

RESEARCH ARTICLE

Green material selection for sustainability: A hybrid MCDM approach

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Abstract

Green material selection is a crucial step for the material industry to comprehensively improve material properties and promote sustainable development. However, because of the subjectivity and conflicting evaluation criteria in its process, green material selection, as a multi-criteria decision making (MCDM) problem, has been a widespread concern to the relevant experts. Thus, this study proposes a hybrid MCDM approach that combines decision making and evaluation laboratory (DEMATEL), analytical network process (ANP), grey relational analysis (GRA) and technique for order performance by similarity to ideal solution (TOPSIS) to select the optimal green material for sustainability based on the product's needs. A nonlinear programming model with constraints was proposed to obtain the integrated closeness index. Subsequently, an empirical application of rubbish bins was used to illustrate the proposed method. In addition, a sensitivity analysis and a comparison with existing methods were employed to validate the accuracy and stability of the obtained final results. We found that this method provides a more accurate and effective decision support tool for alternative evaluation or strategy selection.

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Introduction

While rapid urbanization and industrialization exacerbate the rate of resource shortages and environmental pollution worldwide, the promotion of sustainability has been increasing and gaining public momentum [1–3]. In the summit of the Group of Twenty (G20), sustainability in the global economy was one of the most crucial issues that have become highly appreciated. Subsequently, collective action plans regarding the sustainable development agenda in 2030 were formulated by the G20 leaders. Moreover, a large body of literature and research studies on sustainability, particularly involving material selection, have been generated by the relevant experts in recent years [4–7].

Green material selection, also called sustainable material selection, plays a significant role throughout the design-manufacturing process, which seeks to guarantee product performance and reduce the entire life-cycle impact to the environment and human health. Thus, it has been the subject of many studies [8–10]. Akadiri *et al.* [11] presented a novel model for

building material selection via the fuzzy extended analytical hierarchy process (AHP) techniques. Maniya and Bhatt [12] applied the preference selection index method to seek a proper material that meets the design engineers' requirements. Chatterjee *et al.* [13] explored a new integrated multi-criteria decision making (MCDM) method that combines the complex proportional assessment method and the evaluation of mixed data method to select the optimal material alternative. However, when selecting the suitable green material for design products, various criteria or attributes, e.g., cost, physical property and environmental performance, should be considered simultaneously rather than only considering a single criterion for design engineers. Obviously, each material has distinctive performance for different properties, and no one can satisfy all the relevant properties. Therefore, green material selection should be viewed as a complex MCDM problem. To address this problem, a systematic and reasonable method is required.

Up to now, there are two types of methods to solve MCDM problem: synthetical assessment approaches [14–24], e.g., multi-attribute utility theory, technique for order performance by similarity to ideal solution (TOPSIS) and approaches based on the theory of life cycle assessment [25]. In addition, some integrated methods have been successfully applied to overcome the shortcomings of single one [26–29], e.g., AHP and TOPSIS, AHP and *vlse kriterijumska optimizacija kompromisno resenje* (VIKOR). However, this existing decision analysis approaches still have some problems to be solved in the decision model [30]. Therefore, to obtain the optimal material more reasonably and reduce subjectivity, it is essential to promote and optimize the assessment process.

This study proposes a hybrid MCDM approach combining DANP and G-TOPSIS that integrated GRA with TOPSIS to select optimal green material for sustainability based on product's needs. Among them, DEMATEL is used to analyze the interrelationship and influence of each criterion, and ANP is employed to calculate the final weights of criteria and evaluate each alternative to select the optimal green material via G-TOPSIS. An empirical application of rubbish bins is used to illustrate this hybrid MCDM method. In addition, a sensitivity analysis and comparison with existing methods are employed to validate the accuracy and stability of the obtained final results. In comparison with existing studies, this work has the following three distinctive contributions: 1) Establish a suitable hierarchy structure of each criterion, considering the economic, environment and physical properties. 2) Propose a hybrid MCDM approach that combines DANP and G-TOPSIS to obtain the weight of each criterion and select the optimal green material logically and effectively. 3) To reduce/avoid subjectivity and irrationality, a nonlinear programming is applied to make G-TOPSIS more reasonable.

The remainder of this paper is organized as follows. Section 2 describes the literature review. The hybrid MCDM method is proposed in Section 3. In Section 4, the proposed method is presented and applied to the case of rubbish bins. Analysis and discussion of the results are presented in Section 5. In last section, the conclusions are presented.

Literature review

Material selection has great importance in the design and development of products, and it is also critical for the success and competitiveness of the producers. Improper selection of materials may result in damage or failure of an assembly and significantly decreases the performance of products, thus negatively affecting productivity, profitability and reputation of an organization [31–32]. In the literature, many investigations and studies have been conducted in various contexts to select material alternative based on different requirements/backgrounds which include eco-innovation, green manufacturing, market demand and so on, for real engineering processes [16, 33–36]. Note that sustainability as a philosophy has been gradually

entering design and manufacturing industries for products to combat climate change under umbrella terms [37–39]. It is essential to carry out the study of material selection under the background of sustainable development [40–41].

The selection of material alternatives is a multi-objective problem subject to compound constraints which can be viewed as a complex MCDM problem [23]. The objectives and criteria in the material selection process are often in conflicts and it involves trade-offs amongst decisive criteria. To ease out the material selection procedure and make the right decision, a systematic and efficient approach is required. Nowadays, a lot of mathematical techniques have been developed and applied in material selection field. For example, Anojkumar *et al.* [42] developed a hybrid MCDM method by combining four MCDM methods for solving pipes material selection difficulty in sugar industry to choose the best pipe material. Liu *et al.* [31] presented an interval 2-tuple linguistic VIKOR (ITL-VIKOR) method for solving the material selection problem under uncertain and incomplete information environment. Huang *et al.* [43] presented a new MCDM model and uncertainty analysis method for the environmentally conscious material selection problem. TOPSIS method is employed and uncertainty analyses were performed for model flexibility and efficiency by addressing the materials selection challenge. Liu *et al.* [44] proposed a hybrid decision making approach integrating induced aggregation operators into VIKOR in an MCDM problem regarding the selection of materials and the results are compared for different types of standardized distance aggregation operators. Table 1 presents the commonly used approaches in material alternatives evaluation and selection.

The literature review demonstrates that the majority of researchers concentrated on material selection methods applying MCDM approaches. Although the existing methods provide many useful tools for material selection. However, most of them still ignore some aspects, e.g., physical properties is rarely considered which plays an significant role in the assessment process for green material alternatives; TOPSIS method as a commonly used tool is not suitable to assess all kinds of material alternatives due to its measurement scale is distance. Therefore, this study proposes a hybrid MCDM approach combining DANP and G-TOPSIS that integrated GRA with TOPSIS to select optimal green material for sustainability based on product's needs and formulate a new hierarchical structure including economic, environment, and physical properties.

Solution methodology

A hybrid MCDM approach that combines DANP and G-TOPSIS is proposed to select the optimal green material alternative for certain product. DANP is applied to analyze the influences and interrelationships among each criterion and obtain the final weights of each criterion. The optimal alternative will be evaluated via G-TOPSIS. The specific procedures and processes of both phases are summarized in the following sub-sections.

DANP

ANP, as an extension of AHP, was proposed by Saaty to address the interdependence and feedback among each criterion and alternative in the practical problem [61, 62]. However, the normalization method of supermatrix is not appropriate because each cluster, which originates from the allocation of each criterion in a column, has the same weight in the traditional process. There are varying degrees of impact among the clusters of criteria in the practical problem [29, 63]. Thus, DEMATEL is applied to improve the normalization process in ANP, namely DANP. It has been successfully employed in various fields, e.g., vendor selection and material selection [6, 64–65]. The procedure can be summarized as shown in Appendix A.

Table 1. Applications of MADM methods for material selection in different areas.

Type	Method	Author(s)	Problem
MCDM approaches	AHP	Desai <i>et al.</i> [45]	Material selection in product design
	TOPSIS	Rahman <i>et al.</i> [46]	A decision support system for optimal roofing material selection
	VIKOR	Prasenjit <i>et al.</i> [9]	Material selection application
	GRA	Zhao <i>et al.</i> [41]	Commercially available materials selection in sustainable design
Hybrid MCDM approaches	AHP and TOPSIS	Kumar and Singal [34]	Penstock material selection in small hydropower plants
		Rao <i>et al.</i> [16]	Material selection for a given engineering design
		Anojkumar <i>et al.</i> [47]	Material selection in sugar industry
	ANP and TOPSIS	Onut <i>et al.</i> [48]	Selection of the suitable material handling equipment
	TOPSIS and DOE	Tansel Ic [49]	Robot selection problem
	TOPSIS and VIKOR	Shanian and Savadogo [50]	Selection of mass produced non-heat-treatable cylindrical cover material.
	DANP and VIKOR	Hsu <i>et al.</i> [51]	The best vendor selection for conducting the recycled material
		Liu <i>et al.</i> [52]	Material selection with target-based criteria
Finite element analysis and ELECTRE	Shanian <i>et al.</i> [53]	Materials selection of gas turbine components	
MCDM approaches with uncertain theory	Fuzzy TOPSIS	Maity and Chakraborty [54]	Grinding wheel abrasive material selection
		Mayyas <i>et al.</i> [55]	Eco-material selection
	Fuzzy ANP and PROMETHEE	Tuzkaya <i>et al.</i> [56]	Material handling equipment selection problem
	Fuzzy AHP and VIKOR	Anojkumar <i>et al.</i> [42]	Pipe material selection in sugar industry
	Interval 2-tuple linguistic VIKOR	Liu <i>et al.</i> [31]	Material selection for an engineering design
	Fuzzy VIKOR	Girubha <i>et al.</i> [57]	Material selection of an automotive component
	Fuzzy extended AHP	Akadiri <i>et al.</i> [11]	Sustainable materials selection for building projects
	Fuzzy AHP and TOPSIS	Anojkumar <i>et al.</i> [42]	Pipe material selection in sugar industry
		Aly <i>et al.</i> [58]	Best design concept and material selection process
		Rathod <i>et al.</i> [59]	Phase change material selection
Fuzzy AHP, VIKOR and TOPSIS	Anojkumar <i>et al.</i> [60]	Material selection in sugar industry	

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G-TOPSIS

TOPSIS is an MCDM method proposed by Hwang and Yoon in 1981 [66]. The operating principle is that the optimal solution must satisfy certain conditions, i.e., the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution [67, 68]. It has been commonly applied in various fields, e.g., weapon selection, material selection, and alternative evaluation [69–72]. However, some problems cannot be resolved by TOPSIS in several special cases, e.g., when the distances of the alternatives to positive-ideal and negative-ideal solutions is equal. Thus, G-TOPSIS, which integrates GRA with TOPSIS, is proposed to obtain the final rank of each alternative and select the optimal green material for certain product. Additionally, to avoid the subjectivity and irrationality, a nonlinear programming model with constraints is proposed to obtain the integrated closeness index based on the similarity closeness index from GRA and the distance closeness index from TOPSIS. The procedure can be summarized as follows:

Step 1: Construct a decision matrix for the selection of the optimal material. The decision matrix $X = [x_{ij}]_{n \times m}$ can be presented as Eq (1).

$$X = \begin{matrix} & B_1 & \cdots & B_j & \cdots & B_m \\ \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \end{matrix} \quad (1)$$

where x_{ij} is a crisp value that indicates the performance rating of each alternative A_i ($i = 1, 2, \dots, n$) with respect to each criterion B_j ($j = 1, 2, \dots, m$).

Step 2: Obtain the normalized decision matrix Z combined with the weight vector of criteria ω that is obtained via DANP.

For the benefit criteria, the normalized value y_{ij} could be calculated as

$$y_{ij} = \frac{x_{ij}}{\max_i x_{ij}}, (i = 1, 2, \dots, n; j = 1, 2, \dots, m) \quad (2)$$

For the cost criteria, the normalized value y_{ij} could be calculated as

$$y_{ij} = \frac{\min_i x_{ij}}{x_{ij}}, (i = 1, 2, \dots, n; j = 1, 2, \dots, m) \quad (3)$$

$$Z = \omega^T Y = \begin{matrix} & B_1 & \cdots & B_j & \cdots & B_m \\ \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} \omega'_1 y_{11} & \cdots & \omega'_j y_{1j} & \cdots & \omega'_m y_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \omega'_1 y_{i1} & \cdots & \omega'_j y_{ij} & \cdots & \omega'_m y_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \omega'_1 y_{n1} & \cdots & \omega'_j y_{nj} & \cdots & \omega'_m y_{nm} \end{bmatrix} \end{matrix} \quad (4)$$

Step 3: Establish the positive-ideal and negative-ideal solutions. Based on the operating principle of TOPSIS, the positive-ideal and negative-ideal solutions play a significant role in the arithmetic process and can be obtained as Eqs (5) and (6).

$$Z_j^+ = \left\{ \max_{1 \leq i \leq n} (\{z_{ij}\}_{i=1}^n) \mid j \in J^+, \min_{1 \leq i \leq n} (\{z_{ij}\}_{i=1}^n) \mid j \in J_- \right\} = (z_1^+, z_2^+, \dots, z_m^+) \quad (5)$$

$$Z_j^- = \left\{ \min_{1 \leq i \leq n} (z_{ij}) \mid j \in J^+, \max_{1 \leq i \leq n} (z_{ij}) \mid j \in J_- \right\} = (z_1^-, z_2^-, \dots, z_m^-) \tag{6}$$

where J^+ represents the index set for which the greater the better, and J represents the index set for which the smaller the better.

Step 4: Calculate the grey correlation coefficient between the i th alternative and positive-ideal alternative regarding the j th criterion. The procedure is presented as follows:

$$r_{ij}^+ = \frac{\min_i \min_j |z_j^+ - z_{ij}| + \rho \max_i \max_j |z_j^+ - z_{ij}|}{|z_j^+ - z_{ij}| + \rho \max_i \max_j |z_j^+ - z_{ij}|} \tag{7}$$

where $\rho \in [0, 1]$ indicates the resolution factor. As a general rule, $\rho = 0.5$ [22]. The grey correlation coefficient matrix regarding each alternative and positive-ideal solution is shown in Eq (8).

$$R^+ = \begin{matrix} & & B_1 & \cdots & B_j & \cdots & B_m \\ \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} r_{11}^+ & \cdots & r_{1j}^+ & \cdots & r_{1m}^+ \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{i1}^+ & \cdots & r_{ij}^+ & \cdots & r_{im}^+ \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{n1}^+ & \cdots & r_{nj}^+ & \cdots & r_{nm}^+ \end{bmatrix} \end{matrix} \tag{8}$$

The grey correlation degree between the i th alternative and the positive-ideal solution can be obtained according to Eq (9).

$$R_i^+ = \frac{1}{m} \sum_{j=1}^m r_{ij}^+, (i = 1, 2, \dots, n) \tag{9}$$

Step 5: Obtain the grey correlation coefficient between the i th alternative and negative-ideal solution regarding the j th index in the same way of Step 4.

$$r_{ij}^- = \frac{\min_i \min_j |z_j^- - z_{ij}| + \rho \max_i \max_j |z_j^- - z_{ij}|}{|z_j^- - z_{ij}| + \rho \max_i \max_j |z_j^- - z_{ij}|} \tag{10}$$

The grey correlation coefficient matrix regarding each alternative and negative-ideal

solution is shown in Eq (11).

$$R^- = \begin{matrix} & B_1 & \cdots & B_j & \cdots & B_m \\ A_1 & \begin{bmatrix} r_{11}^- & \cdots & r_{1j}^- & \cdots & r_{1m}^- \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ A_i & \begin{bmatrix} r_{i1}^- & \cdots & r_{ij}^- & \cdots & r_{im}^- \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ A_n & \begin{bmatrix} r_{n1}^- & \cdots & r_{nj}^- & \cdots & r_{nm}^- \end{bmatrix} \end{bmatrix} \end{matrix} \end{matrix} \quad (11)$$

The grey association degree between the *i*th alternative and the negative-ideal can be obtained according to Eq (12).

$$R_i^- = \frac{1}{m} \sum_{j=1}^m r_{ij}^-, (i = 1, 2, \dots, n) \quad (12)$$

Step 6: Obtain the separation measures. The separation of each alternative from the positive-ideal solution D_i^+ is calculated as

$$D_i^+ = \sqrt{\sum_{j=1}^m [z_{ij} - z_j^+]^2}, (i = 1, 2, \dots, n) \quad (13)$$

Similarly, the separation of each alternative from the negative-ideal solution D_i^- is calculated as

$$D_i^- = \sqrt{\sum_{j=1}^m [z_{ij} - z_j^-]^2}, (i = 1, 2, \dots, n) \quad (14)$$

Step 7: Apply the dimensionless method to R_i^+ , R_i^- , D_i^+ and D_i^- .

$$\hat{M}_i = \frac{M_i}{\max_{1 \leq i \leq n} M_i}, (i = 1, 2, \dots, n) \quad (15)$$

where M_i represents R_i^+ , R_i^- , D_i^+ and D_i^- .

Step 8: Calculate the similarity closeness index and the distance closeness index. For GRA approach, R_i^+ represents the grey correlation degree between the *i*th alternative and the positive-ideal solution. The larger the value R_i , the more similar the alternative *i* to the positive-ideal alternative, the better the alternative. Similarly, for TOPSIS approach, the larger the value D_i , the larger the separation of alternative *i* from the negative-ideal alternative, the

better the alternative.

$$R_i = \frac{\hat{R}_i^+}{\hat{R}_i^+ + \hat{R}_i^-}, (i = 1, 2, \dots, n) \tag{16}$$

$$D_i = \frac{\hat{D}_i^-}{\hat{D}_i^+ + \hat{D}_i^-}, (i = 1, 2, \dots, n) \tag{17}$$

Step 9: Construct the integrated closeness index. To avoid subjectivity and irrationality, non-linear programming is applied to calculate the integrated closeness index CS_i based on the similarity closeness index and the distance closeness index. Assuming that these two indices have the same weight, the nonlinear programming model with constraints can be structured as follows:

$$\begin{cases} \min \sum_{i=1}^n [(\xi_i)^2 + (\delta_i)^2] \\ \xi_i = CS_i - R_i \\ \delta_i = CS_i - D_i \\ s.t. \min(R_i, D_i) \leq CS_i \leq \max(R_i, D_i) \\ 0 < CS_i < 1 \end{cases}, (i = 1, 2, \dots, n)$$

Subsequently, a complex method and a penalty function method can be employed to address this nonlinear programming model [73–74]. Note that the larger the value CS_i , the better the alternative.

A hybrid MCDM method

To select the optimal alternative more objectively and rationally, this work proposes a novel hybrid MCDM approach that combines DANP and G-TOPSIS. This method applies the quantitative analysis and weight allocation features of DANP and the comprehensive optimization ability of G-TOPSIS to avoid some of the shortcomings and deficiencies of each method alone. A detailed flowchart is shown in Fig 1.

Phase 1: Obtain the weights of each criterion for optimal green material selection via DANP.

The integrated DEMATEL and ANP process presented in Section 2.1 is applied to get the weights of each criterion while accounting for dependence and feedback. A hierarchical structure regarding the evaluation criteria is built, as shown in Fig 2. According to the classification of each criterion, DEMATEL is applied to analyze the interrelationship and influence of each criterion, and ANP is employed to calculate the weights of criteria.

Phase 2: Determine the final rank and select the optimal green material for certain product by G-TOPSIS.

The final rank of each alternative and optimal green material can be calculated via G-TOPSIS combining GRA and TOPSIS. Additionally, to avoid subjectivity and irrationality in the integration process, a nonlinear programming model with constraints is proposed to obtain the integrated closeness index CS_i based on the similarity closeness index R_i from GRA and the distance closeness index D_i from TOPSIS. Note that CS_i falls between 0 and 1. The larger the value of CS_i , the better the performance of the material alternatives.

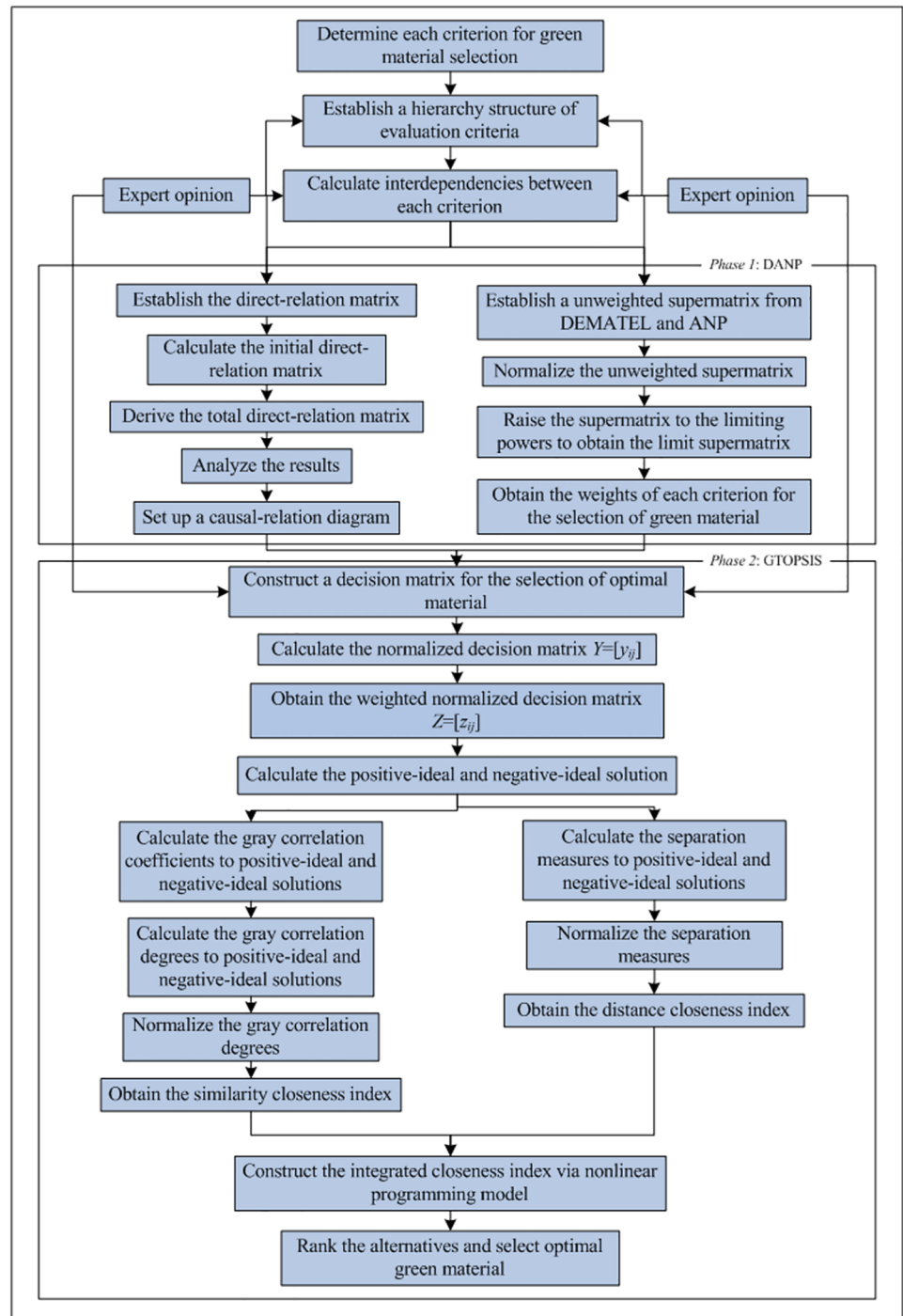


Fig 1. The flowchart of proposed novel hybrid method.

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Verification of the empirical case

An empirical case of rubbish bins is provided to demonstrate this integrated method, i.e., DANP and G-TOPSIS. In the following sections, the background, the hierarchical structure of criteria and the optimization processes will be discussed respectively.

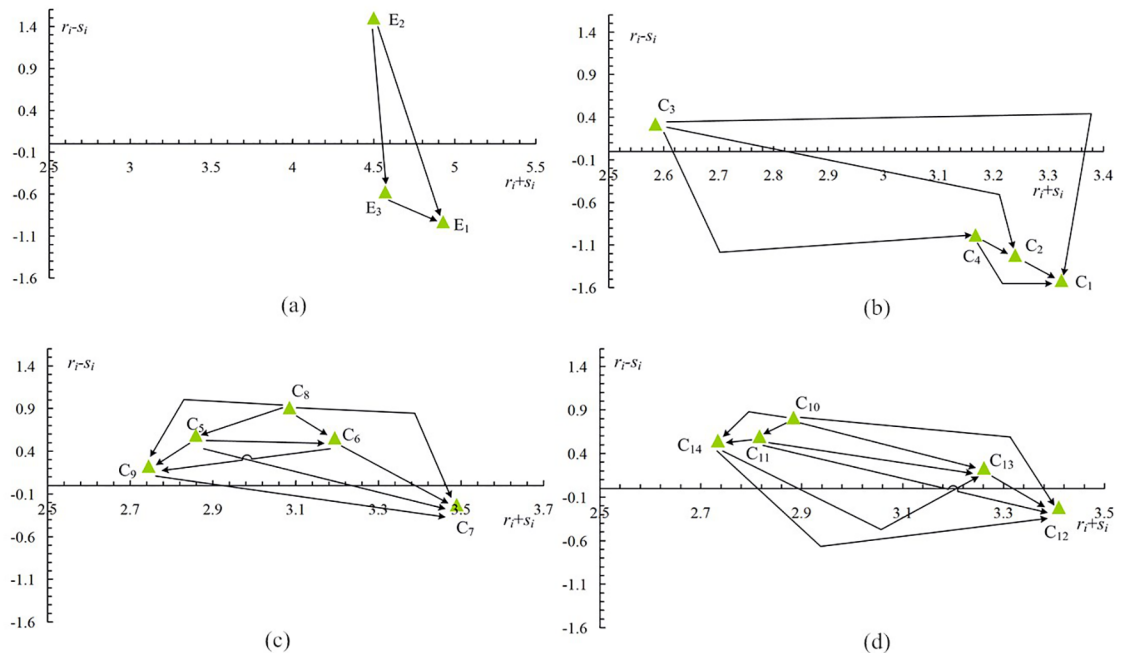


Fig 2. Causal influence diagrams for the dimensions and criteria.

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Background and data collection

As a common tool for daily life, the utilization and production of rubbish bins continue to increase; material selection is also an MCDM problem that must be treated with caution for sustainability. Currently, several commonly used material for rubbish bins are aluminum (Al), ABS plastic (ABS) and polyurethane (PU). In addition, production and recycling are closely related. While selecting a suitable material for production, it is necessary to choose corresponding product recovery and disposal strategies, i.e., recycling and remanufacturing (REM), recycling and incineration (INC), and recycling and landfill (LND). Thus, there are five material alternatives, i.e., Al-REM, ABS-INC, ABS-LND, PU-INC and PU-LND.

Raw data and related information can be gathered via experts from various fields, e.g., scholars of college and supervisors of enterprise, through questionnaire surveys. In this research, six experts, including two scholars who specialize in material selection, two supervisors from related companies with a good reputation, and two customers who have used these products for over three years, were interviewed to obtain the direct-relation matrix of each criterion and the decision matrix for the selection of optimal material. This investigation was conducted in August 2016. According to the statistical data from the six questionnaires, the inconsistent rate is 4.6% [75]. Thus, it can be summarized that the credibility is 95.40%, and additional questionnaires will not impact the optimization results.

Hierarchical criteria of material selection

This large number of materials, coupled with the complex relationships between the different selection parameters, often make the selection of a materials for a given component a difficult task. The establishment of hierarchical criteria is a crucial step in green material selection, and it has great influence upon the accuracy and reliability of material alternatives evaluation. In selecting materials, designers and engineers have to take into account a large number of

Table 2. Hierarchical structure of criteria for material selection.

Goal level	Cluster level	Criterion level	Definitions	Attributes	References
Green material selection (G ₁)	Economic (E ₁)	Initial cost (C ₁)	The cost which is to be spent the material manufacturing	Cost	[5, 29, 51, 75, 78, 81–84]
		Maintenance cost (C ₂)	The cost which is to be spent for the maintenance in its effective lifetime	Cost	
		Disposal cost (C ₃)	The cost which is to be spent for end of life disposal of the material	Cost	
		Tax contribution (C ₄)	Tax involved and contributed by the material	Benefit	
	Environment (E ₂)	Energy saving (C ₅)	Net energy saved by the material	Benefit	[5, 29, 75, 82–87]
		Potential for recycling and reuse (C ₆)	Recycling and reuse capability of the material	Benefit	
		Raw material extraction (C ₇)	Limited extraction of the raw material for the manufacturing of the final material	Benefit	
		Usage of water (C ₈)	Usage of water involved in the life cycle of the material	Cost	
		CO ₂ emission (C ₉)	CO ₂ emission of the material in its useful life time	Cost	
	Physical property (E ₃)	Density (C ₁₀)	The estimated measure of content per functional and lexical units in total	Benefit	
		Rigidity (C ₁₁)	The capacity to resist a hard object pressed into its surface of local materials	Cost	
		Tensile strength (C ₁₂)	The ability to resist permanent deformation and destruction	Benefit	
		Elongation at break (C ₁₃)	The ratio of the original length and the displacement value when pull-off	Benefit	
		Tensile modulus (C ₁₄)	Elastic when stretched for materials	Cost	

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criteria. These criteria for material include social (e.g. operational life, esthetics, health and safety), technical (e.g., maintainability, resistance to decay, life expectancy), environmental (e.g., energy saving, potential for recycling and reuse, raw material extraction) and economic (initial cost, maintenance cost, disposal cost) [6, 76–78]. Physical properties have been applied in material selection, which plays an significant role in the assessment process for green material alternatives for real engineering processes [79–80]. However, there are rarely hierarchical structures that combining the physical properties with other important attributes, i.e., economic and environment, in the previous studies. In addition, there are no relatively accurate index weights for physical properties in the evaluation process of material selection.

Therefore, to discover and inherit more suitable sustainable properties/criteria, we reviewed the existing literature and interviewed experienced experts from colleges/enterprises. Thus, the hierarchical structure of criteria for their green material selection was built, as tabulated in Table 2. The structure includes three levels, i.e., goal, cluster and criterion. The goal level (G) is green material selection (G₁). The cluster level (E) involves economic (E₁), environment (E₂), and physical (E₃) properties. Economic properties include initial cost (C₁), maintenance cost (C₂), disposal cost (C₃), and tax contribution (C₄). Environment properties include energy saving (C₅), potential for recycling and reuse (C₆), raw material extraction (C₇), usage of water (C₈), and CO₂ emission (C₉). Physical properties include density (C₁₀), rigidity (C₁₁), tensile strength (C₁₂), elongation at break (C₁₃), and tensile modulus (C₁₄). The attributes of each criterion are shown in Table 2. Note that rigidity (C₁₁) and tensile modulus (C₁₄) are fixed index (the closer the attribute value is to a fixed value t_i , the better the attribute). The fixed value t_i is determined by the type of the product. To simplify the optimization process, we convert fixed index into cost index by calculating the evaluation value, i.e., the absolute value of

Table 3. The averaged direct-relation matrix for criteria.

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂	C ₁₃	C ₁₄
C ₁	0	1	1	1	1	1	1	1	1	1	1	1	1	1
C ₂	2	0	1	2	1	1	1	1	1	1	1	1	1	1
C ₃	2	2	0	2	1	1	2	1	1	1	1	1	1	1
C ₄	2	1	1	0	1	1	1	1	1	1	1	3	1	1
C ₅	3	4	3	4	0	1	3	1	1	1	1	1	3	1
C ₆	4	3	3	3	2	0	4	2	2	1	1	2	1	1
C ₇	3	3	2	3	1	1	0	1	1	2	3	3	1	1
C ₈	4	4	3	3	2	1	3	0	2	1	1	2	4	1
C ₉	3	3	1	4	2	1	2	1	0	1	1	2	1	1
C ₁₀	3	3	2	3	2	3	3	1	2	0	2	1	2	1
C ₁₁	2	3	1	1	1	3	2	2	2	2	0	3	1	2
C ₁₂	3	2	2	2	1	2	2	1	2	1	1	0	4	1
C ₁₃	3	3	1	1	1	2	3	2	1	1	1	4	0	3
C ₁₄	3	3	1	3	1	2	2	1	2	1	1	3	2	0

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the difference between the initial value with the fixed value. The smaller the evaluation value, the better the criterion.

Weighting of criteria via DANP method

The calculation procedure is structured by combining DEMATEL with ANP (in Section 2.1 and Appendix A). As shown in Appendix A, the direct-relation matrix could be formulated from the responses of six experts (Due to space limitations, the averaged direct-relation matrix for criteria and dimensions are only given here as shown in Tables 3 and 4).

Based on the calculation steps of DANP, the final weight of each criterion can be acquired as follows: a) the normalized initial direct-relation matrix can be calculated using Eqs (18) and (19); b) the total direct-relation matrix is obtained through Eq (20); c) each row sum vector r and column sum vector s of the total direct-relation matrix T are separately produced, as shown in Eqs (21) and (22), and the results are shown in Tables 5 and 6; d) the causal influence diagram is established based on the $r_i + c_i$ and $r_i - c_i$ values respectively. The causal influence diagrams of criteria and the dimensions are shown in Fig 2; e) the unweighted supermatrix can be developed through Eqs (23)–(28); f) the weighted supermatrix can be obtained according to Eqs (29)–(31); and g) the result of limiting the weighted supermatrix is shown in Table 6.

Rank the material alternatives via G-TOPSIS method

The calculation procedure is structured by combining GRA with TOPSIS (in Section 2.2). By reviewing the related literature [5, 26] and investigations by experts, a decision matrix for five material alternatives, i.e., AI-REM, ABS-INC, ABS-LND, PU-INC and PU-LND, is constructed,

Table 4. The averaged direct-relation matrix for the dimensions.

	E ₁	E ₂	E ₃
E ₁	0	1	2
E ₂	3	0	2
E ₃	2	1	0

<https://doi.org/10.1371/journal.pone.0177578.t004>

Table 5. Sum of the influences given and received regarding criteria.

	Criteria	r_i	c_i	$r_i + c_i$	$r_i - c_i$
1	Initial cost (C_1)	0.9052	2.4182	3.3234	-1.5131
2	Maintenance cost (C_2)	1.0104	2.2290	3.2393	-1.2186
3	Disposal cost (C_3)	1.4522	1.1325	2.5847	0.3197
4	Tax contribution (C_4)	1.0920	2.0752	3.1672	-0.9832
5	Energy saving (C_5)	1.7247	1.1342	2.8588	0.5905
6	Potential for recycling and reuse (C_6)	1.8758	1.3185	3.1944	0.5573
7	Raw material extraction (C_7)	1.6316	1.8584	3.4900	-0.2268
8	Usage of water (C_8)	1.9976	1.0878	3.0854	0.9097
9	CO ₂ emission (C_9)	1.4857	1.2593	2.7450	0.2264
10	Density (C_{10})	1.8480	1.0359	2.8839	0.8121
11	Rigidity (C_{11})	1.7071	1.1092	2.8163	0.5979
12	Tensile strength (C_{12})	1.5968	1.8124	3.4093	-0.2156
13	Elongation at break (C_{13})	1.7483	1.5130	3.2613	0.2353
14	Tensile modulus (C_{14})	1.6407	1.0929	2.7336	0.5478

<https://doi.org/10.1371/journal.pone.0177578.t005>

as shown in Table 7. Note that the value of t_i is 55 for the rigidity (C_{11}) and the value of t_i is 10 for the tensile modulus (C_{14}).

The ranking of five material alternatives can be calculated via G-TOPSIS method, as described in Section 2.2. The steps can be divided into the following five parts: a) from Steps 1 to 2, the normalized decision matrix Z combined with the weight vector of criteria ω is obtained; b) the positive-ideal and negative-ideal solutions can be calculated using Step 3; c) the grey correlation coefficient between the i th alternative and the positive-ideal alternative regarding the j th criterion is obtained via Step 4, and similarly, the grey correlation coefficient between the i th alternative and the negative-ideal solution regarding the j th index can be calculated using Step 5; d) the similarity closeness index and the distance closeness index are acquired according to Steps 6–8; and e) the integrated closeness index is gained using a nonlinear programming model with constraints as shown in Step 9, and the final rank can be obtained, with the ranking presented in Table 8.

Table 6. Sum of the influences given and received regarding the dimensions.

	Criteria	r_i	c_i	$r_i + c_i$	$r_i - c_i$
1	Economic (E_1)	2.0000	2.9286	4.9286	-0.9286
2	Environment (E_2)	3.0000	1.5000	4.5000	1.5000
3	Physical property (E_3)	2.0000	2.5714	4.5714	-0.5714

<https://doi.org/10.1371/journal.pone.0177578.t006>

Table 7. A decision matrix for five material alternatives.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10} /g.cc ⁻¹	C_{11} /HBS	C_{12} /MPa	C_{13} /%	C_{14} /GPa
AI-REM	2	3	3	3	3	3	4	3	3	2.72	50	169	8	25.0
ABS-INC	2	3	2	3	2	3	3	2	2	1.34	100	90	2	7.9
ABS-LND	3	2	3	2	2	4	2	4	3	1.34	100	90	2	7.9
PU-INC	3	3	2	3	4	2	3	4	3	1.15	60	27	10	4.5
PU-LND	4	4	2	4	4	3	3	3	4	1.15	60	27	10	4.5
Weight	0.052	0.061	0.067	0.052	0.086	0.112	0.054	0.092	0.083	0.053	0.076	0.069	0.074	0.069

<https://doi.org/10.1371/journal.pone.0177578.t007>

Table 8. Ranking of five material alternatives.

	R_i	Rank	D_i	Rank	CS_i	Rank
AI-REM	0.6228	1	0.7036	1	0.6632	1
ABS-INC	0.3965	5	0.3914	5	0.3940	5
ABS-LND	0.4762	4	0.4871	3	0.4816	3
PU-INC	0.4901	3	0.4609	4	0.4755	4
PU-LND	0.5472	2	0.5097	2	0.5285	2

<https://doi.org/10.1371/journal.pone.0177578.t008>

Analysis and discussion

Comparison to existing methods

To prove the feasibility and validity of the proposed method, GRA, TOPSIS and VIKOR [9, 88] were applied to compare their outcomes. Note that the same weights of criteria were applied in the calculation process of the four methods. The analysis is conducted on the basis of the same illustrative example. Based on Table 8, the integrated closeness indices of the four methods, i.e., GRA, TOPSIS, VIKOR and G-TOPSIS, can be figured in Fig 3.

From Fig 3, it can be summarized that the final ranks of material alternatives via the four methods are basically consistent. Thus, this proposed method, i.e., DANP and G-TOPSIS, is a reasonable and effective method to evaluate the performance of material alternatives and select the optimal green material. Subsequently, based on the results of the four methods, the first material alternative, that is AI-REM, is the optimal green material to produce rubbish bins. In addition, the ranks of the five material alternatives are different using the four methods. The causes of this phenomenon are summarized as follows: 1) the degree of information utilization is different in different information aggregation methods, and a large amount of information can be easily lost in the aggregation process; 2) the operating principium of TOPSIS is based on the distance from the positive-ideal solution and the negative-ideal solution; however, it does not consider the degree of similarity to the ideal solution; and 3) similarly. GRA only

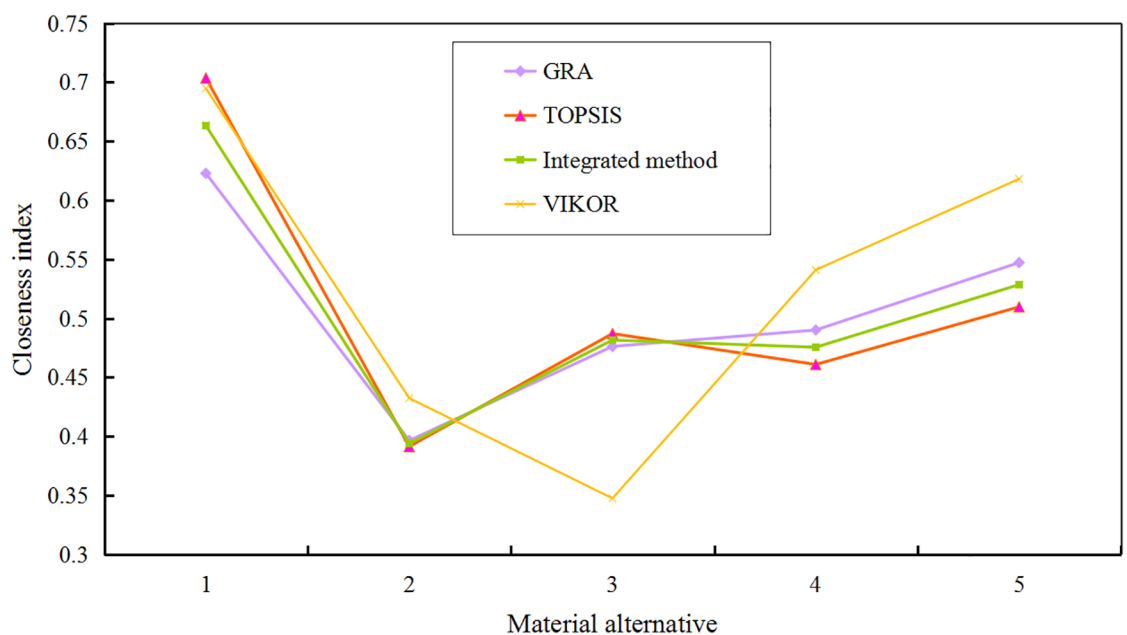


Fig 3. The closeness indices of the four methods.

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Table 9. The 19 experiments of sensitivity analysis.

Expt. No.	Weights	The integrated closeness index (CS)					Rank
		Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	
1	$\omega_{C1} = 0.35, \omega_{C2-C14} = 0.05$	0.4679	0.3306	0.5272	0.5417	0.6377	5>4>3>1>2
2	$\omega_{C2} = 0.35, \omega_{C1, C3-C14} = 0.05$	0.6359	0.4896	0.3642	0.5363	0.6324	1>5>4>2>3
3	$\omega_{C3} = 0.35, \omega_{C1-C2, C4-C14} = 0.05$	0.7026	0.3411	0.5444	0.4006	0.4406	1>3>5>4>2
4	$\omega_{C4} = 0.35, \omega_{C1-C3, C5-C14} = 0.05$	0.5824	0.4429	0.3640	0.4894	0.6321	5>1>4>2>3
5	$\omega_{C5} = 0.35, \omega_{C1-C4, C6-C14} = 0.05$	0.5888	0.3315	0.3705	0.6101	0.6386	5>4>1>3>2
6	$\omega_{C6} = 0.35, \omega_{C1-C5, C7-C14} = 0.05$	0.5832	0.4436	0.5883	0.3746	0.5204	3>1>5>2>4
7	$\omega_{C7} = 0.35, \omega_{C1-C6, C8-C14} = 0.05$	0.7093	0.4327	0.3547	0.4790	0.5092	1>5>4>2>3
8	$\omega_{C8} = 0.35, \omega_{C1-C7, C9-C14} = 0.05$	0.6440	0.3332	0.5959	0.6120	0.5745	1>4>3>5>2
9	$\omega_{C9} = 0.35, \omega_{C1-C8, C10-C14} = 0.05$	0.6420	0.3315	0.5281	0.5426	0.6386	1>5>4>3>2
10	$\omega_{C10} = 0.35, \omega_{C1-C9, C11-C14} = 0.05$	0.7144	0.3302	0.3652	0.3549	0.3846	1>5>3>4>2
11	$\omega_{C11} = 0.35, \omega_{C1-C10, C12-C14} = 0.05$	0.7241	0.6152	0.6331	0.3236	0.3446	1>3>2>5>4
12	$\omega_{C12} = 0.35, \omega_{C1-C11, C13-C14} = 0.05$	0.7198	0.5451	0.5668	0.3353	0.3599	1>3>2>5>4
13	$\omega_{C13} = 0.35, \omega_{C1-C12, C4-C14} = 0.05$	0.6571	0.3089	0.3365	0.6489	0.6687	5>1>4>3>2
14	$\omega_{C14} = 0.35, \omega_{C1-C13} = 0.05$	0.7278	0.2997	0.3254	0.5751	0.5928	1>5>4>3>2
15	$\omega_{C1-C8} = 0.125, \omega_{C9-C14} = 0$	0.5311	0.3799	0.4606	0.5238	0.6139	5>1>4>3>2
16	$\omega_{C1-C8} = 0, \omega_{C9-C14} = 0.167$	0.7027	0.4133	0.4361	0.4239	0.4373	1>5>3>4>2
17	$\omega_{C1-C4} = 0.25, \omega_{C5-C14} = 0$	0.4613	0.3988	0.4116	0.4803	0.6039	5>4>1>3>2
18	$\omega_{C5-C9} = 0.2, \omega_{C1-C4, C10-C14} = 0$	0.6014	0.3746	0.5273	0.5691	0.6283	5>1>4>3>2
19	$\omega_{C1-C9} = 0, \omega_{C10-C14} = 0.2$	0.7117	0.4254	0.4254	0.4128	0.4128	1>3 = 2>5 = 4

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takes into account the degree of similarity to the ideal solution, thereby easily resulting in information loss. Therefore, we propose a hybrid MCDM approach combining DANP and G-TOPSIS to obtain the weight of each criterion and select the optimal green material logically and effectively. In addition, nonlinear programming is applied to make G-TOPSIS more reasonable.

Sensitivity analysis

To monitor the robustness of the evaluation and selection for green materials, a sensitivity analysis that contains 19 experiments is conducted according to the weight change of each criterion. Table 9 presents the details of the experiment. For each condition, the integrated closeness indices of each material alternative are calculated. From Table 9, in the first 14 experiments, weights of each criterion are set as higher respectively, whereas the other criteria are set to be same. In experiment 15, the weights of criteria (C₁–C₈) = 0.125, whereas the other criteria weights are equal to zero. In experiment 16, the weights of criteria (C₉–C₁₄) = 0.167, whereas the other criteria weights are equal to zero. In experiment 17, the weights of all criteria of economic (C₁–C₄) = 0.25, whereas the other criteria weights are equal to zero. In experiment 18, the weights of all criteria of environment (C₅–C₉) = 0.2, whereas the other criteria weights are equal to zero. In experiment 19, the weights of all criteria of physical property (C₁₀–C₁₄) = 0.2, whereas the other criteria weights are equal to zero.

As shown in Table 9, the changes in the final ranks of the five material alternatives when the weights of the criteria are changed can be figured in Fig 4. According to Table 9 and Fig 4, the following conclusions can be obtained as follows: 1) out of the 19 experiments, alternative 1, that is Al-REM, has the highest score in the 11 experiments, i.e., experiment numbers (2, 3, 7–12, 14, 16, 19); hence, the ranking of the solutions of the five material alternatives is relatively sensitive to the criteria weights; and 2) the final ranking of the alternatives changes

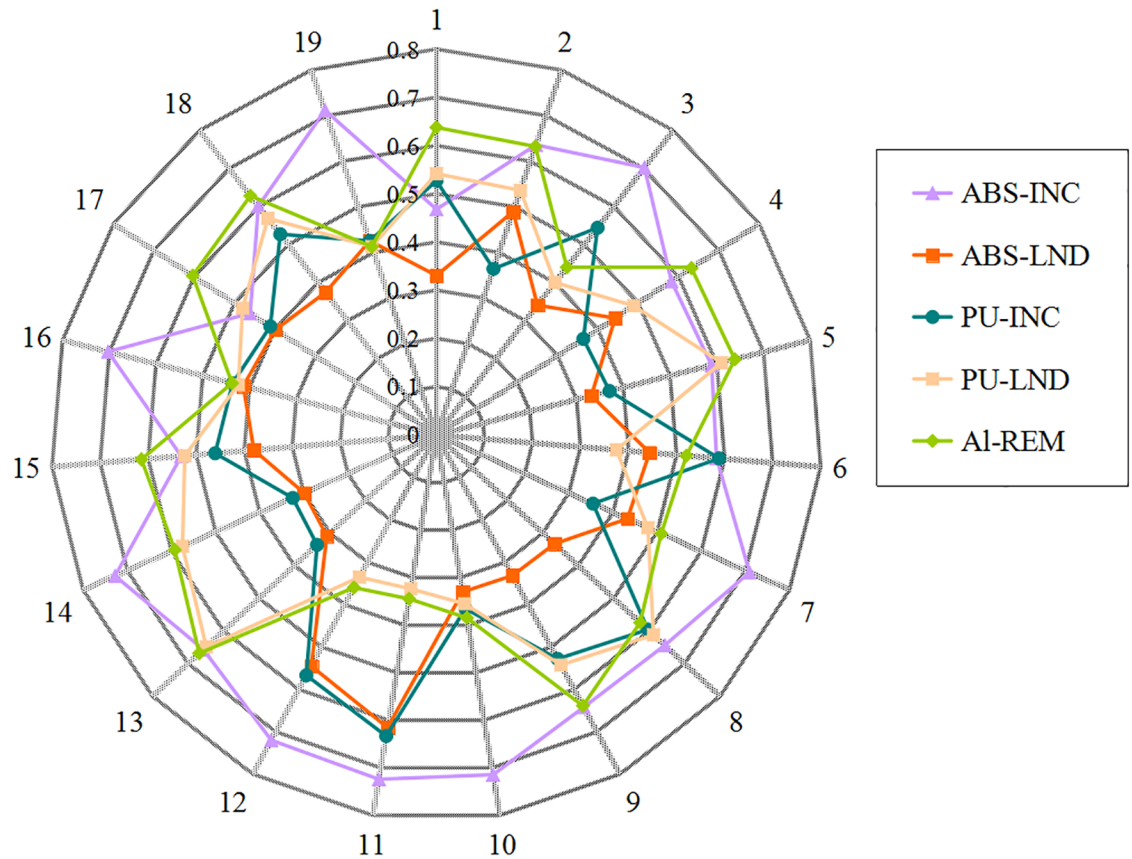


Fig 4. Sensitivity analysis.

<https://doi.org/10.1371/journal.pone.0177578.g004>

greatly with the weight vary of each criterion. Therefore, obtaining the weight of each criterion reasonably and scientifically plays a significant role in the selection of the optimal green material.

Discussion

By comparing the results from the three methods and the sensitivity analysis (as shown in Figs 3 and 4), it can be confirmed that this hybrid MCDM method is effective for the selection of the optimal choice from the material/design alternatives. Additionally, to illustrate that this method is better than the traditional methods, the significance of the present study can be summarized as follows:

From Table 6 and Fig 2, it can be seen that each cluster has feedback and dependence. In other words, the status of each cluster is different. In this paper, the degree that cluster 1 is affected by the other clusters (4.9286) is higher than the degrees for the others (4.5000, 4.5714). Thus, cluster 1 should occupy a greater proportion in the operation process. However, in the traditional method, e.g., AHP and ANP, it is assumed that each cluster has the same weight. The final weights of each cluster are either higher or lower than the realistic values. Therefore, this paper combines DEMATEL to improve the normalization of ANP in the unweighted supermatrix, and the results confirmed that it can be used to obtain the final weights of each cluster more reasonably. In addition, as shown in Table 8 and Fig 3, the final ranks from different methods are unstable, e.g., PU-INC is better than ABS-LND via DANP-GRA, in contrast,

ABS-LND is better than PU-INC via DANP-TOPSIS. The reason for this difference is that each single method has its limitations, which will impact the final rank (the detailed limitation is summarized in the sub-section G-TOPSIS). Therefore, G-TOPSIS is proposed to rank the material alternatives effectively. To avoid subjectivity and irrationality, a nonlinear programming model with constraints is proposed to obtain the integrated closeness index based on the similarity closeness index from GRA and the distance closeness index from TOPSIS. In addition, a comparison and a sensitivity analysis are employed to confirm the accuracy and effectiveness.

The practical implication could be summarized from our study as follows: 1) by DANP, it can be seen that potential for recycling and reuse (C_6) (0.112), usage of water (C_8) (0.092), and energy saving (C_5) (0.086) are found to have a large impact on the green material selection since these criteria carry relatively larger weights. Thus, their reasonable control can greatly contribute to a better design for engineers/designers. In addition, the results of the sensitivity analysis illustrate the importance of establishing a qualified group of experts/designers in the design evaluation. 2) The selection of the optimal material alternative is essential for the sustainable development of products. The main contribution of this work is the definition and development of an effective evaluation framework to guide managers to assess green material alternatives. To the best of our knowledge, no studies exist on devising a hybrid MCDM method that integrates DANP and G-TOPSIS to solve a green material selection problem for sustainable development. The results confirm that this method overcomes the one-sidedness of DANP-TOPSIS and DANP-GRA and makes the evaluation results more objective and realistic. In addition, the results of comparing with VIKOR confirmed that the final rank of this proposed approach is credible. Clearly, this study provides a more accurate, effective and systematic decision support tool for green material selection. In addition, this study can be useful for researchers to better understand the green material selection problem theoretically, as well as to organizations in designing/developing a better green design evaluation system.

Conclusion

Sustainable development is a difficult and restrained task for all walks of life, e.g., the manufacturing industry and the environmental protection agency. It has also been a great concern to countries, especially developing countries. In addition, previous research studies have proposed many solutions and optimization methods, with determining how to select the optimal material being one of the key problems. In this paper, we proposed a hybrid MCDM approach that combines DANP and G-TOPSIS to evaluate the material alternatives and select the optimal material for sustainability. This method not only handles the complex interactions and interdependences among dimensions and criteria, but also provides a visible causal relationship diagram to obtain the weights of each criterion for material selection. In addition, it combines GRA and TOPSIS in view of the lack of a single MCDM method, and a nonlinear programming model with constraints is proposed to obtain the integrated closeness index to avoid subjectivity and irrationality during the integration process. An empirical application of rubbish bins was used to illustrate the proposed method. A sensitivity analysis and a comparison with existing methods were employed to validate the stability of the final results. The results of the research in this paper show the following:

1. the proposed approach combining DANP and G-TOPSIS is a reasonable and effective tool for green material selection based on the results of an empirical case, a comparison of methods, and a sensitivity analysis;

2. a suitable hierarchical structure of each criterion considering the economic, environment and physical properties was built for material selection, and
3. the weights of each criterion are obtained via DANP and a causal influence diagram for dimensions and criteria is built.

As future work, our studies will focus on three direction: 1) on the basis of this study, we will integrate other significant impact criteria, e.g., social, technical and interior environment characteristics factors in the hierarchical structure, and formulate a more complete index system; 2) this hybrid method could be applied to other fields. For example, green performance assessment and design alternative selection, and a computer-assisted design support system will be designed and applied in the assessment process; 3) by noting that the raw data from the experts have uncertain and imprecise features, uncertainty theory must be integrated in MCDM methods for further development [89–90].

Appendix A

Step 1: Calculate the direct-relation matrix. The degree of direct impact that criterion i exerts on criterion j , which is denoted by d_{ij} , can be formulated by several experts/engineers in this field based on assumed scales, i.e., "no influence (0)", "very low influence (1)", "low influence (2)", "high influence (3)" and "very high influence (4)". Subsequently, A direct-relation matrix $A = [a_{ij}]_{n \times n}$ is produced through the mean of each same criterion in the various matrices of the experts/engineers.

Step 2: Establish the initial direct-relation matrix. The initial direct-relation matrix $D = [d_{ij}]_{n \times n}$ can be derived through normalizing the matrix A as shown in Eqs (18) and (19).

$$D = s \times A \tag{18}$$

$$s = \min \left[\frac{1}{\max_i \sum_{j=1}^n |a_{ij}|}, \frac{1}{\max_j \sum_{i=1}^n |a_{ij}|} \right] \tag{19}$$

Step 3: Derive the total direct-relation matrix. Along the powers of D , e.g., $D^2, D^3, \dots, D^\alpha$, the indirect impact of each criterion is decreasing continuously. As α approaches infinity, then $D^\alpha = [0]_{n \times n}$ where $0 \leq d_{ij} < 1, 0 < \sum_i d_{ij} \leq 1$ and $0 < \sum_j d_{ij} \leq 1$; at least one column sum $\sum_i d_{ij}$ or one row sum $\sum_j d_{ij}$ is equal to 1. Therefore, the total direct-relation matrix $T = [t_{ij}]_{n \times n}$ can be obtained through Eq (20).

$$T = D^1 + D^2 + \dots + D^\alpha = D(I - D)(I - D)^{-1} = D(I - D)^{-1} \tag{20}$$

where $\lim_{\alpha \rightarrow \infty} D^\alpha = [0]_{n \times n}$.

Step 4: Analyze the results. Each row sum vector r and column sum vector s of total direct-relation matrix T are separately produced, as shown in Eqs (21) and (22), where r_i denotes the sum of total influences of criterion i on the other criteria. Similarly, c_j denotes the sum of total influences that criterion j has received from the other criteria. Additionally, $(r_i + c_i)$ and $(r_i - c_i)$ should be calculated to analyze the results. $(r_i + c_i)$, as an index, can indicate the degree of the central role that criterion i plays in this problem when $i = j$. Regarding $(r_i - c_i)$,

if it's positive, criterion i affects other criteria; in contrast, criterion i is impacted by other criteria [32, 36].

$$r = (r_i)_{n \times 1} = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1} \tag{21}$$

$$c = (c_j)_{n \times 1} = (c_j)'_{1 \times n} = \left[\sum_{i=1}^n t_{ij} \right]'_{1 \times n} \tag{22}$$

Step 5: Establish a causal-relation diagram. By mapping the data set of $(r_i + c_i, r_i - c_i)$, a causal-relation diagram can be structured to provide an effective method to determine how the preferred values in each dimension/cluster and criterion can be improved.

Step 6: Calculate the unweighted supermatrix. Two different total direct-relation matrices are then obtained from DEMATEL, i.e., $T_C = [t_C^{ij}]_{n \times n}$ which pertains to n criteria and $T_D = [t_D^{ij}]_{m \times m}$ which is devoted to m dimensions/clusters from T_C as shown in Eq (23).

$$T_C = \begin{matrix} & & & & D_1 & \dots & D_j & \dots & D_m \\ & & & & c_{11} \dots c_{1n_1} & & c_{j1} \dots c_{jn_j} & & c_{m1} \dots c_{mn_m} \\ & & & & \vdots & & \vdots & & \vdots \\ D_1 & & & & \left[\begin{matrix} T_C^{11} & \dots & T_C^{1j} & \dots & T_C^{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ T_C^{i1} & \dots & T_C^{ij} & \dots & T_C^{im} \\ \vdots & & \vdots & \ddots & \vdots \\ T_C^{m1} & \dots & T_C^{mj} & \dots & T_C^{mm} \end{matrix} \right] & & & & \\ & & & & c_{i1} & & \vdots & & \vdots \\ & & & & \vdots & & \vdots & & \vdots \\ & & & & c_{m1} & & \vdots & & \vdots \\ D_m & & & & \vdots & & \vdots & & \vdots \\ & & & & c_{mn_m} & & & & \end{matrix} \tag{23}$$

In addition, a new matrix T_C^δ will be established by normalizing the total direct-relation

matrix T_C , as shown in Eqs (24) and (25).

$$T_C^\delta = \begin{matrix} & & D_1 & \cdots & D_j & \cdots & D_m \\ & & c_{11} \cdots c_{1n_1} & & c_{j1} \cdots c_{jn_j} & & c_{m1} \cdots c_{mn_m} \\ & c_{11} & & & & & \\ D_1 & \vdots & \left[\begin{array}{ccccc} T_C^{\delta 11} & \cdots & T_C^{\delta 1j} & \cdots & T_C^{\delta 1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ T_C^{\delta i1} & \cdots & T_C^{\delta ij} & \cdots & T_C^{\delta im} \\ \vdots & & \vdots & \ddots & \vdots \\ T_C^{\delta m1} & \cdots & T_C^{\delta mj} & \cdots & T_C^{\delta mm} \end{array} \right] & & \\ & c_{1n_1} & & & & & \\ \vdots & & & & & & \\ & c_{i1} & & & & & \\ D_j & \vdots & & & & & \\ & c_{in_i} & & & & & \\ \vdots & & & & & & \\ & c_{m1} & & & & & \\ D_m & \vdots & & & & & \\ & c_{mn_m} & & & & & \end{matrix} \quad (24)$$

An explanation for the normalization $T_C^{\delta 11}$ is explained in detail which is shown as Eqs (25) and (26). Similarly, other $T_C^{\delta ij}$ values can be obtained in the same manner.

$$T_C^{\delta 11} = [t_{cij}^{\delta 11}]_{m_1 \times m_1} = \begin{bmatrix} t_{c11}^{11}/d_{c1}^{11} & \cdots & t_{c1j}^{11}/d_{c1}^{11} & \cdots & t_{c1m_1}^{11}/d_{c1}^{11} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{ci1}^{11}/d_{ci}^{11} & \cdots & t_{cij}^{11}/d_{ci}^{11} & \cdots & t_{cim_1}^{11}/d_{ci}^{11} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{cm_1 1}^{11}/d_{cm_1}^{11} & \cdots & t_{cm_1 j}^{11}/d_{cm_1}^{11} & \cdots & t_{cm_1 m_1}^{11}/d_{cm_1}^{11} \end{bmatrix} \quad (25)$$

$$d_{ci}^{11} = \sum_{j=1}^{m_1} t_{ij}^{11}, i = 1, 2, \dots, m_1 \quad (26)$$

Let the total direct-relation matrix match and fill into the interdependence clusters. An unweighted supermatrix W can be obtained based on transposing the normalized total

direct-relation matrix T_C^δ , as shown in Eq (27).

$$W = (T_C^\delta)' = \begin{matrix} & & D_1 & \cdots & D_j & \cdots & D_m \\ & & c_{11} \cdots c_{1n_1} & & c_{j1} \cdots c_{jn_j} & & c_{m1} \cdots c_{mn_m} \\ D_1 & c_{11} & & & & & \\ & \vdots & & & & & \\ & c_{1n_1} & & & & & \\ & \vdots & & & & & \\ & c_{i1} & & & & & \\ D_j & \vdots & W^{lj} & \cdots & W^{jj} & \cdots & W^{nj} \\ & c_{in_i} & & & & & \\ & \vdots & & & & & \\ & c_{m1} & & & & & \\ D_m & \vdots & W^{ln} & \cdots & W^{in} & \cdots & W^{mn} \\ & c_{mm_m} & & & & & \end{matrix} \quad (27)$$

An explanation for the W^{11} is explained in detail which is shown as Eq (28). Similarly, other W^{ij} values can be obtained in the same manner.

$$W^{11} = \begin{matrix} & c_{11} & \cdots & c_{1i} & \cdots & c_{1m_1} \\ c_{11} & \left[\begin{matrix} t_{c11}^{\delta 11} & \cdots & t_{ci1}^{\delta 11} & \cdots & t_{cm_1 1}^{\delta 11} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{c1j}^{\delta 11} & \cdots & t_{cij}^{\delta 11} & \cdots & t_{cm_1 j}^{\delta 11} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ t_{c1m_1}^{\delta 11} & \cdots & t_{cim_1}^{\delta 11} & \cdots & t_{cm_1 m_1}^{\delta 11} \end{matrix} \right] \\ \vdots & & & & & \\ c_{1j} & & & & & \\ \vdots & & & & & \\ c_{1m_1} & & & & & \end{matrix} \quad (28)$$

Step 7: Calculate the weighted supermatrix. Each column will be summed for normalization as Eq (29).

$$T_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_D^{i1} & \cdots & t_D^{ij} & \cdots & t_D^{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_D^{n1} & \cdots & t_D^{nj} & \cdots & t_D^{nn} \end{bmatrix} \quad (29)$$

A new matrix T_D^δ can be established by normalizing the total direct-relation matrix T_D , as

shown in Eq (30).

$$T_D^\delta = [t_D^{\delta ij}] = \begin{bmatrix} t_D^{11}/d_1 & \dots & t_D^{1j}/d_1 & \dots & t_D^{1n}/d_1 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_D^{i1}/d_i & \dots & t_D^{ij}/d_i & \dots & t_D^{in}/d_i \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_D^{n1}/d_n & \dots & t_D^{nj}/d_n & \dots & t_D^{nn}/d_n \end{bmatrix} \quad (30)$$

To obtain the weighted supermatrix, the normalized total direct-relation matrix T_D^δ must be multiplied as shown in Eq (31).

$$W^\delta = T_D^\delta \times W = \begin{bmatrix} t_D^{\delta 11} \times W^{11} & \dots & t_D^{\delta i1} \times W^{i1} & \dots & t_D^{\delta n1} \times W^{n1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_D^{\delta 1j} \times W^{1j} & \dots & t_D^{\delta ij} \times W^{ij} & \dots & t_D^{\delta nj} \times W^{nj} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_D^{\delta 1n} \times W^{1n} & \dots & t_D^{\delta in} \times W^{in} & \dots & t_D^{\delta nn} \times W^{nn} \end{bmatrix} \quad (31)$$

Step 8: Limit the weighted supermatrix. Limit the weighted supermatrix by raising it to a sufficiently large power k until the supermatrix converges and becomes a long-term stable supermatrix to obtain the global priority vector ω .

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References

1. Lang DJ, Wiek A, Bergmann M, Stauffacher M, Martens P, Moll P, et al. Transdisciplinary research in sustainability science: practice, principles, and challenges. *Sustainability Science*. 2012; 7: 25–43.
2. Blackstock KL, Kelly GJ, Horsey BL. Developing and applying a framework to evaluate participatory research for sustainability. *Ecological Economics*. 2007; 60: 726–742.
3. Brundiers K, Wiek A. Educating students in real-world sustainability research: vision and implementation. *Innovative Higher Education*. 2011; 36: 107–124.
4. Turkay M, Saracoglu O, Arslan MC. Sustainability in supply chain management aggregate planning from sustainability perspective. *Plos One*. 2016; 11(1).
5. Viegas CV, Bond AJ, Vaz CR, Borchardt M, Pereira GM, Selig PM, et al. Critical attributes of sustainability in higher education: a categorisation from literature review. *Journal of Cleaner Production*. 2016; 126: 260–276.
6. Govindan K, Shankar KM, Kannan D. Sustainable material selection for construction industry—A hybrid multi criteria decision making approach. *Renewable & Sustainable Energy Reviews*. 2015; 55: 1274–1288.
7. Singh S, Olugu EU, Musa SN, Mahat AB, Wong KY. Strategy selection for sustainable manufacturing with integrated AHP-VIKOR method under interval-valued fuzzy environment. *International Journal of Advanced Manufacturing Technology*. 2016; 84(1–4): 547–563.
8. Kou G, Lu Y, Peng Y, Shi Y. Evaluation of classification algorithms using MCDM and rank correlation. *International Journal of Information Technology & Decision Making*, 2012; 11(01): 197–225.
9. Prasenjit C, Vijay MA, Shankar C. Selection of materials using compromise ranking and outranking methods. *Materials & Design*. 2009; 30(10): 4043–4053.
10. Shanian A, Savadogo O. A material selection model based on the concept of multiple attribute decision making. *Materials & Design*. 2006; 27(4): 329–337.
11. Akadiri PO, Olomolaiye PO, Chinyio EA. Multi-criteria evaluation model for the selection of sustainable materials for building projects. *Automation in Construction*. 2013; 30: 113–125.
12. Maniya K, Bhatt MG. A selection of material using a novel type decision-making method: Preference selection index method. *Materials & Design*. 2010; 31(4): 1785–1789.
13. Chatterjee P, Athawale VM, Chakraborty S. Materials selection using complex proportional assessment and evaluation of mixed data methods. *Materials & Design*. 2011; 32(2): 851–860.
14. Roth R, Field F, Clark J. Materials selection and multi-attribute utility analysis. *Journal of Computer-Aided Materials Design*. 1993; 1(3): 325–342.
15. Wang Y, Xi CY, Zhang S, Zhang WY, Yu DJ. Combined approach for government E-tendering using GA and TOPSIS with intuitionistic fuzzy information, *Plos One*. 2015; 10(7).
16. Rao RV, Davim JP. A decision-making framework model for material selection using a combined multiple attribute decision-making method. *International Journal of Advanced Manufacturing Technology*. 2008; 35(7–8): 751–760.
17. Nguyen HT, Dawal SZM, Nukman Y, Aoyama H. An integrated approach of fuzzy linguistic preference based AHP and fuzzy COPRAS for machine tool evaluation, *Plos One*. 2015; 10(9).
18. Chatterjee P, Athawale VM, Chakraborty S. Selection of materials using compromise ranking and outranking methods. *Materials & Design*. 2009; 30: 4043–4053.
19. Rao RV. A decision making methodology for material selection using an improved compromise ranking method. *Materials & Design*. 2008; 29: 1949–1954.
20. Jahan A, Mustapha F, Ismail MY, Sapuan SM, Bahraminasab M. A comprehensive VIKOR method for material selection. *Materials & Design*. 2011; 32: 1215–1221.
21. Altuntas S, Selim H, Dereli T. A fuzzy DEMATEL-based solution approach for facility layout problem: a case study. *International Journal of Advanced Manufacturing Technology*. 2014; 73(5–8): 749–771.
22. Chan JWK. Application of grey relational analysis for ranking material options. *International Journal of Computer Applications in Technology*. 2006; 26(4): 210–217.
23. Chan JWK, Tong TKL. Multi-criteria material selections and end-of-life product strategy: grey relational analysis approach. *Materials & Design*. 2007; 28: 1539–1546.

24. Rezaei J. Best-worst multi-criteria decision-making method: some properties and a linear model. *Omega-International Journal of Management Science*. 2015; 53: 49–57.
25. Coelho CRV, Pernollet F, van der Werf HMG. Environmental life cycle assessment of diets with improved omega-3 fatty acid profiles. *Plos One*. 2016; 11(8).
26. Kou G, Lin C. A cosine maximization method for the priority vector derivation in AHP. *European Journal of Operational Research*, 2014; 235(1): 225–232.
27. Tavana M, Zareinejad M, Di Caprio D, Kaviani MA. An integrated intuitionistic fuzzy AHP and SWOT method for outsourcing reverse logistics. *Applied Soft Computing*. 2016; 40: 544–557.
28. Ng CY, Chuah KB. Evaluation of design alternatives' environmental performance using AHP and ER approaches. *IEEE Systems Journal*. 2014; 8(4): 1182–1189.
29. Yang YPO, Shieh HM, Tzeng GH. A VIKOR technique based on DEMATEL and ANP for information security risk control assessment. *Information Sciences*. 2013; 232: 482–500.
30. Liu HC, You JX, Lu C, Chen YZ. Evaluating health-care waste treatment technologies using a hybrid multi-criteria decision making model. *Renewable and Sustainable Energy Reviews*, 2015, 41: 932–942.
31. Liu HC, Liu L, Wu J. Material selection using an interval 2-tuple linguistic VIKOR method considering subjective and objective weights. *Materials & Design*, 2013; 52: 158–167.
32. Çalişkan H, Kurşuncu B, Kurbanoğlu C, Güven ŞY. Material selection for the tool holder working under hard milling conditions using different multi criteria decision making methods. *Materials & Design*, 2013; 45: 473–479.
33. Hosseiniou SA, Mansour S, Shirazi MA. Social life cycle assessment for material selection: a case study of building materials. *The International Journal of Life Cycle Assessment*, 2014; 19(3): 620–645.
34. Kumar R, Singal SK. Penstock material selection in small hydropower plants using MADM methods. *Renewable and Sustainable Energy Reviews*, 2015; 52: 240–255.
35. Prendeville S, O'Connor F, Palmer L. Material selection for eco-innovation: SPICE model. *Journal of Cleaner Production*, 2014; 85: 31–40.
36. Castro-Lacouture D, Sefair JA, Flórez L, Medaglia AL. Optimization model for the selection of materials using a LEED-based green building rating system in Colombia. *Building and Environment*, 2009; 44(6): 1162–1170.
37. Kuo TC, Hsu CW, Li JY. Developing a green supplier selection model by using the DANP with VIKOR. *Sustainability*, 2015; 7(2): 1661–1689.
38. Bissoli-Dalvi M, Nico-Rodrigues EA, de Alvarez CE, Fuica GES, Montarroyos DCG. The sustainability of the materials under the approach of ISMAS. *Construction and Building Materials*, 2016; 106: 357–363.
39. Mayyas A, Qattawi A, Omar M, Shan D. Design for sustainability in automotive industry: A comprehensive review. *Renewable and Sustainable Energy Reviews*, 2012; 16(4): 1845–1862.
40. Florez L, Castro-Lacouture D. Optimization model for sustainable materials selection using objective and subjective factors. *Materials & Design*, 2013; 46: 310–321.
41. Zhao R, Su H, Chen X, Yu Y. Commercially available materials selection in sustainable design: An integrated multi-attribute decision making approach. *Sustainability*, 2016; 8(1): 79.
42. Anojkumar L, Ilangkumaran M, Sasirekha V. Comparative analysis of MCDM methods for pipe material selection in sugar industry. *Expert Systems with Applications*, 2014; 41(6): 2964–2980.
43. Huang H, Zhang L, Liu Z, Sutherland JW. Multi-criteria decision making and uncertainty analysis for materials selection in environmentally conscious design. *The international journal of advanced manufacturing technology*, 2011; 52(5–8): 421–432.
44. Liu HC, Mao LX, Zhang ZY, Li P. Induced aggregation operators in the VIKOR method and its application in material selection. *Applied Mathematical Modelling*, 2013; 37(9): 6325–6338.
45. Desai S, Bidanda B, Lovell MR. Material and process selection in product design using decision-making technique (AHP). *European Journal of Industrial Engineering*, 2012; 6(3): 322–346.
46. Rahman S, Odeyinka H, Perera S, Bi Y. Product-cost modelling approach for the development of a decision support system for optimal roofing material selection. *Expert Systems with Applications*, 2012; 39(8): 6857–6871.
47. Anojkumar L, Ilangkumaran M, Vignesh M. A decision making methodology for material selection in sugar industry using hybrid MCDM techniques. *International Journal of Materials and Product Technology*, 2015; 51(2): 102–126.
48. Onut S, Kara SS, Mert S. Selecting the suitable material handling equipment in the presence of vagueness. *The International Journal of Advanced Manufacturing Technology*, 2009; 44(7–8): 818–828.

49. İç YT. An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies. *Robotics and Computer-Integrated Manufacturing*, 2012; 28(2): 245–256.
50. Huang HH, Liu ZF, Zhang L, Sutherland JW. Materials selection for environmentally conscious design via a proposed life cycle environmental performance index. *The International Journal of Advanced Manufacturing Technology*, 2009; 44(11–12): 1073–1082.
51. Hsu CH, Wang FK, Tzeng GH. The best vendor selection for conducting the recycled material based on a hybrid MCDM model combining DANP with VIKOR. *Resources, Conservation and Recycling*, 2012; 66: 95–111.
52. Liu HC, You JX, Zhen L, Fan XJ. A novel hybrid multiple criteria decision making model for material selection with target-based criteria. *Materials & Design*. 2014; 60: 380–390.
53. Shanian A, Milani AS, Vermaak N, Bertoldi K, Scarinci T, Gerendas M. A combined finite element-multiple criteria optimization approach for materials selection of gas turbine components. *Journal of Applied Mechanics*, 2012; 79(6): 061019.
54. Maity SR, Chakraborty S. Grinding wheel abrasive material selection using fuzzy TOPSIS method. *Materials and Manufacturing Processes*, 2013; 28(4): 408–417.
55. Mayyas A, Omar MA, Hayajneh MT. Eco-material selection using fuzzy TOPSIS method. *International Journal of Sustainable Engineering*, 2016; 9(5): 292–304.
56. Tuzkaya G, Gülsün B, Kahraman C, Ozgen D. An integrated fuzzy multi-criteria decision making methodology for material handling equipment selection problem and an application. *Expert systems with applications*, 2010; 37(4): 2853–2863.
57. Girubha RJ, Vinodh S. Application of fuzzy VIKOR and environmental impact analysis for material selection of an automotive component. *Materials & Design*, 2012; 37: 478–486.
58. Aly MF, Attia HA, Mohammed AM. Integrated fuzzy (GMM)-TOPSIS model for best design concept and material selection process. *International Journal of Innovative Research in Science, Engineering and Technology*, 2013; 2(11): 6464–6486.
59. Rathod MK, Kanzaria HV. A methodological concept for phase change material selection based on multiple criteria decision analysis with and without fuzzy environment. *Materials & Design*, 2011; 32(6): 3578–3585.
60. Anojkumar L, Ilangkumaran M, Vignesh M. A decision making methodology for material selection in sugar industry using hybrid MCDM techniques. *International Journal of Materials and Product Technology*, 2015; 51(2): 102–126.
61. Saaty TL. *Decision making with dependence and feedback: Analytic network process*, RWS Publ Pittsburgh, 1996.
62. Kou G, Ergu D, Lin CS, Chen Y. Pairwise comparison matrix in multiple criteria decision making. *Technological and Economic Development of Economy*, 2016; 22(5): 738–765.
63. Ou Yang YP, Shieh HM, Leu JD, Tzeng GH. A novel hybrid MCDM model combined with DEMATEL and ANP with applications. *International Journal of Operational Research*. 2008; 5(3): 160–168.
64. Chiu WY, Tzeng GH, Li HL. A new hybrid MCDM model combining DANP with VIKOR to improve e-store business. *Knowledge-Based Systems*. 2013; 37: 48–61.
65. Tzeng GH, Chiang CH, Li CW. Evaluating intertwined effects in e-learning programs: a novel hybrid MCDM model based on factor analysis and DEMATEL. *Expert Systems with Applications*. 2007; 32(4): 1028–1044.
66. Hwang CL, Yoon K. *Multiple attributes decision making methods and applications*. Berlin: Springer, 1981.
67. Oztaysi B. A decision model for information technology selection using AHP integrated TOPSIS-Grey: The case of content management systems. *Knowledge-Based Systems*. 2014; 70: 44–54.
68. Patil SK, Kant R. A fuzzy AHP-TOPSIS framework for ranking the solutions of knowledge management adoption in supply chain to overcome its barriers. *Expert Systems with Applications*. 2014; 41: 679–693.
69. Deviren D, Yavuz S, Kilinc N. Weapon selection using the AHP and TOPSIS methods under fuzzy environment. *Expert Systems with Applications*. 2009; 36(4): 8143–8151.
70. Ahmadi MH, Ahmadi MA. Multi objective optimization of performance of three-heat-source irreversible refrigerators based algorithm NSGAI. *Renewable & Sustainable Energy Reviews*. 2016; 60: 784–794.
71. Tavana M, Li ZJ, Mobin M, Komaki M, Teymourian E. Multi-objective control chart design optimization using NSGA-III and MOPSO enhanced with DEA and TOPSIS. *Expert Systems with Applications*. 2016; 50: 17–39.
72. Behzadian M, Otaghsara SK, Yazdani M, Ignatius J. A state-of-the-art survey of TOPSIS applications. *Expert Systems with Applications*. 2012; 39(17): 13051–13069.

73. Sun Y, Huang GH, Li YP, Xu Y, Cao MF. An interval fuzzy robust nonlinear program for the planning of municipal solid waste management systems under uncertainty. *Engineering Optimization*, 2009; 41 (11): 989–1016.
74. Corazza M, Fasano G, Gusso R. Particle Swarm Optimization with non-smooth penalty reformulation, for a complex portfolio selection problem. *Applied Mathematics and Computation*, 2013; 224: 611–624.
75. Wang YL, Tzeng GH. Brand marketing for creating brand value based on a MCDM model combining DEMATEL with ANP and VIKOR methods. *Expert Systems with Applications*. 2012; 39(5): 5600–5615.
76. Govindan K, Shankar KM, Kannan D. Sustainable material selection for construction industry—A hybrid multi criteria decision making approach. *Renewable and Sustainable Energy Reviews*, 2016; 55: 1274–1288.
77. Kou G, Peng Y, Wang G. Evaluation of clustering algorithms for financial risk analysis using MCDM methods. *Information Sciences*, 2014; 275: 1–12.
78. Kou G, Ergu D, Shang J. Enhancing data consistency in decision matrix: Adapting Hadamard model to mitigate judgment contradiction. *European Journal of Operational Research*, 2014; 236(1): 261–271.
79. Athawale VM, Kumar R, Chakraborty S. Decision making for material selection using the UTA method. *The International Journal of Advanced Manufacturing Technology*, 2011; 57(1): 11–22.
80. Do JY, Kim DK. AHP-based evaluation model for optimal selection process of patching materials for concrete repair: Focused on quantitative requirements. *International Journal of Concrete Structures and Materials*, 2012; 6(2): 87–100.
81. Häkkinen T. Assessment of indicators for sustainable urban construction. *Civil Engineering and Environmental Systems*. 2007; 24(4): 247–259.
82. Nguyen BK, Altan H. Tpsi-tall-building projects sustainability indicator. *Procedia Engineering*. 2011; 21: 387–394.
83. Florez L, Castro D, Irizarry J. Measuring sustainability perceptions of construction materials. *Construction Innovation Information Process Management*. 2013; 13(2): 217–234.
84. Ortiz O, Castells F, Sonnemann G. Sustainability in the construction industry: a review of recent developments based on LCA. *Construction and Building Materials*. 2009; 23(1): 28–39.
85. Tsai CY, Chang AS. Framework for developing construction sustainability items: The example of highway design. *Journal of Cleaner Production*. 2012; 20(1): 127–136.
86. Castellano J, Castellano D, Ribera A, Ciurana J. Development of a scale of building construction systems according to CO₂ emissions in the use stage of their life cycle. *Building and Environment*. 2014; 82: 618–627.
87. Li GX, Kou G, Lin CS, Xu L, Liao Y. Multi-attribute decision making with generalized fuzzy numbers. *Journal of the Operational Research Society*, 2015; 66(11): 1793–1803.
88. Tian GD, Zhou MC, Zhang HH, Jia HF. An integrated AHP and VIKOR approach to evaluating green design alternatives[C]// *Networking, Sensing, and Control (ICNSC)*, 2016 IEEE 13th International Conference on. IEEE, 2016: 1–6.
89. Liu HC, You JX, You XY, Shan MM. A novel approach for failure mode and effects analysis using combination weighting and fuzzy VIKOR method. *Applied Soft Computing*, 2015; 28: 579–588.
90. Liu HC, You JX, Li ZW, Tian GD. Fuzzy Petri nets for knowledge representation and reasoning: A literature review. *Engineering Applications of Artificial Intelligence*, 2017; 60: 45–56.