Material Selection in Green Design: A Method Combining DEA and TOPSIS

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Abstract: In order to rationalize material selection in green design, this study presents an attempt to combine the methods of generalized Data Envelopment Analysis (DEA) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). By establishing a green material index system, the G-CCR model of generalized DEA was first used to select effective materials from the candidate samples, and TOPSIS was then used to sort the effective suppliers. The combined DEA/TOPSIS model helps to rank the materials by quality, and then integrate both the merits of G-CCR model and the key characteristics of TOPSIS. The results of this study showed that the combined DEA/TOPSIS model can screen and exclude materials with poor performance when selecting wood for the furniture industry. Therefore, the combined model that is presented in this study provides a more rational and evidentiary basis for material selection in green design.

Keywords: material selection; green design; DEA; TOPSIS

1. Introduction

Over the past centuries, industrial design has not only modernized our lifestyle and living environment, but it has also accelerated the consumption of resources and caused great damage to the world’s ecological balance. The excessive commercialization of industrial design has made the field a major driving force of unrestrained human consumption. “Planned obsolescence” is the extreme manifestation of this. This being the case, designers have had to rethink their roles and responsibilities within the industrial sector, and green design has emerged as a consequence of this. Green design is a new trend combining traditional design with the essential relationship between humanity and nature, is guided by ideas of sustainable development and the natural circular economy, and it is aimed at realizing the sustainable utilization of natural resources, the sustainable growth of green wealth, and the constant improvement of both the ecological environment and quality of life. The main idea of green design is to achieve the expected quality level with longer service life and reduced resource consumption [1]. Therefore, it is sometimes called “design for the future”. The concept of green development has been unprecedentedly highlighted in both China’s 13th Five-year Plan and the EU’s Europe 2020 Strategy for its next decade of economic development. In order to realize balance between humanity and nature and within different segments of humanity itself, it is particularly significant to integrate the concepts of green design into the fields of technology, machinery, landscaping, architecture, and other key fields. The use of green industrial design in the manufacturing industry serves as the foundation of cleaner production and the basis for expanding green design concepts into various fields (for example, environmentally friendly urban design will be much less meaningful if non-environmentally friendly products are used to achieve it), and the source of numerous relevant theory and technology. To that end, this paper focuses on exploring material selection in green design.

Material selection has always been a hot topic in green design research, and it is usually the main determinant factor of the operability and practical significance of green
design. Goals, such as improving product life cycle (including reusability and recyclability), maintaining or increasing product quality, and reducing the quantity and toxicity of waste generated during manufacturing (to reduce the adverse impact of products on the environment and human health) can all be, at least partly, realized through the careful selection of raw materials [1]. Earlier material selection methods have mostly been cost-oriented. With the increasing public concern for sustainable development, material selection is required to follow the principles of green design, to improve product quality, and streamline production processes, thereby relieving adverse impacts on the environment and human health [2]. It is easy to understand that material cost controls are crucial in the cost management of all industries. For example, material costs in the construction industry are often 50% higher than the totals of all other costs [3]. Ensuring the quality of the supplied materials and the stability of the supply is essential for controlling production processes and ensuring the quality of final products [4]. When selecting materials for green design, it is necessary to use rational and evidentiary methods to identify and evaluate material properties, so as to select the most competitive and conforming green materials [5].

In this paper, the screening function of the DEA model was used to reduce the impact of the changed decision environment on the decision-making results, after which the ranking function of TOPSIS was used to identify the optimal results. In other words, a new set of green material selection methods was created by combining DEA and TOPSIS in order to better serve the production practices of green design. This method weakens the negative impact of the reversed order in TOPSIS on the decision-making process by deploying the screening function of DEA, which improves the efficiency of utilizing existing information within the selection and evaluation process, and it improves the objectivity and applicability of the selection and evaluation processes.

2. Literature Review
2.1. Two Methods of Material Selection

One method of material selection is to apply life cycle theory. Some of the studies relevant to this point include incorporating life cycle assessment into material selection and making it the basis of environmental impact assessment. Within the construction industry, this theory can be used to evaluate the impact of construction activities on the environment [6]. Within the manufacturing industry, this metric can be applied to measure the impact of material acquisition, processing, and final product recycling on the environment [7]. However, within actual practice, it is difficult for engineering designers to achieve accurate life cycle assessment, as restricted by the uneven quality of data, hard-to-divide temporal cycles, and the need for varied measurement methods across different product life cycles [8].

Another method is to use multi-attribute decision-making for the material performance index. By sorting or scoring (on a prioritized basis) the filtered supply schemes after screening material priorities across different scenarios, the optimal material selection scheme will be the scenario that is ultimately selected [9,10]. At present, increasing amounts of multi-attribute decision-making and evaluation models are applied to material selection that meets different needs [11,12]. Common methods that are used in this field include AHP, Fuzzy, ELECTER, DEA, VIKOR, Grey, and TOPSIS [13–16]. These methods are applicable to different scenarios because of their own characteristics, advantages, and disadvantages. The AHP method is the easiest to use to hierarchically combine the weights of various indexes [17]. With its simple operation process and reduction in dimensions, it is suitable for most simple evaluation scenarios [18]. This simplicity also means that it is not effective for use in complex scenarios that have more attributes to be evaluated [19,20], while the multi-dimensional filtering results in serious information distortion [21]. Most scholars’ modeling of attribute decision-making in difficult-to-quantify circumstances is usually based on Fuzzy [22,23]. The application value of such methods is generally limited by the evaluation of subjective attributes. In more extreme conditions, the large input volume may reduce the decision to a single attribute [24]. In direct contrast to Fuzzy is the
ELECTER method, which cannot effectively process vague information, but requires less input [25,26]. The DEA method can directly process original data, has been gradually applied to multi-attribute decision-making [27,28]. The efficiency results are only transmitted to the effective entities [29], and the strict limit on the number of decision-making units [30] are the major obstacles to its further expansion and utilization. The TOPSIS method can use known information, with fewer limits on data restriction or data distribution [31–33]. This method only provides a sorting order, and it shows hardly any absolute difference between the advantages and disadvantages of different schemes [34]. In order to solve these problems, the VIKOR method has been introduced into the decision-making model. It is less applicable to decision-making that is based on scarce and fuzzy information [35], but it can measure the gap between each option and present the ideal solutions [36,37]. In decision-making based on scarce and fuzzy information, Grey is often used instead of VIKOR [38,39]. The disadvantage of this method is that its increased sensitivity to weight weakens the robustness of its analysis results [40]. A decision-making model combining TOPSIS with other methods is often used to overcome the shortcomings of different models, to expand their application and improve the credibility of the results [41–43]. However, few of these studies explored solutions to the reversed order and rank that are produced by this model [44].

2.2. G-DEA and TOPSIS

2.2.1. DEA Method

The economic interpretation of the DEA model is mainly based on the production function theory of economics, modeling the production function using the effective production frontier. As a result, the efficiency value that it produces reflects the information of the evaluated entity relative to top-producing entities [45]. However, in reality, many problems with a given model’s evaluation reference set go beyond this. This study intended to use a DEA method with more extensive methodology that retains all of the properties of the traditional version [46], and it can perform evaluations according to any given reference set, with a generalized DEA (G-DEA). The breakthrough of G-DEA in the sample set provides increased applicability (standard DEA generally requires a given numerical relationship between the number of indexes and the number of decision-making units: the number of decision-making units (DMUs) must be greater than or equal to four times of the sum of the number of output indexes and the number of input indexes [45]). G-DEA can provide the information expected by the decision-makers via independent selection of the reference set, and it can perform evaluations based on different reference sets.

The comprehensive G-DEA model is referred to as Sam-CCWY, and the G-BCC or G-CCR model can be obtained by taking 0 or 1 as the parameters $\sigma_1, \sigma_2, \sigma_3$. In this study, the G-CCR model is used, and Table 1 shows the output and input variables for the model.

Table 1. Economic and Environmental Indexes for Different Green Materials.

| Category | Index          |
|----------|----------------|
| Input    | Direct cost    |
|          | Manufacturing cost |
|          | Environmental cost |
| Output   | Product performance |

G-CCR can be expressed as:

$$\begin{align*}
\text{Max } V p(d) &= \mu^T yp \\
\text{s.t. } &\omega^T x_j - \mu^T y_j \geq 0, \ j = 1, \cdots, \pi \\
&\omega^T x_p = 1 \\
&\omega \geq 0, \mu \geq 0
\end{align*}$$

(1)
where \( V_p(d) \) is the efficiency value, \( * V_p(d) \) means efficiency, \( x_p = (x_{1p}, x_{2p}, \ldots, x_{mp})^T \) represents the input index value of decision-making unit \( p \); \( y_p = (y_{1p}, y_{2p}, \ldots, y_{sp})^T \) represents the output index value of decision-making unit \( p \); \( \bar{x}_j = (\bar{x}_{1j}, \bar{x}_{2j}, \ldots, \bar{x}_{mj})^T \) represents the input index value of sample \( j \); \( \bar{y}_j = (\bar{y}_{1j}, \bar{y}_{2j}, \ldots, \bar{y}_{sj})^T \) represents the output index value of sample \( j \); \( \omega = (\omega_1, \omega_2, \ldots, \omega_m)^T \) represents the weight of the input indexes; \( \mu = (\mu_1, \mu_2, \ldots, \mu_s)^T \) represents the weight of the output indexes; and, \( d \) is the shift factor of a positive number. The effective judgment conditions are as follows: \( V(d) = 1 \), or \( V(d) > 1 \). \( \omega_0 > 0, \mu_0 > 0 \) when \( d = 1 \), the weak efficiency of G-CCR(1) is recorded as G-DEA weak efficiency, and the G-CCR(1) efficiency is recorded as the G-DEA efficiency.

The CCR model can be used to evaluate multiple suppliers based on different indexes, in order to select the most effective suppliers based on the samples and eliminate the ineffective ones, thereby providing an objective decision-making basis for decision makers. However, CCR can only show the relative effectiveness of the decision-making units, and it cannot rank all decision-making units. Sometimes there may be multiple relatively effective decision-making units, so after employing this method, other analytical tools may be needed to complete the sorting of the decision-making units [44,47].

2.2.2. TOPSIS Method

TOPSIS is a multi-attribute decision-making method that was proposed by Hwang and Yoon in 1981. It ranks the schemes to be evaluated according to their relative similarity to the ideal solution and evaluates their relative merits. Indeed, TOPSIS stands for Technique for Order Preference by Similarity to Ideal Solution, and it is commonly and effectively used in multi-attribute decision-making analysis [48].

The similarity in this methodology is the weighted Euclidean distance. The ideal optimal solution is an assumed best solution, with all of the index values ranking best among the alternative schemes. The worst solution relative to the ideal scenarios is an assumed worst solution, with all index values representing the worst level among the alternative schemes. This method calculates the sum of the Euclidean distances, \( d_i^+, d_i^- \) between each scheme, along with the optimal and worst schemes, and then converts them to relative proximity with \( C_i = \frac{d_i^-}{d_i^+ + d_i^-} \). Based on the principle that greater relative proximity results in increased similarity, all of the schemes can be ranked and the optimal scheme can be determined.

The general steps of the TOPSIS method are as follows:

1. Set the evaluation index set and standardize the indexes
2. When there are \( n \) indexes and \( m \) schemes, the evaluation matrix is as follows:

\[
D = \begin{bmatrix}
    x_{11} & x_{12} & \cdots & x_{1n} \\
    x_{21} & x_{22} & \cdots & x_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]

The benefit indexes are standardized by \( a_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_k x_{kj}}} \) and the cost indexes are standardized by \( a_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_k x_{kj}}} \), thereby obtaining the standardized evaluation matrix \( A \), which is standardized by \( r_{ij} = \frac{a_{ij}}{\sqrt{\sum_k a_{kj}}} \) to obtain matrix \( R \).
(2) Establish the weighted evaluation matrix \( V \) with weight vector \( W = (w_1, w_2, \ldots, w_m) \) and determine the weight using the entropy weight method.

\[
w_j = \frac{h_j}{\sum h_j} \left( h_j = 1 - e_j, e_j = -\frac{1}{\ln m} \sum r_{ij} \ln r_{ij} \right),
\]

where \( e \) is the entropy and \( 0 \leq e_j \leq 1 \).

\[
V = R \times W
\]

(3) Determine the ideal optimal and worst solutions

Ideal optimal solution: 
\[
A^+ = \{ \max v_{ij} | i = 1, 2, \ldots, m \} = \{ v_1^+, v_2^+, \ldots, v_n^+ \};
\]

Ideal worst solution: 
\[
A^- = \{ \min v_{ij} | i = 1, 2, \ldots, m \} = \{ v_1^-, v_2^-, \ldots, v_n^- \}.
\]

(4) Calculate the comprehensive distance and sort the solutions according to their relative proximity.

The distance from scheme \( i \) to the ideal optimal solution is 
\[
* d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2},
\]

\( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \). The distance from scheme \( i \) to the ideal worst solution is 
\[
* d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2},
\]

\( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \). The relative proximity was 
\[
* C_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \ldots, m.
\]

TOPSIS’ advantages include flexible application, simple mathematical calculation methods, and objectivity of results. However, TOPSIS and other ideal point decision-making methods will produce a reversed order due to the relativity of the ideal points used in decision-making \([31,49]\). Therefore, it is necessary to choose a screening method to lower the impact of this reversed order on decision-making.

3. Combined DEA/TOPSIS Method

When using the TOPSIS model to solve multi-attribute decision-making problems, the increase or decrease in decision-making schemes may produce a different decision-making environment that makes it possible to reverse the order of decision-making results. In view of this, schemes with lower ranking and poor index values are first excluded after an initial screening of decision-making schemes, which makes the decision-making environment more rational and avoiding the influence of any undesired schemes on final decision-making.

TOPSIS can sort all reviewed schemes, but it must screen these schemes before sorting. G-CCR can screen the schemes as well, but they are not as satisfactory as TOPSIS in terms of total ordering. Therefore, the combination of G-CCR and TOPSIS can weaken the impact of TOPSIS’ reversed order on decision-making processes, and it can also provide comprehensive ordering of optimal schemes, thereby providing a basis for decision-making. This method is named the combined G-DEA/TOPSIS model, as it screens the decision-making schemes using the G-CCR model (i.e., it screens the decision-making units in G-CCR, as represented by screening of the candidate suppliers in supplier selection), and then sorts the schemes via TOPSIS.

Specifically, the combined DEA/TOPSIS method can be implemented in green design while using the following four steps:

1. Step one: determine the evaluation index system;
2. Step two: score the materials;
3. Step three: use G-CCR screening to screen for improved samples with greater efficiency; and,
4. Step four: calculate the order using TOPSIS;
4. Example of Wood Selection for Furniture

With the rapid expansion of the furniture manufacturing industry, the consequent pollution, environmental hazards, and natural resource consumption are also increasing. The furniture industry’s transition to green manufacturing is of great importance for sustainable global development. Some developed countries have taken actions to reduce the environmental damage that is caused by furniture enterprises [50]. A feasible means of this is to transform the furniture manufacturing industry through green design [51]. Combined with the above, this study considered the green potential of the industry from the perspective of material selection in green furniture design.

4.1. Step One: Evaluation Index System

Based on the combination of DEA and TOPSIS, this study limited the number of indexes used to establish the index system that is based on the possible sample environment. Specifically, based on the material selection decision-making used in green design scenarios, the economic and environmental indexes used to evaluate the alternative green materials are listed in the table below, while the input and output items, respectively, determine the economic and environmental cost and the overall output of the materials [25, 33, 52].

Profits generally drive the production activities of most manufacturers, because the survival and financial status of any given enterprise usually determines their business operations [53, 54]. On the premise of considering the economic aspects, enterprise decision-making must be guided by both market demand and the value to society based on the principles of environmental protection [55, 56], thereby leading to more sustainable production processes, preparation processes, and material selection schemes [57, 58]. The economic indexes of direct cost, manufacturing cost, manufacturing defects, and sales profit were considered herein for designing basic indexes. Given the increasing focus on the inherent conflict between economic growth and environmental protection, the best strategy for achieving sustainable development is to improve cleaner production [59–61]. In order to alleviate the adverse impact of products on both human health and the environment as a whole, the careful selection of materials and material integration schemes serve as vital initial steps for realizing cleaner production [62].

The design of the index system shown in Table 1 is thus produced and applied to the selection of wood in furniture manufacturing. A recent study has determined the criteria for selecting sustainable materials based on ease of processing, economic efficiency, and environmental friendliness [63]. The ease of processing mainly depends on need for additional processing steps, compatibility with other materials. Economic efficiency reflects the cost of purchasing, processing, and transportation. Environmental friendliness covers pollution, resource utilization, energy consumption, and recyclability. However, all material selection decisions depend on the established project objectives, priorities, limitations, and constraints. As a result, the priorities and selection of key environmental and economic indexes are vital to the decision-making of major stakeholders regarding specific projects. In most studies, multi-criteria decision-making models are used to evaluate the selection criteria of sustainable materials [6–8]. Life cycle environmental impact and costs were prioritized in the sustainability assessments of these such studies. However, the environmental and cost savings of green materials cannot be directly compared quantitatively. In this study, a new index system was designed for scoring, as shown in Table 2.
Table 2. Economic and Environmental Indexes for Different Materials.

| Index                    | Characterization Method | Source                                                                 |
|--------------------------|-------------------------|------------------------------------------------------------------------|
| Direct cost              | Material price          | In terms of the development of China’s green furniture manufacturing industry, increasing numbers of manufacturers are shifting closer toward social responsibility and environmental protection policies, and are doing so to abide by legal requirements and administrative orders and leave a favorable impression on their consumers. Nevertheless, it is transparently clear that low-cost materials are still favored, and economy is often prioritized when selecting materials [62]. |
| Manufacturing cost       | Processing cost         | Similar to other material selection criteria, wood’s processing cost is also one of its key factors. Different kinds of wood processed in the same way may result in various degrees of purchaser satisfaction. This is mainly caused by affinity to coatings, textures, required design space based on hardness, and other attributes of different woods [64]. |
| Environmental cost       | Regeneration period     | In terms of shipping distance, the main consideration is generally cost, and sometimes wood from a distant origin may be selected in order to meet specific design requirements [65]. In the selection of green materials, it is often believed that the farther the shipping distance, the higher the transportation cost, and also the greater the environmental pressure [49]. |
|                          | Shipping distance       | Theoretical research on the product life cycle of the household goods industry provides new perspectives for discussion of this issue [66]. Obviously, cutting trees with long growth cycles has a greater impact on the ecological footprint than cutting those with shorter ones [67]. On the other hand, precious woods, usually with longer growth cycles, create higher product satisfaction. Therefore, green material selection in furniture manufacturing is undoubtedly faced with tradeoffs. |
|                          | Scrap rate              | For wood, the raw material of the vast majority green furniture design, another key criterion is the scrap rate, which creates both economic costs and environmental pressures. Due to varying textures of different woods, the leftover materials in the processing process can, to varying degrees, be reused for other purposes [68,69]. |
| Product performance      | Expected product price  | In some studies, the attributes of the finished product are separated for evaluation when discussing the material selection scheme [38,49]. Considering that the evaluation of furniture product quality is often affected by cultural and other subjective factors [70], this study condenses product performance into the expected price of the product. |

4.2. Step Two: Score the Materials

In this study, several kinds of common wood shown in Figure 1 were selected for scoring. The index values of different kinds of wood are measured, estimated, and shown in Table 3 (These data are sourced from www.chinatimber.com accessed on 7 March 2021, including real-time information (price, main producing areas and expected sales volume;) covering all major types of commercially used wood. Data regarding wood properties are mainly derived from the World Commercial Timber Dictionary (Zhang Yuren, et al. China Customs Press, July 2020); all index data are standardized for entry into the model). The decision-making units that are involved at different stages of sorting all differ. The decisive factor separating them is the performance of the material in the last round of efficiency scoring. It should be noted that the scores of various wood indicators considered in the table are based on the premise that the household manufacturer is located in Mianyang City; the index score of a certain kind of material mainly considers the following aspects: firstly, the price of the wood is calculated according to the low price of the wood in Guangdong, Shanghai, and Harbin Wood Markets (China’s three major wood trading markets) in the recent three months; secondly, the freight distance is calculated according to the distance from the lowest price market to the local market. Subsequently, the regeneration cycle and expected price of products are determined according to the maturity period of wood and the market performance of finished products, respectively. Finally, the two subjective indicators of processing cost and waste rate are mainly determined by consulting the relevant people in the industry and consulting the wood category books mentioned above.
Thereby, the relative efficiency of all assessed wood types are obtained (see Table 4) after undergoing calculation in the generalized DEA model using the sample set.

![Types of Wood Commonly Used in Furniture Manufacturing.](image)

**Figure 1.** Types of Wood Commonly Used in Furniture Manufacturing.

**Table 3.** Index Values of Wood Types.

| Material Type | Material Price | Direct Cost | Manufacturing Cost | Environmental Cost | Scrap Rate |
|---------------|----------------|-------------|--------------------|--------------------|------------|
| A: Oak        | 15             | 80          | 90                 | 69.23              | 84.01      | 82.66      |
| B: Rubber wood| 9              | 84.5        | 84                 | 15.38              | 80.74      | 40.37      |
| C: Camphorwood| 4              | 81          | 95                 | 7.69               | 93.17      | 44.21      |
| D: Beech      | 12             | 83          | 77                 | 15.38              | 92.36      | 36.52      |
| E: Walnut     | 39             | 81.5        | 96                 | 76.92              | 80.49      | 90.35      |
| F: Mahogany   | 96             | 82.5        | 95                 | 96.38              | 85.62      | 98.04      |
| G: Elm        | 7              | 81.5        | 87                 | 53.85              | 89.16      | 63.44      |
| H: Birch      | 7              | 82.5        | 79                 | 23.08              | 86.68      | 48.06      |
| I: Ash wood   | 16             | 84          | 92                 | 30.77              | 86.92      | 68.06      |
| J: Poplar     | 5              | 84          | 76                 | 15.38              | 88.07      | 32.68      |

**Table 4.** Relative Efficiency Values of Woods.

| Timber       | A | B | C | D | E | F | G | H | I | J |
|--------------|---|---|---|---|---|---|---|---|---|---|
| Efficiency Value at Stage I | 0.89 | 1 | 1 | 1 | 1 | 0.98 | 1 | 1 | 0.96 | 1 |
| Efficiency Value at Stage II | \ | 1 | 1 | 0.87 | 1 | \ | 1 | 1 | \ | 1 |

Notes: "\" indicates that the material did not qualify in the previous round of efficiency scoring and was not sorted in this round.

4.3. **Step Three: Use G-CCR Screening to Screen for Improved Samples with Greater Efficiency**

Using the generalized DEA method for the preliminary selection of various materials, we can find that the efficiency value of most of the materials remains at 1, which is, most of the materials are still in the sample set after the generalized DEA method selection, and will participate in at least the next round of sorting, and the materials with substandard efficiency will be excluded as inferior materials. Before the second round of sorting, because the sample set has changed, it is necessary to re-select samples. The results are shown at the bottom of Table 3. It can be found that material D will not participate in the last round of sorting.

4.4. **Step Four: Calculate the Order Using TOPSIS**

Being combined with the selection of materials in the third step, this study ranked the materials by calculating the comprehensive distance between the optimal solution and
the worst solution. Finally, the ranking results and the changes of the material ranking in different stages were shown in the following figure (Figure 2).

Figure 2. Change in Sorting. Notes: Only units judged effective to least the first round of DEA analysis are shown.

5. Results and Discussion

The efficiency values of different materials are evaluated first. The main reason for performing material efficiency indexation in different stages is that candidate materials are constantly eliminated from the candidate set. Thanks to the advantage of the number of decision-making units in the generalized DEA model, it is unlikely to reach any erroneous efficiency conclusions that result from a too-small number of candidate materials. During the three-stage ranking, the DEA method is used to select efficient candidate materials, and these are ranked based on the comprehensive distance between each decision-making unit and the optimal solution. This is repeated to obtain the optimal solutions for given scenarios.

In the first stage of efficiency evaluation, materials A, F, and I were excluded and they were not ranked in the second round. In the second stage, material D was excluded from the third round of ranking. Therefore, Figure 2 shows the ranking of seven types of materials at maximum. After observing the ranking changes of different stages, it was found that the ranking of different wood types intersected. This confirms the problem of reversed order in TOPSIS, which affects final decision-making. More specifically, there is a possibility that certain poor-quality material types may crowd out the high-quality ones in the final ranking. By comparing different rankings, it was found that the presence of oak, beech, mahogany, and ash wood in the final ranking will have an impact on the decision-making results. Therefore, it is necessary to screen the samples before trying to use TOPSIS method. The relatively fewer effective woods selected through the generalized CCR model are lower in the initial ranking, and having a subsequent sorting after excluding these woods would be referential for obtaining more robust and accurate results. In fact, the poplar and birch woods selected in this study are far less popular in the furniture market than oak (being preferred by the European and American market) or beech (preferred in the southern China market). One reason is that material selection preferences change very little in the short term due to fixed design traditions in the furniture manufacturing industry. The other
reason is that the material selection study in this paper was based in Mianyang, China (affecting the shipping distance calculations for different kinds of woods).

It is also clear that it is feasible to exclude decision-making units with lower ranks at different ranking stages, and the use of loose or strict screening rules can be determined according to specific situations. However, the efficiency calculations in the DEA can be modified according to the super efficiency model, thereby obtaining more rigorous initial screening results. The generalized super efficiency model [71] (which makes it possible to compare effective DMUs) is used to choose effective alternative decision-making units for the TOPSIS ranking method, and the selection strictness is slightly improved, as seen in Table 5 and Figure 3. Specifically, the effective units are compared, and only those with an evaluated efficiency value greater than 1 in the previous round are included in each sorting. It can be seen that tightening the selection set and the first simulation round produce some differences in the final result, with material B being excluded from the sorting.

Table 5. Relative Efficiency Values Obtained by Super Efficiency Method.

| Timber | A  | B  | C  | D  | E  | F  | G  | H  | I  | J  |
|--------|----|----|----|----|----|----|----|----|----|----|
|        |    |    |    |    |    |    |    |    |    |    |
| Efficiency Value in Stage I | 0.78 | 0.91 | 0.64 | 1.04 | 1.14 | 0.74 | 1.11 | 1.36 | 0.96 | 1.16 |
| Efficiency Value in Stage II | \ | \ | \ | 0.62 | 1.07 | \ | 1.09 | 1.43 | \ | 1.76 |

Notes: "\" indicates that the material is not qualified in the previous round of efficiency scoring and will not be sorted in this round.

![Figure 3. Stricter Screening Methods and the Ranking Results. Notes: the color of the materials in the figure have been made consistent for ease of comparison.](image)

In the results of this paper, there are several types of ranking that are not consistent with intuition and even the current situation of the industry. This paper focuses on the reasons why camphorwood, which is very popular in Southwest China, and mahogany, which is often used to make high-end furniture, do not perform well or even be eliminated in the ranking. The first is camphorwood, which is cheap, durable, and has a short regeneration cycle. Its poor performance is mainly due to the softer wood of most local camphorwood varieties, which is not suitable for making large furniture, while the imported camphorwood has lost its price advantage. In addition, the local camphorwood varieties need to consider how to reduce alkanes, phenols, and other factors in the process of processing. The toxic effect of organic components, such as alkenes and anisole on
human beings, increases the waste rate in disguised form. The second is mahogany. It is obvious that the regeneration cycle of mahogany in most categories is often comparable to its price advantage, which makes the performance of this kind of wood not outstanding in this study.

In practical production applications, it is obvious that material selection cannot follow a fixed logic. For example, in the material sorting that is described herein, the weight of different properties of materials is determined through the entropy weight method, the rationality of which is seriously restricted by the amount of data available in the calculation of information entropy, and the subjective intention of the decision makers is usually ignored [72]. What is more, there is no comprehensive consideration of the change in material prices and environmental performance of the materials (such as the improved environmental friendliness of a traditional material that results from technical advancement). That is to say, a more comprehensive solution for material selection in green design may be needed in the future.

6. Conclusions

Rational and evidentiary selection of construction material suppliers is crucial to achieve the three goals of project management. On the basis of constructing an index system for the selection of green materials, this paper applied a combined DEA/TOPSIS method to sort the various materials according to their advantages and disadvantages, integrating the random selection of sample sets from G-CCR with the flexibility and simple calculation methods that are used in the TOPSIS method, reducing the impact of the reversed order that is produced by the TOPSIS model on decision-making, and improving the rationality and consistency of the selection and evaluation process. In terms of specific results, the following points should be noted when using this method to select materials. Firstly, the material performance indexes to be investigated shall be decided according to the principles of green design. The green indexes that are to be considered are often expressed differently under different circumstances (such as the variable ‘wood growth cycle’ reviewed herein). Secondly, in determining performance index weight, the entropy weight method provides the least biased results, although possible room for improvement remains if given added input from knowledgeable personnel. Therefore, it may be necessary to ultimately produce an alternative methodology in the future. Finally, the flexibility of the DEA model ensures greater operational space and more explanatory methods when selecting alternative samples, which is often very important for application to actual production conditions.

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