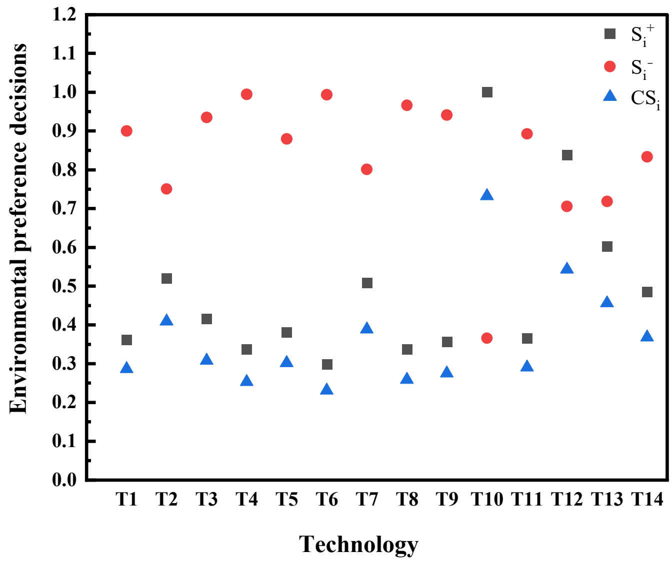

Figure 8. Results of the environmental preference decision−making assessment.

(3) Promotion and application preference

When the subject of evaluation is a technology promotion and application preference maker, the evaluation will focus more on the promotion and application of the technology, and the technology will be evaluated with a focus on the promotability of the technology. When evaluating the decision making of the promotion and application preference, the maturity of the technology, the advancement of the technology, and the promotion potential of the technology (the expected penetration rate) are selected as the evaluation indexes,

The four indicators of the technology's stability are taken as the assessment indicators. The results of the diffusion preference assessment are shown in Figure 9 below.

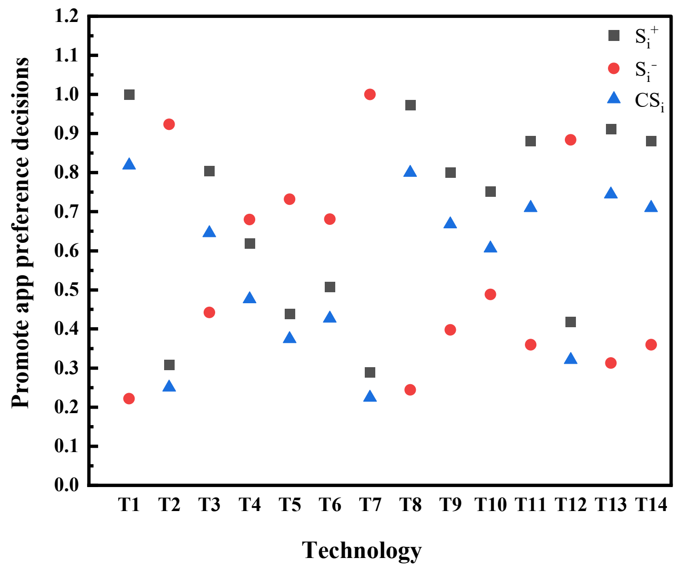

Figure 9. Results of the extension application preference decision evaluation.

It can be seen that when the promotion application preference decision is evaluated, the evaluation results of each technique in order of magnitude are T1 > T8 > T13 > T14 =

T11 > T9 > T3 > T10 > T4 > T6 > T5 > T12 > T2 > T7. Technology 1 is closest to the positive ideal solution, farthest from the negative ideal solution, and has the highest correlation and relative closeness to the ideal solution, i.e., the evaluation results of Technology 1 in promoting application preference decision making are optimal among the evaluation techniques. Comparisons can be made under different decision preferences based on the combined assessment results of each assessment technique; see Figure 10.

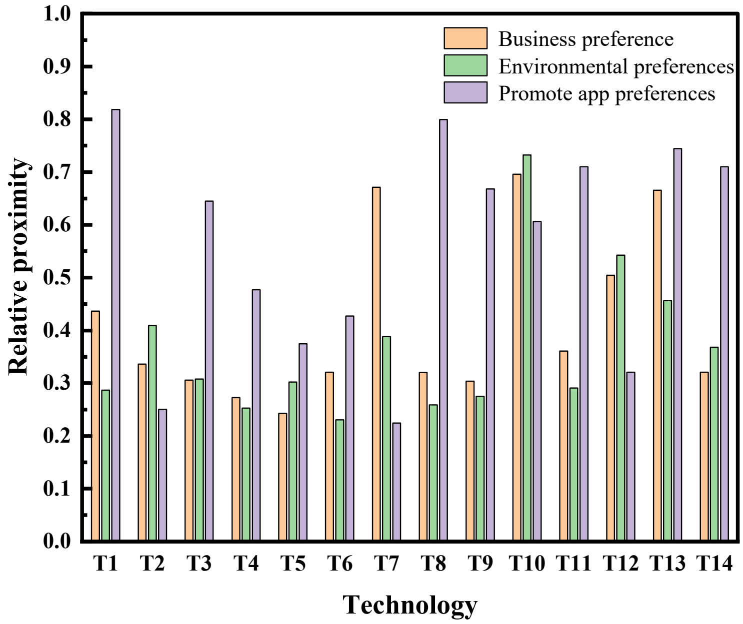

Figure 10. Comparison of relative proximity across technologies with different decision preferences.

As can be seen from Figure 10, the vertical coordinates represent the relative closeness of the technologies under the three preference types. Most of the relative closeness of the technologies under the diffusion and application preference is greater than the environmental and enterprise preferences. Most of the relative closeness of the technologies under the enterprise preference is better than that of the environmental preference. A higher relative closeness indicates that its distance from the most desirable solution is smaller and its performance is better. Due to the environmental preference, enterprise preference and diffusion, and application preference, the technical performance index, economic index, and diffusion index are selected as the respective assessment indexes. The results show that, on the one hand, the gap between the selected technologies in the diffusivity indicator is smaller than the other two guideline-level indicators, and the gap between the technologies in the economic indicator is smaller than the technology performance indicator. Alternatively, the environmental performance, i.e., the technological performance, is the main obstacle to improving the score of the comprehensive assessment of the technologies, followed by the economics of the technologies. Therefore, the main direction of technology development is to improve the energy savingness, CO_2 reduction, and resource recovery rate of the technology.

4.5. Uncertainty Analysis

Due to various uncertainties in the technical performance, such as measurement bias, changes in the application environment, and fluctuations in the technical performance itself, the collected technical parameters may be different from the real parameters. Therefore, it is necessary to analyse the influence of the uncertainty of technical parameters on the calculation results [41].

The upper and lower boundaries of the technical parameters are set as the fluctuation range of the technical parameters. Then, 10,000 samples are sampled using the Latin hypercubic sampling method, and these samples are repeatedly calculated [18,19]. The calculation results are shown in Figures 11 and 12 below [42].

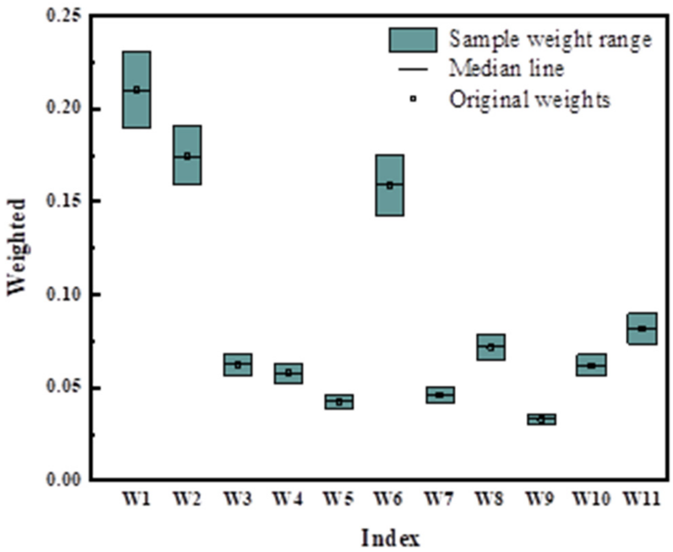

Figure 11. Indicator weight range of Latin hypercube samples.

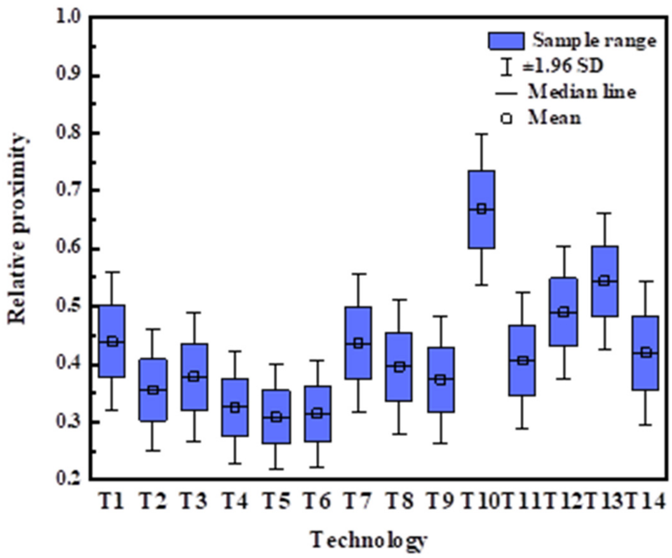

Figure 12. Relative closeness range of Latin hypercube sampling techniques.

As can be seen from Figure 11, under the original technical parameters, the weight of assessment indicator W1 is 0.2098, while the sample weight of the indicator ranges from 0.1898 to 0.2303. The rest of the assessment indicators are the same as W1, and the sample weights of the indicators are concentrated in a specific range. Comparing the range of indicator weights under the original parameters with the range of indicator weights under the sample parameters, we can see that the sample weights fluctuate within a range of approximately 10% up and down, centred on the original weights. Therefore, the uncertainty of the technical parameters has little effect on the results of the indicator weights. As shown in Figure 12, by comparing the technical relative closeness under the original parameters with the technical relative closeness of the random samples, we can find that the original relative closeness of most of the selected techniques is greater than the median of the random results, and the sample relative closeness fluctuates within a range of more than 10% centred on the original relative closeness. This also demonstrates the need for uncertainty analysis. The fluctuation of technical parameters will affect not only the performance of the technology itself but also the indicator weights and the comprehensive evaluation results of the technology. However, the impact on the indicator weights is small, and the impact on the comprehensive evaluation results of the technology is considerable. Therefore, when carrying out the comprehensive assessment of technologies, try to select technical parameters with smaller errors for assessment calculations, or, when decision makers make decisions, combine the original calculation results with uncertainties to make choices.

5. Conclusions

The development status and technology evaluation status of green and low-carbon technology in China's iron and steel industry are discussed in this study. A comprehensive evaluation model is established by combining and optimising the entropy weight method, grey correlation analysis method, and TOPSIS method. The Latin hypercube sampling and evaluation model is introduced to analyse the uncertainty of technical parameters. It is expected that by constructing a comprehensive evaluation method system of green energy-saving and low-carbon technologies, the relevant technologies will be evaluated, the implementation and implementation of energy-saving and low-carbon work in China's iron and steel industry will be promoted, and the release and update of the national or industry advanced green, energy-saving, and low-carbon technology catalogue and the elimination and update of energy-saving and low-carbon technologies of various iron and steel enterprises will be provided with a scientific and reasonable basis and reference. The following conclusions were drawn:

(1) By constructing a top-down, three-level structure of the comprehensive evaluation index system of green and low-carbon technologies in the iron and steel industry, it was found that technical performance indicators had the most significant impact on the comprehensive assessment results, the second was the economic index, and the least impact was from the promotion index. The weights of the eleven index layers were calculated and compared, and the energy saving index w_1 had the greatest impact on the comprehensive evaluation of technology. The w_2 of CO_2 emission reduction indicators and economic benefit indicators also had a considerable impact on w_6, and the calculation results were consistent with fundamental data analysis.

(2) The comprehensive assessment of green and low-carbon technologies in the iron and steel industry found that under different preference coefficients, Technology 10 was the closest to the positive ideal solution, the farthest from the negative ideal solution, and had the highest correlation with the ideal solution and the highest relative closeness, with the best comprehensive assessment result among the assessed technologies among a number of assessment indicators. The technical parameters of Technology 10 in several indicators with large weights, such as energy saving, carbon dioxide emission reduction, and economic benefits, were better than other technical indicator parameters, so the final comprehensive assessment results were optimal. That is, when $\lambda = 0, 0.5, 1$, CS_i was 0.580, 0.670, and 0.794, respectively.

(3) By evaluating the three technology preferences in the steel industry, it was concluded that Technology 10 was closest to the positive ideal solution and furthest from the negative ideal solution. It had the highest correlation and relative closeness to the most ideal solution, and the assessment result in the enterprise preference decision was optimal among the evaluated technologies. By studying environmental preferences, it was concluded that Technology 10 outperformed the other technologies in both energy savings and CO_2 emission reduction, two indicators with considerable weighting, and had the best final assessment result. However, its performance in resource recovery rate was average. Focusing on the diffusibility of the technology to assess the technology, it was found that technology maturity, technological sophistication, technology diffusion potential (expected penetration rate), and technological stability all performed optimally on the four indicators. Technology 1 had the best assessment results among the assessed technologies in terms of diffusion and application

preference decision making. The main influencing factor affecting the comprehensive level of the technology was the performance of the technology, followed by the economic benefits of the technology; at the same time, the results of the uncertainty analysis showed that fluctuations in the technical parameters will not only affect the performance of the technology itself, but will also affect the indicator weights and the comprehensive evaluation results of the technology, but have a smaller impact on the indicator weights and a more considerable impact on the comprehensive evaluation results of the technology.

The methodology for assessing the iron and steel industry in this study could subsequently be extended to other areas. Consideration needs to be given to the characteristics of different industries and environments, taking into account the environmental, social, and economic factors in the field. Differences in production processes, resource utilisation, and emission characteristics in the target areas should be clarified, the role of the technology assessment method in promoting rational resource utilisation and recycling should be highlighted in the promotion process, demonstration projects should be set up to show cases where the technology assessment method has been successfully applied to the iron and steel industry in other fields, and a step-by-step strategy should be adopted, starting with small-scale pilot projects and gradually expanding to wider applications.

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