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Optimal Lightweight Material Selection for Automobile Applications Considering Multi-Perspective Indices

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ABSTRACT As a significant technology in the automotive manufacturing industry, weight reduction in vehicle design has attracted much attention. Its effect on energy saving and emission reduction is prominent. The application of lightweight material is commonly adopted as a primary way of weight reduction. However, material selection is often subject to multi-perspective performance characteristics, e.g., mechanical and societal properties, and therefore, an effective multi-criteria decision-making (MCDM) method is needed. This paper presents a systematic hierarchical structure of multi-perspective indices for optimal lightweight material selection, including mechanical, durability, societal, and technical properties. A hybrid evaluation approach (G-TOPSIS) integrating grey relation analysis and technique for order performance by similarity to ideal solution (TOPSIS) is applied to evaluate lightweight material alternatives and obtain an optimal one. A case study, i.e., 17 kinds of lightweight materials, is conducted to verify the hierarchical structure and the MCDM method. In addition, a sensitivity analysis is conducted to monitor the robustness of solution ranking to changes. The results show that this method provides an effective decision-making tool for optimal lightweight material selection for automobile applications.

INDEX TERMS Material selection, automobile applications, decision making, data modeling, Internet-of-Things.

I. INTRODUCTION

With the rapid progress of industrialization and urbanization, automobiles have become an indispensable means of transportation in modern society [1]. Car ownership has basically become an important indicator for measuring the industrial level and the quality of economic development of a country/region. Vehicle ownership in China had reached 217 million in 2017, increasing by 11.85% over the previous year. But simultaneously, it has sparked serious concerns about resource and ecological environment degradation which have seriously affected the human life [2].

The rapid development of transportation not only brings about the problem of vast oil consumption, but also poses a difficult challenge to the protection of ecological environment. Transportation industry has currently been the second-largest producer of anthropogenic greenhouse gas emissions. Around 93% are generated by road transportation, i.e., vehicle emission. Besides, 40% of the oil consumption of nearly 75 million barrels is applied in transportation systems per day all over the world [3]. Therefore, studies on energy conservation and emission reduction have been gaining public momentum especially in automotive industry.

The automotive industries are experiencing innovations to improve vehicle efficiency and reduce emissions during their application, meanwhile ensuring specific performance of vehicles. These approaches can be summarized as follows: drive train efficiency improvement [4], development of new energy vehicles [5], alternative fuel systems [6] and vehicle weight reduction [7]. Among them, vehicle weight reduction has been considered as one of the most effective solutions and weight reduction of 57 kg is equivalent to 0.09–0.21 km per liter fuel economy increase. Reducing vehicle mass is basically achieved through two key technologies: structural lightweight design, where components/parts in vehicle are optimized to realize higher performance, and lightweight materials substitution, where lighter weight materials are applied in car manufacturing [2]. In recent years, some commonly used lightweight materials are high-strength steel, aluminium alloy, magnesium alloy, engineering plastics and composite material. As material products develop towards the higher performance in many directions, materials that meet the performance requirement for automobile application have come in a winder range [8]. Therefore, deciding how to select the optimal lightweight material considering multi-perspective indices has become a thorny problem for designers, which can be considered as a multi-criteria decision making (MCDM) problem.

A series of systemic theoretical explorations on the material selection for commercial manufacture has been reported in recent years. Poulikidou *et al.* [9] present a new selection approach and verify it by its application in the design of automotive component, i.e., truck roof panel. Cho *et al.* [10] propose a novel design method combining material selection and shape optimization for weight reduction, and a case study of urban transit car-body is carried out to verify this hybrid approach. Mayyas *et al.* [11] develop a method that combines quality function deployment and analytical hierarchy process for material selection for the structural panels of car-body. Zhang *et al.* [12] present a hybrid MCDM approach to realize green material selection based on hierarchy indicator structure considering economic, environment and physical properties. Govindan *et al.* [13] formulate a comprehensive evaluation index system that combines economic, environment and society indicators and propose a hybrid MCDM methodology, i.e., DANP and technique for order performance by similarity to ideal solution (TOPSIS) to evaluate the best sustainable construction material. However, few studies that carry out optimal lightweight material selection for automobile applications considering multi-perspective indices, e.g., mechanical and technical properties can be found.

This paper presents a systematic hierarchical structure of multi-perspective indices including mechanical, durability, societal and technical properties for optimal lightweight material selection. A hybrid evaluation approach (G-TOPSIS) integrating grey relation analysis (GRA) and TOPSIS is applied to evaluate lightweight material alternatives and obtain the optimal one. A case study, i.e., 17 kinds of lightweight materials, is carried out to verify the hierarchical structure and the MCDM method. In addition, a sensitivity analysis is conducted to monitor the robustness of solution ranking to changes.

The paper is organized as follows: Section 2 introduces the hybrid evaluation approach that is G-TOPSIS. The verification of an empirical case, i.e., 17 kinds of lightweight materials, is presented to demonstrate the new hierarchical structure of evaluation indicators and the applied MCDM methodology in Section 3. Section 4 presents comparison and sensitivity analysis. Finally, the conclusions of this paper are drawn in Section 5.

II. METHODOLOGY

In this section, a systematic hierarchical structure of multi-perspective indices including mechanical, durability, societal and technical properties for optimal lightweight material selection is formulated. In addition, a hybrid evaluation approach, i.e., G-TOPSIS, is applied to obtain the optimal lightweight material from a wider range of material alternatives. The methodology flowchart for optimal lightweight material selection is shown in Fig. 1. The detailed procedures and explanation of these phases are summarized in the sub-sections.

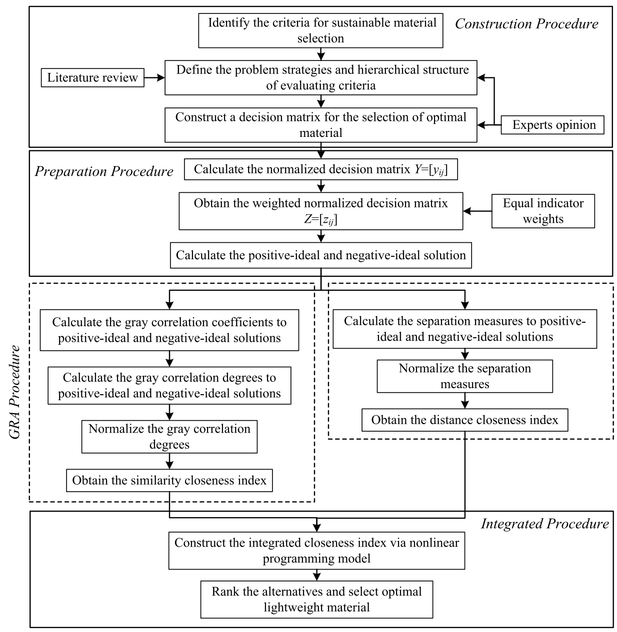

FIGURE 1. Methodology flowchart.

A. HIERARCHICAL STRUCTURE OF LIGHTWEIGHT MATERIAL SELECTION FOR AUTOMOBILE APPLICATIONS

As shown in Section 1, many quantitative and qualitative criteria should be taken into consideration in the process of material selection. For different field of engineering application, the emphasis point and evaluation indicators should also be distinct. In automotive manufacturing field, mechanical and technical properties are commonly considered in the hierarchical structure of evaluation indicators. However, other properties, e.g., durability, also need to be included as indispensable criteria for automobile applications. Therefore, we formulate a systematic hierarchical structure that considers mechanical, durability, societal and technical properties for the lightweight material selection.

As shown in Table 1, the goal level is optimal lightweight material selection for automobile applications; criterion level includes mechanical property (C_1), durability property (C_2), societal property (C_3) and technical property (C_4). Mechanical property includes five criteria, i.e., density (F_1), modulus of elasticity (F_2), yield strength (F_3), tensile strength (F_4) and recycle fraction (F_5). Durability property includes three criteria, i.e., corrosion resistance (F_6), thermal performance (F_7) and wear resistance (F_8). Societal property includes two criteria, i.e., NVH (F_9) and crashworthiness (F_{10}).

TABLE 1. The hierarchical structure of multi-perspective indices for optimal lightweight material selection.

Goal level	Criterion level	Symbol	Factor/attribute level	Symbol	References
Optimal lightweight material selection	Mechanical property	C_1	Density (g/cm^3)	F_1	[7, 10, 12]
			Modulus of elasticity (GPa)	F_2	
			Yield strength (MPa)	F_3	
			Tensile strength (MPa)	F_4	
			Recycle fraction (%)	F_5	
	Durability property	C_2	Corrosion resistance	F_6	
			Thermal performance	F_7	
			Wear resistance	F_8	
	Societal property	C_3	Health and Wellness (NVH)	F_9	[8, 12, 14-18]
			Crashworthiness	F_{10}	
	Technical property	C_4	Forming	F_{11}	[6, 8, 10-12, 19-22]
			Joining	F_{12}	
			Painting	F_{13}	

Technical property includes three criteria, i.e., forming (F_{11}), joining (F_{12}) and painting (F_{13}).

B. A HYBRID EVALUATION APPROACH

TOPSIS, first presented by Hwang and Yoon, has become a common approach for solving MCDM problems [23]. It adopts the distance relationship between each alternative and the positive/negative-ideal solution as the operating principium, and can be applied to evaluate the location relationship among them. It has been successfully used in many fields, e.g., alternative evaluation and selection [22], [24]–[28]. However, the deficiency of this method is obvious and can be summarized below: 1) the norms of assessment are simplistic, as only the distance factor is considered; 2) it cannot be solved when the distance relationships of the alternative to positive-ideal and negative-ideal solutions are equal in the MCDM problems. Therefore, a hybrid evaluation approach combining GRA and TOPSIS and considering multi-perspective indices is proposed [12] and applied to evaluate lightweight material alternatives for automobile applications and obtain the optimal one. The procedure can be summarized as follows:

Step 1: Construct the decision matrix $X = [x_{ij}]$ $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$, where n represents the number of optional alternatives; m represents that of indicators in the hierarchical structure for optimal lightweight material selection. x_{ij} indicates a value decided by decision makers based on the priority level of each alternative i corresponding to each indicator j.

Step 2: Calculate the weighted-normalized matrix $Z = [z_{ij}]$ $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$.

For the benefit indicators, the normalized value $y_{ij} = x_{ij}/\max_i x_{ij} (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$; For the cost indicators, the normalized value is $y_{ij} = \min_i x_{ij}/x_{ij} (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$. The weighted-normalized value $z_{ij} = w_j * y_{ij}$. w_j represents the weight of the jth indicator in the hierarchical structure. Note that the weight vector of each criterion is equal in this paper.

Step 3: Calculate the positive-ideal and negative-ideal solutions as,

$$\begin{aligned} Z^+ &= [z_j^+] \\ &= [\max_{1\le i\le n}\left(\{z_{ij}\}_{i=1}^n\right)\Big| j\in J^+,\ \min_{1\le i\le n}\left(\{z_{ij}\}_{i=1}^n\right)\Big| j\in J^-], \\ &\qquad (j = 1, 2, \ldots, m) \end{aligned} \tag{1}$$

$$\begin{aligned} Z^- &= [z_j^-] \\ &= [\min_{1\le i\le n}\left(\{z_{ij}\}_{i=1}^n\right)\Big| j\in J^+,\ \max_{1\le i\le n}\left(\{z_{ij}\}_{i=1}^n\right)\Big| j\in J^-], \\ &\qquad (j = 1, 2, \ldots, m) \end{aligned} \tag{2}$$

where J^+ denotes the indicator to be maximized. J^- denotes the indicator to be minimized.

Step 4: Calculate the gray correlation coefficient of each alternative from positive/negative-ideal solutions. Note that "$*$" represents "$+$" or "$-$" and $\rho = 0.5$ in this paper.

$$\mathrm{r}_{ij}^* = \frac{\min_i \min_j \left|z_j^* - z_{ij}\right| + \rho \max_i \max_j \left|z_j^* - z_{ij}\right|}{\left|z_j^* - z_{ij}\right| + \rho \max_i \max_j \left|z_j^* - z_{ij}\right|} \tag{3}$$

The gray correlation degree between each alternative and positive/negative-ideal solution can be obtained by

$$R_i^* = \frac{1}{m}\sum_{j=1}^m r_{ij}^*, \quad (i = 1, 2, \ldots, n) \tag{4}$$

Step 5: Calculate the separation measures using the dimensional Euclidean distance. The separation D_i^* of each alternative from the positive/negative-ideal solutions can be obtained by

$$D_i^* = \sqrt{\sum_{j=1}^m \left[z_{ij} - z_j^*\right]^2}, \quad (i = 1, 2, \ldots, n) \tag{5}$$

Step 6: Apply dimensionless method to the R_i^+, D_i^+, D_i^+ and D_i^-, respectively.

The normalized value $\tilde{\theta}_i$ is calculated as

$$\tilde{\theta}_i = \frac{\theta_i}{\max_{1\le i\le n} \theta_i}, \quad (i = 1, 2, \ldots, n) \tag{6}$$

TABLE 2. The decision matrix for lightweight material alternatives.

Material alternatives	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}	F_{13}
Low strength steels	7.85	205	200	260	85%	5	9	9	5	7	8	9	9
High strength steels	7.85	205	470	535	85%	5	9	9	5	7	8	9	9
Advanced high strength steels	7.85	200	860	1150	85%	6	10	8	4	9	5	7	9
Ultra-high strength steels	7.85	205	970	1250	85%	5	9	9	4	8	5	7	9
Stainless steels	7.85	205	310	620	85%	5	9	9	5	8	6	8	9
Aluminum alloy 7×××series	2.80	72	385	460	95%	7	8	6	9	4	8	5	9
Aluminum alloy 6×××series	2.80	70	260	310	95%	7	8	6	9	4	8	5	8
Aluminum alloy 5×××series	2.80	69.5	170	220	95%	7	8	6	9	4	8	5	8
Aluminum extrusion profiles	2.70	70	160	215	95%	7	8	6	9	4	8	5	8
Cast aluminum	2.70	73	210	290	95%	7	9	6	9	4	7	6	8
Magnesium alloy	1.79	45	130	237	90%	3	8	6	8	3	5	4	7
Ti alloy	4.50	108	1100	1200	90%	9	9	6	6	8	4	5	7
Thermoplasticsting plastics (PP)	0.90	1.60	35	35	20%	9	5	6	3	6	9	7	9
Thermosetting plastics (UP)	1.20	3.16	51.3	65	5%	9	5	5	3	6	9	7	9
Carbon fiber/epoxy Composites	1.61	115	1100	1400	5%	9	6	7	3	9	8	7	8
S-glass fiber/epoxy Composites	1.83	23.8	354.5	448.8	5%	9	6	7	3	6	8	7	8
Epoxy-glass fiber(sheet molding compound)	7.85	205	200	260	85%	5	9	9	5	7	8	9	9

where θ_i expresses the R_i^+, R_i^-, D_i^+ and D_i^-; $\tilde{\theta}_i$ expresses the $\tilde{R}_i^+$, $\tilde{R}_i^-$, $\tilde{D}_i^+$ and $\tilde{D}_i^-$.

Step 7: Calculate the similarity closeness and the distance closeness by

$$\tilde{R}_i = \frac{\tilde{R}_i^+}{\tilde{R}_i^+ + \tilde{R}_i^-}, \quad (i = 1, 2, \ldots, n) \tag{7}$$

$$\tilde{D}_i = \frac{\tilde{D}_i^-}{\tilde{D}_i^+ + \tilde{D}_i^-}, \quad (i = 1, 2, \ldots, n) \tag{8}$$

Step 8: Obtain the ultimate decision index H_i using a nonlinear programming model by

$$\begin{aligned} &\min \Re = \sum_{i=1}^{n} [(H_i - \tilde{R}_i)^2 + (H_i - \tilde{D}_i)^2] \\ &\text{s.t. } \min(\tilde{R}_i, \tilde{D}_i) \leq H_i \leq \max(\tilde{R}_i, \tilde{D}_i) \\ &\qquad 0 < H_i < 1 \end{aligned} \tag{9}$$

Step 9: Determine the rank of each alternative based on the values of the ultimate decision index. Note that the greater the value, the better the alternative.

III. A CASE STUDY FOR AUTOMOBILE APPLICATIONS

To verify this proposed hierarchical structure and the hybrid MCDM method, a case study, i.e., 17 kinds of lightweight materials for automobile applications, is carried out.

A. LIGHTWEIGHT MATERIAL ALTERNATIVES AND DATA COLLECTION

Recently, with the development of material science, traditional materials have been improved, expanding their area of application. In addition, composite materials have also been developed rapidly and applied in various fields. In the field of automobile application, a wider range of materials has been used to reduce the mass of car-body, e.g., high-strength steel and aluminum alloy. Based on the literature review and expert interview, 17 kinds of lightweight materials, i.e., low-strength steels, high-strength steels, advanced high-strength steels, ultra-high strength steels, stainless steels, aluminum alloy 7××× series, aluminum alloy 6××× series, aluminum alloy 5××× series, aluminum extrusion profiles, cast aluminum, magnesium alloy, Ti alloy, thermoplasticsting plastics (PP), thermosetting plastics (UP), carbon fiber/epoxy composites, S-glass fiber/epoxy composites and epoxy-glass fiber (sheet molding compound), are included in the case study to verify the proposed hierarchical structure and the hybrid MCDM method in this paper.

Four decision makers, including two experts who specialize in automobile design and two senior engineers from an reputable automobile manufacture enterprise, were interviewed to obtain the initial data and related information through questionnaire surveys. This investigation was conducted in October 08 in 2017. The decision matrix for lightweight material alternatives to each criterion in the hierarchical structure for optimal lightweight material selection is formulated as shown in Table 2.

B. OPERATIONS AND RESULTS

The initial data are obtained from decision makers as shown in Table 2. The next step is to evaluate the lightweight material alternatives, i.e., 17 kinds of lightweight materials, and obtain the optimal one based on the hybrid MCDM approach that has been presented in Section 2. The detailed steps of the optimal lightweight material selection are summarized below.

Based on Step 2 in sub-section 2.2, the weighted-normalized matrix can be calculated as shown in Table 5. Note that the weights of each criterion are equal in this case. The positive-ideal solution and negative-ideal one are obtained using Eqs. (1) and (2) as shown in Table 6. Then, the gray correlation degree and the separation measures can be calculated through Eqs. (3)-(5) and the results are shown in

TABLE 3. Comparison results obtained from three approaches.

Material alternatives	TOPSIS method		This hybrid method		GRA method	
	D_i	Order	H_i	Order	R_i	Order
Low strength steels	0.5989	6	0.5998	6	0.6007	5
High strength steels	0.6553	4	0.6381	3	0.6208	2
Advanced high strength steels	0.7203	1	0.6713	1	0.6222	1
Ultra-high strength steels	0.7177	2	0.6685	2	0.6194	3
Stainless steels	0.6325	5	0.6172	5	0.6020	4
Aluminum alloy 7×××series	0.5430	9	0.5419	9	0.5408	9
Aluminum alloy 6×××series	0.5164	10	0.5174	11	0.5185	11
Aluminum alloy 5×××series	0.5020	12	0.5064	12	0.5107	12
Aluminum extrusion profiles	0.5000	13	0.5047	13	0.5094	13
Cast aluminum	0.5160	11	0.5193	10	0.5226	10
Magnesium alloy	0.3974	14	0.4027	15	0.4080	17
Ti alloy	0.6796	3	0.6237	4	0.5678	7
Thermoplasticsting plastics (PP)	0.3187	17	0.3652	17	0.4116	15
Thermosetting plastics (UP)	0.3235	16	0.3669	16	0.4103	16
Carbon fiber/epoxy Composites	0.5834	8	0.5671	8	0.5508	8
S-glass fiber/epoxy Composites	0.3920	15	0.4235	14	0.4550	14
Epoxy-glass fiber(sheet molding compound)	0.5989	6	0.5998	6	0.6007	5

TABLE 4. The weight vectors of sensitivity analysis.

No.	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	w_{12}	w_{13}
1	0.28	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
2	0.06	0.28	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
3	0.06	0.06	0.28	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
4	0.06	0.06	0.06	0.28	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
5	0.06	0.06	0.06	0.06	0.28	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
6	0.06	0.06	0.06	0.06	0.06	0.28	0.06	0.06	0.06	0.06	0.06	0.06	0.06
7	0.06	0.06	0.06	0.06	0.06	0.06	0.28	0.06	0.06	0.06	0.06	0.06	0.06
8	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.28	0.06	0.06	0.06	0.06	0.06
9	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.28	0.06	0.06	0.06	0.06
10	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.28	0.06	0.06	0.06
11	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.28	0.06	0.06
12	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.28	0.06
13	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.28
14	0.10	0.10	0.10	0.10	0.10	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
15	0.04	0.04	0.04	0.04	0.04	0.20	0.20	0.20	0.04	0.04	0.04	0.04	0.04
16	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.15	0.15	0.064	0.064	0.064
17	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.20	0.20	0.20

Table 7. Through the standardization process, the similarity closeness and the distance closeness can be calculated using Eqs. (7) and (8) as shown in Table 8. Finally, the ultimate decision indictor is obtained using a nonlinear programming model as shown in Step 8 and the optimal lightweight material can be selected based on the rank of decision indictors.

The ultimate decision indictor and final rank are shown as follows: the H_1 for low-strength steels is 0.5998; the H_2 for high-strength steels is 0.6381; the H_3 for advanced high-strength steels is 0.6713; the H_4 for ultra-high strength steels is 0.6685; the H_5 for stainless steels is 0.6172; the H_6 for aluminum alloy 7××× series is 0.5419; the H_7 for aluminum alloy 6××× series is 0.5174; the H_8 for aluminum alloy 5××× series is 0.5064; the H_9 for aluminum extrusion profiles is 0.5047; the H_{10} for cast aluminum is 0.5193; the H_{11} for magnesium alloy is 0.4027; the H_{12} for Ti alloy is 0.6237; the H_{13} for thermoplasticsting plastics (PP) is 0.3652; the H_{14} for thermosetting plastics (UP) is 0.3669; the H_{15} for carbon fiber/epoxy composites is 0.5671; the H_{16} for S-glass fiber/epoxy composites is 0.4235; the H_{17} for epoxy-glass fiber (sheet molding compound) is 0.5998. The final rank of lightweight material alternatives is advanced high-strength steels > ultra-high strength steels > high-strength steels > carbon fiber/epoxy composites > stainless steels > low-strength steels > aluminum alloy 7××× series = epoxy-glass fiber (sheet molding compound) > thermoplasticsting plastics (PP) > aluminum alloy 6××× series > aluminum alloy 5××× series > aluminum extrusion profiles > thermosetting plastics (UP) > S-glass fiber/epoxy composites. Therefore, the advanced high-strength steels are the optimal lightweight material for automobile applications.

IV. VERIFICATION AND ANALYSIS

A. COMPARISON WITH THE EXISTING METHODS

In this section, to prove the feasibility and validity of the hybrid method, we apply TOPSIS and GRA methods to

TABLE 5. The weighted-normalized matrix.

No.	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}	F_{13}
1	0.1146	1.0000	0.1818	0.1857	0.8947	0.5556	0.9000	1.0000	0.5556	0.7778	0.8889	1.0000	1.0000
2	0.1146	1.0000	0.4273	0.3821	0.8947	0.5556	0.9000	1.0000	0.5556	0.7778	0.8889	1.0000	1.0000
3	0.1146	0.9756	0.7818	0.8214	0.8947	0.6667	1.0000	0.8889	0.4444	1.0000	0.5556	0.7778	1.0000
4	0.1146	1.0000	0.8818	0.8929	0.8947	0.5556	0.9000	1.0000	0.4444	0.8889	0.5556	0.7778	1.0000
5	0.1146	1.0000	0.2818	0.4429	0.8947	0.5556	0.9000	1.0000	0.5556	0.8889	0.6667	0.8889	1.0000
6	0.3214	0.3512	0.3500	0.3286	1.0000	0.7778	0.8000	0.6667	1.0000	0.4444	0.8889	0.5556	1.0000
7	0.3214	0.3415	0.2364	0.2214	1.0000	0.7778	0.8000	0.6667	1.0000	0.4444	0.8889	0.5556	0.8889
8	0.3214	0.3390	0.1545	0.1571	1.0000	0.7778	0.8000	0.6667	1.0000	0.4444	0.8889	0.5556	0.8889
9	0.3333	0.3415	0.1455	0.1536	1.0000	0.7778	0.8000	0.6667	1.0000	0.4444	0.8889	0.5556	0.8889
10	0.3333	0.3561	0.1909	0.2071	1.0000	0.7778	0.9000	0.6667	1.0000	0.4444	0.7778	0.6667	0.8889
11	0.5028	0.2195	0.1182	0.1693	0.9474	0.3333	0.8000	0.6667	0.8889	0.3333	0.5556	0.4444	0.7778
12	0.2000	0.5268	1.0000	0.8571	0.9474	1.0000	0.9000	0.6667	0.6667	0.8889	0.4444	0.5556	0.7778
13	1.0000	0.0078	0.0318	0.0250	0.2105	1.0000	0.5000	0.6667	0.3333	0.6667	1.0000	0.7778	1.0000
14	0.7500	0.0154	0.0466	0.0464	0.0526	1.0000	0.5000	0.5556	0.3333	0.6667	1.0000	0.7778	1.0000
15	0.5590	0.5610	1.0000	1.0000	0.0526	1.0000	0.6000	0.7778	0.3333	1.0000	0.8889	0.7778	0.8889
16	0.4918	0.1161	0.3223	0.3206	0.0526	1.0000	0.6000	0.7778	0.3333	0.6667	0.8889	0.7778	0.8889
17	0.1146	1.0000	0.1818	0.1857	0.8947	0.5556	0.9000	1.0000	0.5556	0.7778	0.8889	1.0000	1.0000

TABLE 6. The positive-ideal solution and negative-ideal one.

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}	F_{13}
Z+	0.1146	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Z-	1.0000	0.0078	0.0318	0.0250	0.0526	0.3333	0.5000	0.5556	0.3333	0.3333	0.4444	0.4444	0.7778

compare the outcomes with this hybrid method. Note that the weights of each criterion are equal when using the three methods [29], [30]. Table 3 expresses the results of closeness index obtained from the three decision approaches and the order of alternatives.

As shown in Table 3, the optimal material alternative is advanced high-strength steels and the final ranks of these alternatives using these three methods are basically consistent. Therefore, this hybrid MCDM approach is reliable and effective. However, the results about the second alternative are distinct among TOPSIS method and GRA method. The reason for this phenomenon is that the evaluation mechanism is different for these two approaches, i.e., the distance from the positive-ideal solution and the negative-ideal solution alone is for TOPSIS and the degree of similarity to the ideal solution alone is for GRA. Thus, integrating these two methods is necessary such that both distance and similarity are taken into account.

B. SENSITIVITY ANALYSIS

To monitor the robustness of the final rank to the changes of criterion weight vectors, 17 experiments for sensitivity analysis are conducted (denoted by w_i for criterion F_i where $i = 1, 2, \ldots, 13$) [12], [31]. The weight vector of each experiment is presented in Table 4. As shown in Table 4, in the first 13 experiments, weights of each criterion are set as higher (equal to 0.28) successively and the others are equal to 0.06; in experiment 14, weights of mechanical criteria (w_{1-5}) are set as higher (equal to 0.10) and the others are equal to 0.0625; in experiment 15, weights of durability criteria (w_{6-8}) are set as higher (equal to 0.20) and other are equal to 0.04; in experiment 16, weights of societal criteria (w_{9-10}) are set as higher (equal to 0.15) and the others are equal to 0.064; in experiment 17, weights of technical criteria (w_{11-13}) are set as higher (equal to 0.20) and the others are equal to 0.04. The results of 17 experiments are shown in Table 9.

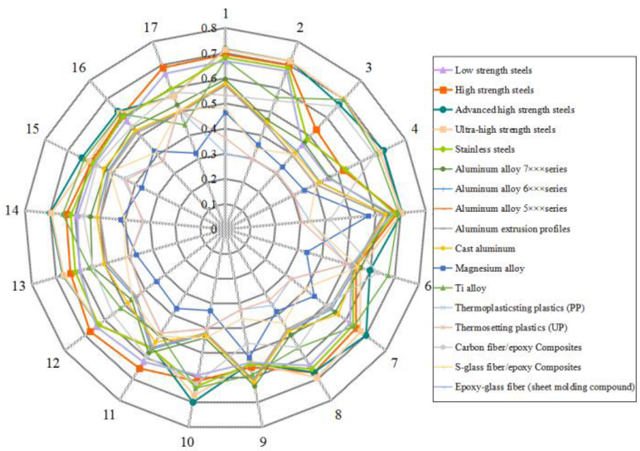

FIGURE 2. Results of sensitivity analysis.

Fig. 2 depicts the results of final ranking of the lightweight material alternatives when the weight vector of each criterion is changed as shown in Tables 4 and 9. It can be seen from Fig. 2 that alternative 3, i.e., advanced high-strength steels, has the highest score in 9 experiments out of 17 experiments (numbers 1-2, 4-5, 7, 10, 13, 15-16). Thus, advanced high-strength steels as the optimal alternative for automobile applications are reliable. In addition, as shown in Table 9, the final

TABLE 7. The positive-ideal solution and negative-ideal one.

	Al. 1	Al. 2	Al. 3	Al. 4	Al. 5	Al. 6	Al. 7	Al. 8	Al. 9	Al. 10	Al. 11	Al. 12	Al. 13	Al. 14	Al. 15	Al. 16	Al. 17
R+	9.4851	9.6307	9.7987	9.8091	9.2736	8.1281	7.8267	7.7863	7.7707	7.8690	6.3944	8.9396	6.8534	6.8246	8.8059	6.9019	9.4851
R-	6.3705	5.9441	6.0111	6.0881	6.1951	6.9725	7.3421	7.5379	7.5597	7.2622	9.3752	6.8745	9.8980	9.9099	7.2559	8.3505	6.3705
D+	1.3455	1.0898	0.8776	0.9011	1.1739	1.4339	1.5483	1.6236	1.6308	1.5484	1.9591	1.0269	2.2903	2.2674	1.4197	1.8923	1.3455
D-	1.9327	1.9927	2.1745	2.2031	1.9431	1.6387	1.5902	1.5745	1.5690	1.5878	1.2427	2.0949	1.0305	1.0430	1.9125	1.1737	1.9327

TABLE 8. The similarity closeness and the distance closeness.

	Al. 1	Al. 2	Al. 3	Al. 4	Al. 5	Al. 6	Al. 7	Al. 8	Al. 9	Al. 10	Al. 11	Al. 12	Al. 13	Al. 14	Al. 15	Al. 16	Al. 17
R	0.6007	0.6208	0.6222	0.6194	0.6020	0.5408	0.5185	0.5107	0.5094	0.5226	0.4080	0.5678	0.4116	0.4103	0.5508	0.4550	0.6007
D	0.5989	0.6553	0.7203	0.7177	0.6325	0.5430	0.5164	0.5020	0.5000	0.5160	0.3974	0.6796	0.3187	0.3235	0.5834	0.3920	0.5989

TABLE 9. The results of 17 experiments for sensitivity analysis.

No.	Al. 1	Al. 2	Al. 3	Al. 4	Al. 5	Al. 6	Al. 7	Al. 8	Al. 9	Al. 10	Al. 11	Al. 12	Al. 13	Al. 14	Al. 15	Al. 16	Al. 17
1	0.6689	0.6947	**0.7158**	0.7134	0.6820	0.5958	0.5818	0.5750	0.5708	0.5797	0.4649	0.6747	0.3018	0.3629	0.5325	0.4833	0.6689
2	0.6743	0.6986	**0.7165**	0.7161	0.6867	0.4645	0.4512	0.4461	0.4461	0.4568	0.3600	0.5613	0.2970	0.2987	0.5481	0.3430	0.6743
3	0.4543	0.5356	0.6713	**0.6989**	0.4826	0.4651	0.4216	0.3978	0.3951	0.4113	0.3357	0.6971	0.3022	0.3047	0.6607	0.4016	0.4543
4	0.4573	0.5238	**0.7028**	0.6853	0.5338	0.4611	0.4201	0.4004	0.3989	0.4175	0.3493	0.6720	0.3028	0.3061	0.6622	0.4040	0.4573
5	0.6624	0.6863	**0.7057**	0.7036	0.6744	0.6527	0.6388	0.6317	0.6309	0.6400	0.5711	0.6914	0.3367	0.3064	0.4187	0.3347	0.6624
6	0.5214	0.5402	0.5978	0.5573	0.5279	0.5592	0.5430	0.5353	0.5343	0.5445	0.3351	**0.6734**	0.5053	0.5064	0.6304	0.5487	0.5214
7	0.6209	0.6520	**0.7006**	0.6747	0.6355	0.5470	0.5285	0.5199	0.5186	0.5611	0.4422	0.6405	0.3275	0.3287	0.5045	0.3927	0.6209
8	0.6370	0.6700	0.6688	**0.6935**	0.6528	0.4934	0.4755	0.4678	0.4666	0.4772	0.3846	0.5538	0.3560	0.3321	0.5515	0.4394	0.6370
9	0.5395	0.5583	0.5415	0.5416	0.5461	**0.6342**	0.6177	0.6095	0.6084	0.6191	0.5193	0.5880	0.3256	0.3267	0.4617	0.3618	0.5395
10	0.5900	0.6149	**0.6999**	0.6724	0.6368	0.4395	0.4257	0.4201	0.4191	0.4271	0.3289	0.6427	0.4019	0.4028	0.6240	0.4413	0.5899
11	0.6198	**0.6501**	0.5522	0.5522	0.5571	0.5797	0.5612	0.5523	0.5511	0.5276	0.3704	0.4916	0.4856	0.4867	0.5950	0.5002	0.6198
12	0.6428	**0.6740**	0.6315	0.6301	0.6321	0.4659	0.4503	0.4438	0.4426	0.4869	0.3433	0.5213	0.4172	0.4183	0.5600	0.4616	0.6427
13	0.6027	0.6401	**0.6717**	0.6687	0.6200	0.5507	0.5001	0.4897	0.4881	0.5020	0.3682	0.5622	0.3939	0.3952	0.5474	0.4132	0.6027
14	0.5908	0.6355	0.6995	0.6953	0.6171	0.5384	0.5132	0.5004	0.4985	0.5124	0.4173	0.6493	0.3255	0.3308	0.5663	0.4023	0.5908
15	0.5807	0.5953	**0.6373**	0.6059	0.5862	0.5322	0.5210	0.5159	0.5152	0.5400	0.3713	0.6262	0.4541	0.4408	0.5704	0.5128	0.5807
16	0.5836	0.6105	**0.6343**	0.6245	0.6050	0.5469	0.5293	0.5212	0.5201	0.5310	0.4204	0.6218	0.3669	0.3681	0.5516	0.4114	0.5836
17	0.6632	**0.6882**	0.5664	0.5659	0.5964	0.5297	0.5027	0.4975	0.4968	0.5043	0.3244	0.4448	0.5118	0.5128	0.5847	0.5115	0.6632

rank of alternatives has an obvious change when the weight vector of criteria is adjusted. Therefore, the weight vector of each criterion plays a significant role in material selection for automobile applications.

V. CONCLUSIONS

Selecting the optimal lightweight material considering multi-perspective indices is a difficult and restrained challenge for automobile applications. This paper presents a systematic hierarchical structure of multi-perspective indices including mechanical, durability, societal and technical properties for optimal lightweight material selection. A hybrid evaluation approach integrating GRA and TOPSIS is applied to evaluate lightweight material alternatives and obtain the optimal one. A case study, i.e., 17 kinds of lightweight materials, is carried out to verify the hierarchical structure and this MCDM method. In addition, a sensitivity analysis is conducted to monitor the robustness of solution ranking to changes. This research is of guiding significance to the light-weight design and performance optimization of automobiles for the automotive industry. Besides, the results show that the advanced high-strength steels are the optimal lightweight material for automobile applications.

In future work, we will add environmental property in the hierarchical structure of optimal lightweight material selection for automobile applications. In addition, fuzzy theory will be integrated in the evaluation process.

APPENDIX

See Tables 5–9.

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