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Hybrid MCDM Model of ARAS -TOPSIS - GRA for Materials Selection Problem

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Abstract- **Academics have moved their focus from constructing single Multi-Criteria Decision Making (MCDM) models to developing hybrid MCDM models, which use a combination of two or more MCDM methods to tackle decision-making challenges since traditional MCDM approaches have become obsolete. The goal of this work was to create novel hybrid MCDM systems using Additive Ratio Assessment (ARAS), the Method for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Gray Relational Analysis (GRA). An example material selection scenario with seven materials and seven criteria is used to demonstrate the efficacy of the hybrid model. Several independent MCDM tools and previously published findings based on the same illustrative circumstance are contrasted with the results from this hybrid model. All of the results from the used methods are harmonious enough to offer that Material 3 is the best option, while Material 2 is the poorest option, among these seven possibilities. Since no single MCDM approach can guarantee the right decision will always be made, it is advised to use a combination of them. As a result, to aggregate the 11 methodology ranks, the Copeland method is used to reach a common conclusion. Findings from the Copeland method indicate that the hybrid model and other standalone MCDM tools may not produce the same material ranking as the final consensus rank. Thus, a multi-pronged strategy is essential. The Spearman Coefficient of Correlation (SCC) also demonstrates that there is a strong ranking correlation between the suggested ranks provided by the various methods.**

Keywords- **Hybrid MCDM, GRA, ARAS, TOPSIS, Material Selection.**

I. INTRODUCTION

MCDM methods are becoming more and more popular as people realize the benefits of being able to compare and contrast numerous potential choices in an unbiased manner. Researchers are digging into this question to fill the gaps in existing MCDM approaches. To further improve the decision-making process, academics have developed unique MCDM models. Every complex decision-making scenario cannot be analyzed and evaluated by a single MCDM tool. As can be seen from the aforementioned works, all MCDM techniques have their advantages and disadvantages. It is also possible to improve decision-making by combining multiple MCDM tools into a single hybrid model, where the benefits of the combined tools outweigh the drawbacks of the individual ones.

Considering the topic at hand, it is only fitting to present a summary of some prominent MCDM applications in the areas of design and manufacturing materials choice. Several versions of the MCDM tools have been utilized to declaim the materials choice problem on numerous occasions. To better understand how MCDM methods can be utilized to address the challenge of material selection, Emovon and Oghenenyerovwho [1] have done a literature review. Vlsekriterijumska Optimizacija Ikompromisno Resenje (VIKOR) was used to select the material for the designed flywheel, and a comparison of VIKOR methods based on regret theory was conducted by Rai, et al. [2]. In their research, Sasanka and Ravindra [3] employed the VIKOR method to determine which magnesium alloy would be most suitable for use in automotive production.

To evaluate materials for a high-performance engine's valve seats, Giorgetti, et al. [4] implemented the fuzzy VIKOR algorithm. Dev, et al. [5] discussed the effectiveness of the (VIKOR) material selection method through a case study of the material selection problem for automotive piston components. To determine the optimal coating material for AISI 4140 steel, Pahan, et al. [6] used the TOPSIS method. Using a series of tests (Jee and Kang [7], Kumar and Ray [8]) ranked possible materials for vehicle exhaust manifolds using the TOPSIS approach. Chandrasekar and Raja [9] employed Fuzzy TOPSIS to determine the optimal composite material to use in place of traditional metal in the construction of automobile torsion bars. The best material for making gears was identified using the TOPSIS technique, Milanai et al., [10]. With the help of fuzzy TOPSIS, we analyzed the problem of choosing abrasive materials for grinding wheels Maily and Chakraborty [11].

Fuzzy Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) was demonstrated by Gul, et al. [12] as a viable method for choosing the best car's gauge cluster material. An application of the PROMETHEE II method, Maity and Chakraborty [13] was made to the task of choosing tool steel materials. Using the AHP approach, Kumar and Kumar [14] identified the best materials for the robotic arms frame to utilize in industrial material handling. The AHP method was used to select the optimal material of the screw from a large pool of candidates, Kiong et al., [15], the authors used an AHP to determine the optimal material for key production Dweiri and Al-Oqla, [16]. Shanian and Savadogo [17] employed the ELECTRE method (Elimination and Et Choice Translating Reality) to determine the optimal substance for mass-producing a cylinder whose cover cannot be heated.

Using the Ashby method, Mehmood, et al. [18] determined the best combination of materials for a microelectromechanical device. Holloway [19] analyzed the question of what kind of materials should be utilized for beverage containers using the Ashby technique. The

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literature has attempted to address the problem of material choice by employing the Complex Proportional Assessment (COPRAS) method. There was a study done on potential interlayer materials for use in laminated glass applications such as automobile windscreens and home window panes Manalo and Magdaluyo, [20]. Maniya and Bhatt [21] employed the Preference Selection Index (PSI) method to analyze the material selection problem of a product used in a high-temperature setting.

Multi-Attribute Utility Analysis (MAUA) was performed by Roth, et al. [22] to determine the best materials for automobile camshafts. The material selection problem for a cryogenic storage tank was evaluated by Dehghan-Manshadi, et al. [23] utilizing a modified weighted product (WPM) method, which scales choice criteria using digital logic mixed with a non-linear normalization technique. COPRAS, MOORA, TOPSIS, ARAS, and VIKOR were used to assess various materials for use in making connecting rods Sen et al. [24]. As mentioned by Anojkumar, et al. [25], the material selection problem for pipes in the industry of sugar was addressed by combining Fuzzy AHP with TOPSIS, VIKOR, ELECTRE, and PROMTHEE. Yadav, et al. [26] conducted tests to see which materials held up best in a tough milling setting. Chatterjee and Chakraborty [27] employed the complex proportional assessment (COPRAS) and ARAS methods to find the best gear material. Researchers looked at the best construction material for a rapid naval vessel. Charaboratya and Chatterjee [28] used the VIKOR PROMETHEE and TOPSIS methods, we found the optimal material for the walls of light-load wagons. Five alternative materials for hacksaw blades were compared and contrasted using the AHP and PROMETHEE methods by Chathani et al. [29].

It has been proposed in the literature that hybrid MCDM models can be used as decision-making tools to probe into material selection problems. The investigation uncovered ten materials besides gears [30]. Grey-TOPSIS and COPRAS-G were used to determine the top 10 alternatives. The problem of selecting hard-magnetic materials was studied using the MOORA and WASPAS techniques by Yazdani et al. [31]. To solve the problem of choosing a hard magnetic material, Chauhan and Vaish [32] compared two methods: VIKOR and TOPSIS. Chatterjee, et al. [33] combined the COPRAS (complex proportional assessment) and EVAMIX (evaluation of mixed data) techniques to address the issue of material selection for a cryogenic storage tank. Rao [34] employed a combination of AHP and an enhanced VIKOR method to investigate the problem of material selection for a product designed for usage in a high-temperature environment. When trying to decide what material to use for a sailboat's mast, Chatterjee, et al. [35] blended the VIKOR and ELECTRE strategies.

The aforementioned literature suggests that some individuals have investigated MCDM strategies for material selection using only themselves as data. Hence, there's a fantastic opportunity to demonstrate the efficacy of many MCDM approaches in tackling material-selection problems by integrating and employing them. As far as the authors are aware, no one has tried to create a hybrid MCDM system out of ARAS, TOPSIS, and GRA.

This paper's objectives are (a) to perform a new crossbred model by joining ARAS with GRA and TOPSIS due to their several vantages over other MCDM methods, and (b) to fix the selection problem of material using this hybrid model in addition to some other solo MCDM methods, including ARAS, COCSO, and GRA, to validate the output results. This research is groundbreaking since it is the first to apply a hybrid MCDM tool to settle the problem of material selection. The tool combines the strengths of the ARAS, TOPSIS, and GRA MCDM methods and attempts to address their shortcomings.

II. MATERIALS AND METHODS

A. Case Study

We apply the suggested ARAS- TOPSIS- GRA hybrid MCDM system to a practical materials-choice problem to demonstrate its viability, applicability, and solution accuracy (the well-known example of a cryogenic storage tank for low-temperature usage). One issue with the choice of materials is illustrated in a 2007 paper by Dehghan-Manshadi, et al. [23]. This case study analyzes seven factors that should be considered while choosing materials: C1, C2, C3, C4, C5, C6, and C7 are all properties that may be measured on a material, and they include toughness index, yield strength, density, specific heat (C7), thermal expansion, thermal conductivity, and Young's modulus. Aluminum 2024-T6 (M1), Aluminum 5052-O (M2), Stainless Steel 301-FH (M3), Stainless Steel 310-3AH (M4), Titanium-6-alpha-vanadium (Ti-6Al-4V) (M5), Inconel 718 (M6), and Copper-Zinc Alloy 70Cu-30Zn (M7) are the seven alternates (M7).

Storage tank materials should be robust and stiff at the predicted working temperature, as well as have other desirable properties such as good weldability, processability, density, specific heat, thermal expansion coefficient, thermal conductivity, and acceptable toughness. To solve the material selection problem, we can look at Table (I), which lists seven criteria and seven options. Considered components, criteria, objectives, weights, and supplies are listed in Table (I).

Table I. Material Selection Problem Data for Cryogenic Storage Tank

Objectives	Max	Max	Max	Min	Min	Min	Min
Weight	0.28	0.14	0.05	0.24	0.19	0.05	0.05
Materials	C1	C2	C3	C4	C5	C6	G7
M1	75.5	420	74.2	2.8	21.4	0.37	0.16
M2	95	91	70	2.68	22.1	0.33	0.16
M3	770	1365	189	7.9	16.9	0.04	0.08
M4	187	1120	210	7.9	14.4	0.03	0.08
M5	179	875	112	4.43	9.4	0.016	0.09
M6	239	1190	217	8.51	11.5	0.31	0.07
M7	273	200	112	8.53	19.9	0.29	0.06

Criteria: (Source: Dehghan-Manshadi, et al. [23].

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In the future, additional researchers came back to the same material selection problem and compared the ranking performance of different common MCDM tools using the same AHP weights. In this article, we take a second look at the material selection problem, and we develop a hybrid MCDM model using ARAS TOPSIS- and GRA to rank the various materials. We will describe the steps used in the MCDM tool and the accompanying mathematical calculations in the following sections.

B. ARAS -TOPSIS- GRA Hybrid MCDM Model

Zavadskas and Turskis [36] came up with a novel MCDM approach they called ARAS. The ARAS procedure calculates how far a solution deviates from perfection. The TOPSIS method, however, was first devised by Hwang and Yoon [37]. To make matters worse, TOPSIS incorrectly concludes that the optimal solution is the one that minimizes the gap between itself and the worst-case scenario, the positive optimum solution (PIS). Although several considerations need to be made before taking a final decision, the GRA method is frequently used. Using the established relationship between the reference sequence and related sequences, this technique ranks the candidates for replacement. Nonlinear interactions between sequences can be quantified using the GRA, which was created by Ertuğrul, et al. [38], and Kuo, et al. [39].

There are several issues with MCDM programs, which is a pity. The fact that ARAS can only maximize attributes is a huge negative. It is necessary to invert the minimization requirements (which are negative) into the maximization criteria (which are positive) before applying them. As a result, the ARAS method may generate contradictory findings. The TOPSIS method, like any other, has its advantages and disadvantages. The fundamental problem with TOPSIS is that it relies on Euclidean distance, which fails to take into account the interdependence of features. On the other hand, the TOPSIS method may have several advantages. TOPSIS also boasts a simple and intuitive logic that makes it easy for anyone to grasp and put to use. It can also be used in a less complicated way.

To understand an absolute assessment of a single alternative and to calculate its deviation magnitude, the TOPSIS method first compares the findings with the better and worst average alternatives. Given TOPSIS's usefulness, its creators are likely to integrate it with ARAS to boost the accuracy of both ranking systems and address their respective shortcomings. Having previously discussed the benefits of TOPSIS, we will now examine the reasons why ARAS and GRA are preferable. On the other hand, ARAS can be seen as a multi-criteria decision-making tool because it scores a limited number of options while still considering all of the important criteria. The main vantage of the ARAS technique is that it facilitates the effective prioritization of alternatives by determining the level of alternative value through a comparison to the (ideally optimal) variant. The process of evaluating and ranking alternatives is simplified when this strategy is employed. According to Zavadskas and Turskis [36], "when an effort is made to rank multiple alternatives and develop ways to improve alternative projects," the ratio with an optimal alternative concept might be used. In recent years, GRA technology has been used for a wide range of problems where there is a shortage of continuous data and complete or accurate information. Although there are many factors to weigh in making a decision, the GRA approach has become increasingly popular. A link is initially established between the reference sequence and other sequences that are comparable, and then candidates for replacement are ranked using this information. GRA, a metric of the nonlinear relevance between sequences, is utilized to repay the drawbacks of the TOPSIS method.

Given the strength of the reasons offered, the authors of this study conclude that it would be irresponsible not to employ a combination of ARAS, TOPSIS, and GRA as their MCDM framework. The writers of this piece believe they can construct a more robust and stable hybrid model by incorporating the best elements of all three MCDM techniques. Using the strengths of ARAS, TOPSIS, and GRA, the following model creates a robust, well-organized, and knowledgeable MCDM environment. The -ARAS-TOPSIS- GRA hybrid MCDM model has several benefits.

Using the idea of optimal alternatives improves the effectiveness of ranking. This mixed model takes into consideration both the quantitative utility degree and the relative proximity coefficient when deciding which variant to prioritize as the optimal (ideally best) variant. This hybrid model is based on a solid, rational, and logical-mathematical foundation. - Accurate, consistent results may be generated using this crossbred model because of its ability to address upper and lower criteria separately, thereby removing inconsistency.

Although many academics have tackled this issue before, using a wide variety of MCDM implementations, the authors of this work felt obligated to return to the same problem and assess the performance of this hybrid tool. The purpose of this research was to improve cooperation between the three existing MCDM programs.

The combination of these three theories results in a novel hybrid known as the ARAS-TOPSIS-GRA Model. I was wondering if you could elaborate on how the GRA method complements the ARAS and TOPSIS frameworks. In-depth instructions for using the ARAS-TOPSIS- GRA hybrid approach are provided here.

Step 1: Constitute the matrix using priority scores given to each alternative on each criterion.

Step 2: Compute the weight (Wj) indicating the importance of the criteria.

Step 3: Here, we begin by constructing an evaluation (decision) matrix, from which an ideal alternative ('AO') is derived by considering the best values of each criterion into account.

Step 4: Determine the normalized decision matrix ($\boldsymbol{r_{ij}}$). In this method, vector normalization is conducted.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n}(x_{ij})^2}}, i = 1, \dots, m; j = 1, \dots, n. \quad (1)$$

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Step 5: Compute the weighted normalized decision matrix: Multiply the columns by r_{ij} the corresponding weights (wj) as:

$$v_{ij} = W_j * r_{ij}, \quad (2)$$

where is W_j the weight of its attribute.

Step 6: Determine the positive ideal solution (A^+) and the negative ideal solution (A^-) by the following formulas:

$$A^+ = \{v_1^+, v_2^+, \dots, v_m^+\}$$

$$\{(max_i v_{ij}/j \in B), min_i v_{ij}/j \in C)\} \quad (3)$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\}$$

$$\{(min_i v_{ij}/j \in B), max_i v_{ij}/j \in C)\} \quad (4)$$

where B and C correspond to the benefit and cost criteria set, respectively.

Step 7: Use the Euclidean distance to compute the measures of separation $\boldsymbol{S_i^+}$ and $\boldsymbol{S_i^-}$ of each alternative from the A^+, and A^-as:

$$S_i^+ = \sqrt{\sum_{i=1}^{m}(V_{ij} - V_j^+)^2}, \quad (5)$$

$$S_i^- = \sqrt{\sum_{i=1}^{m}(V_{ij} - V_j^-)^2} \quad (6)$$

Step 8: Determine the grey relation efficiency for each possible outcome.

To get the grey relationship coefficient between each option and PIS, use the following formula:

$$\gamma_{ij}^+ = \gamma(A_j^+, A_{ij}) = \frac{\underset{i}{min}\,\underset{j}{min}\, s(A_j^+, A_{ij}) + \rho\, \underset{i}{max}\,\underset{j}{max}\, s(A_j^+, A_{ij})}{s(A_j^+, A_{ij}) + \rho\, \underset{i}{max}\,\underset{j}{max}\, s(A_j^+, A_{ij})} \quad (7)$$

where ρ is the recognition coincident,$\rho \in [0,1]$, generally let $\rho = 0.5$.

Use the following formula to calculate the grey relational coincident between each alternative and NIS:

$$\gamma_{ij}^- = \gamma(A_j^-, A_{ij}) = \frac{\underset{i}{min}\,\underset{j}{min}\, s(A_j^-, A_{ij}) + \rho\, \underset{i}{max}\,\underset{j}{max}\, s(A_j^-, A_{ij})}{s(A_j^-, A_{ij}) + \rho\, \underset{i}{max}\,\underset{j}{max}\, s(A_j^-, A_{ij})} \quad (8)$$

Step 9: Calculate the grey relational grade of alternatives.

Use the following formula to calculate the grey relational grade of each alternative:

$$\zeta_i^+ = \sum_{j=1}^{n} \gamma_{ij}^+ \times w_j \text{ and } \sum_{j=1}^{n} w_j = 1 \quad (9)$$

$$\zeta_i^- = \sum_{j=1}^{n} \gamma_{ij}^- \times w_j \text{ and } \sum_{j=1}^{n} w_j = 1 \quad (10)$$

Step 10: How to determine a relational grade of grey based on PIS.

The following formula may be used to determine how well an alternative Ai compares to the A+ in terms of the grey relational grade:

$$\varphi_i = \frac{\zeta_i^+}{\zeta_i^+ + \zeta_i^-}, where\ 0 \le \varphi_i \le 1 \quad (11)$$

Step 11: Finally, the quantitative utility degree (QUi) of each alternative can be calculated as follows:

QUi = Qi/Qo (12)

where Qo is the relative grey relational grade of the ideal material alternative (MO)

Step 12: Sorting the Alternatives

Each option's quantitative utility index (QUi) is calculated, and then the options are ranked from highest to lowest. The closer an option is to PIS, the higher its quantitative usefulness degree. Therefore, the option with the greatest proximity value would be the best option to choose.

III.Applying the hybrid ARAS -TOPSIS- GRA Model

Applying this hybrid tool to the material selection issue posed by Dehghan-Manshadi, et al. [23] allows us to examine its efficacy.

Step 1: Form the matrix by assigning weights to the criteria and ranking the options accordingly. Candidate materials, criteria, and goals are shown in Table 1.

Step 2: Determine the significance of the criteria by computing their weight (W_j). Table (I) shows the weights taken into account by the various techniques in contrast to the suggested model.

Step 3: In this stage, an evaluation (decision) matrix is constructed, and from it, an ideal material alternative ('MO') is derived by considering the best amount of each criterion into account. The nature of the requirements and the optimal alternative MO are laid forth in detail in Table (II).

Step 4: Table (II) is normalized using Equation (1).

Step 5: The weighted values of all criteria are evaluated previously as shown in Table (I) and are used to form the weighted normalized matrix by using (2) as shown in Table (III).

Table II. Customized Evaluation Matrix for ARAS -TOPSIS- GRA Hybrid MCDM Model

	C1	C2	C3	C4	C5	C6	C7
M0	770	1365	217	2.68	9.4	0.016	0.06
M1	75.5	420	74.2	2.8	21.4	0.37	0.16
M2	95	91	70	2.68	22.1	0.33	0.16
M3	770	1365	189	7.9	16.9	0.04	0.08
M4	187	1120	210	7.9	14.4	0.03	0.08
M5	179	875	112	4.43	9.4	0.016	0.09
M6	239	1190	217	8.51	11.5	0.31	0.07
M7	273	200	112	8.53	19.9	0.29	0.06

(Source: authors composition).

Table III. Weighted Normalized Matrix for ARAS -TOPSIS- GRA Hybrid MCDM Model

	C1	C2	C3	C4	C5	C6	C7
M0	0.1823	0.0703	0.0237	0.0406	0.0001	0.0023	0.0103
M1	0.0179	0.0216	0.0081	0.0425	0.0897	0.0282	0.0276
M2	0.0225	0.0047	0.0076	0.0406	0.0926	0.0252	0.0276
M3	0.1823	0.0703	0.0206	0.1198	0.0708	0.0031	0.0138
M4	0.0443	0.0577	0.0229	0.1198	0.0603	0.0023	0.0138
M5	0.0424	0.0451	0.0122	0.0672	0.0394	0.0012	0.0155
M6	0.0566	0.0613	0.0237	0.1291	0.0482	0.0236	0.0121
M7	0.0646	0.0103	0.0122	0.1294	0.0834	0.0221	0.0103
A_j^+	0.1823	0.0703	0.0237	0.0406	0.0001	0.0012	0.0103
A_j^-	0.0179	0.0047	0.0076	0.1294	0.0926	0.0282	0.0276

(Source: authors composition).

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Table IV. Distance Measures from PIS

	S_{c1}^{+}	S_{c2}^{+}	S_{c3}^{+}	S_{c4}^{+}	S_{c5}^{+}	S_{c6}^{+}	S_{c7}^{+}
M0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0011	0.0000
M1	0.1644	0.0487	0.0156	0.0018	0.0896	0.0270	0.0172
M2	0.1598	0.0656	0.0161	0.0000	0.0925	0.0240	0.0172
M3	0.0000	0.0000	0.0031	0.0792	0.0707	0.0018	0.0034
M4	0.1380	0.0126	0.0008	0.0792	0.0603	0.0011	0.0034
M5	0.1399	0.0252	0.0115	0.0265	0.0393	0.0000	0.0052
M6	0.1257	0.0090	0.0000	0.0884	0.0481	0.0224	0.0017
M7	0.1176	0.0600	0.0115	0.0887	0.0833	0.0209	0.0000

(Source: authors composition).

Table V. Distance Measures from NIS

	S_{c1}^{-}	S_{c2}^{-}	S_{c3}^{-}	S_{c4}^{-}	S_{c5}^{-}	S_{c6}^{-}	S_{c7}^{-}
M0	0.0135	0.0022	0.0001	0.0039	0.0043	0.0003	0.0001
M1	0.0000	0.0001	0.0000	0.0038	0.0000	0.0000	0.0000
M2	0.0000	0.0000	0.0000	0.0039	0.0000	0.0000	0.0000
M3	0.0135	0.0022	0.0001	0.0000	0.0002	0.0003	0.0001
M4	0.0003	0.0014	0.0001	0.0000	0.0005	0.0003	0.0001
M5	0.0003	0.0008	0.0000	0.0019	0.0014	0.0004	0.0001
M6	0.0007	0.0016	0.0001	0.0000	0.0010	0.0000	0.0001
M7	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001

(Source: authors composition).

Step 6: With the help of (3) and (4) and Table (III), find the positive $(A_j^{+})$and negative (A_j^{-}) ideal solutions as shown in Table (III).

Step 7: Finding the gap between the PIS and NIS solutions via measurement. Equations (5 and 6) and Tables (IV and V) provide positive and negative separation measurements for each option based on the normalized Euclidean distance.

Step 8: Calculate the Grey Relational Coefficient of Alternatives. Grey relational coefficients, which are estimated by (7) between each alternative and PIS (γ_{ij}^{+}) and are given as shown in Table (VI).

Grey relational coefficients, which are calculated by (8) between each alternative and NIS (γ_{ij}^{-}) and are given as shown in Table (VII).

Step 9: Quantifying the Quality of Grey Relational Alternatives. Table (I) displays the results of solving (9) and (10) for the grey relational grades of the options.

Step 10: Find Grey's Relative Grade (Qi) with PIS. In Table (VIII) we see the results of (11) applied to the relative grey relationship grade (6).

Table VI. Grey Relational Coefficient γ_{ij}^{+}

	C1	C2	C3	C4	C5	C6	C7
M0	1	1	1	1	1	1	1
M1	0.3333	0.4027	0.3398	0.9606	0.3405	0.3333	0.3333
M2	0.3397	0.3333	0.3333	1.0000	0.3333	0.3605	0.3333
M3	1.0000	1.0000	0.7241	0.3591	0.3954	0.8806	0.7143
M4	0.3733	0.7222	0.9130	0.3591	0.4343	0.9267	0.7143
M5	0.3701	0.5652	0.4118	0.6257	0.5406	1.0000	0.6250
M6	0.3954	0.7845	1.0000	0.3341	0.4902	0.3758	0.8333
M7	0.4113	0.3535	0.4118	0.3333	0.3570	0.3925	1.0000

(Source: authors composition).

Table VII. Grey Relational Coefficient γ_{ij}^{-}

	C1	C2	C3	C4	C5	C6	C7
M0	0.3333	0.3333	0.3333	0.3333	0.3333	0.3515	0.3333
M1	1.0000	0.8823	0.9984	0.3426	0.9980	1.0000	1.0000
M2	0.9984	1.0000	1.0000	0.3333	1.0000	0.9751	1.0000
M3	0.3333	0.3333	0.4328	0.9773	0.9002	0.3652	0.4386
M4	0.9510	0.4339	0.3554	0.9773	0.8044	0.3515	0.4386
M5	0.9575	0.5690	0.8596	0.5044	0.6019	0.3333	0.5051
M6	0.9002	0.4019	0.3333	1.0000	0.6846	0.9457	0.3817
M7	0.8608	0.9856	0.8596	1.0000	0.9805	0.9073	0.3333

(Source: authors composition).

Table VIII. Grey relational grades, Relative Grey Relational Grade (Qi), quantitative utility degree (QUi), and rank of each alternative

	ζ_i^{+}	ζ_i^{-}	Qi	Qi/Q0	%	Rank
M0	1.0000	0.3333	Q0=0.75	1.0000		
M1	0.5058	0.8150	0.3829	0.5106	51.0573	6
M2	0.5006	0.8303	0.3761	0.5015	50.1511	7
M3	0.7088	0.5102	0.5814	0.7753	77.5253	1
M4	0.5686	0.6555	0.4625	0.6166	61.6615	4
M5	0.7369	0.5307	0.5813	0.7751	77.5088	2
M6	0.5647	0.6555	0.4628	0.6170	61.7031	3
M7	0.5261	0.7968	0.7968	0.5303	53.026	5

Step 11: Last but not least, we calculate the quantitative utility degree (QUi) of each option using (12), and we provide the results in Table (VIII).

Step 12: Sorting the Alternatives

Each option's quantitative utility index (QUi) is calculated, and then the options are ranked from highest to lowest. The closer an option is to PIS, the higher its quantitative usefulness degree. Therefore, the option with the greatest proximity value would be the best option to choose.

IV. RESULTS, VALIDATION, AND COMPARATIVE ANALYSIS

The correctness of the proposed ARAS TOPSIS-GRA hybrid MCDM system will be confirmed by comparing it to previously published results based on the same illustrative case used in this research, and the benefits of different approaches will be highlighted. In this study, we compare the results of applying the researched problem to three different solo MCDM approaches (ARAS, COCOSO, and GRA). Space and processing limitations only allow for the final totals to be displayed. Many MCDM strategies for material choice have been evaluated in this study.

Similar problems with materials selection have been addressed by other authors in the literature, each employing their unique method of analysis and judgment. The rankings obtained in this investigation and those discovered in the literature are presented in Table (IX) and Fig. 1. It's intriguing to watch how different MCDM algorithms score different options, yet they consistently give M3 the highest

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marks for performance. Although both Material 2 and Material 7 qualify as "worst," Material 7 is favored by more MCDM tools as the poorest choice. It's vital to remember that different methods don't always yield consistent rankings.

Table IX. Ranking Comparisons among Different MCDM Methods

	Method	M1	M2	M3	M4	M5	M6	M7	Best	Worst
Present work	ARAS-TOPSIS-GRA	6	7	1	2	3	4	5	M3	M2
	ARAS	5	6	1	4	2	3	7	M3	M7
	COCOSO	6	7	1	3	2	4	5	M3	M2
	GRA	6	5	1	4	2	3	7	M3	M7
Manshadi et al. (2007) [23]	WPM	5	6	1	4	2	3	7	M3	M7
	digital logic Modified	5	7	1	4	2	3	6	M3	M2
Rao, and Davim [40]	Combined TOPSIS and AHP	5	6	1	4	2	3	7	M3	M7
Chatterjee et al. [33]	COPRAS	6	7	1	3	2	4	5	M3	M2
Chakraborty and Chatterjee [27]	VIKOR	7	6	1	3	2	4	5	M3	M1
	TOPSIS	5	6	1	4	2	3	7	M3	M7
	ROMETHEE	7	6	1	4	3	2	5	M3	M1
Composite Rank		5	7	1	4	2	3	6	M3	M2

(Source: authors composition).

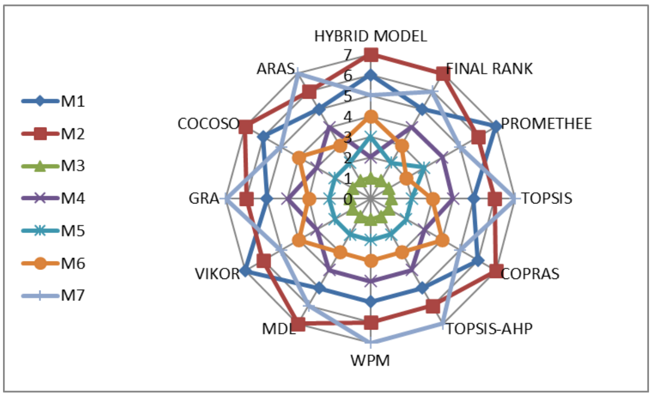

Fig. 1: Graphical Comparisons Among Different MCDM Methods

The challenge that arises is settling on a particular course of action. Attempting to rank the eleven possible approaches considered here would be an exercise in futility. You can use techniques like the Rank Average (Mean), Broda, and Copeland for this purpose.

In our study, we apply the Copeland approach to combine these individual rankings into a single, comprehensive ranking. As part of the proposed strategy, eleven separate criteria are used to score each potential solution. The Copeland technique relied on the pair comparison matrix to keep track of why one solution was preferable to the rest. Winners are the options with more votes, and losers are the ones with fewer. Scores are calculated by subtracting the number of defeats from the total number of successes. The options are sorted in order of their total score at the end. If two or more options end up with the same total score, those options are placed in the same order. The outcomes and pairwise comparison matrices are displayed in Table (X) where "W" and "L" represent the winning and losing conditions, respectively. Options M1 and M7 in the table below can help with it.

According to the results shown in Table (IX), M1 is ranked higher than M7 by ARAS, GRA, MDL, WPM, TOPSIS-AHP, and TOPSIS, and lower by COCOSO, VIKOR, COPRAS, and PROMETHEII. With this result, M1 defeated M7 6-5. The letter W is therefore placed in the M1M7 cell.

The numerical outcomes of the computations using the Copeland approach are displayed in Table (X) and Fig. 2. In this case, we calculated the total number of rows of options using 11 comparison matrices. Due to its superiority over competing methods, M3 has a row sum of 6W, making it the most advantageous solution. Most alternatives cannot subordinate M3, as its row sum is 0L. When comparing two options, the dissimilarity values are the ones whose W sums are different from their L sums. Table (IX) displays the results of a consensus ranking of the materials, calculated from the difference values in Table (X). The Copeland method favors Material M3 over Materials M5, M6, M4, M1, M7, and M2. If we look at the results of the 11 different MCDM techniques, the composite rank may turn out to be the most effective one.

Table X: Calculations for the Copeland Method

	M1	M2	M3	M4	M5	M6	M7	∑ Win	∑Lose	∑Win-∑Lose	Copeland Rank
M1	X	W	L	L	L	L	W	2	4	-2	5
M2	L	X	L	L	L	L	L	0	6	-6	7
M3	W	W	X	W	W	W	W	6	0	6	1
M4	W	W	L	X	L	L	W	3	3	0	4
M5	W	W	L	W	X	W	W	5	1	4	2
M6	W	W	L	W	L	X	W	4	2	2	3
M7	L	W	L	L	L	L	X	1	5	-4	6

(Source: authors composition).

Fig. 3 displays Spearman's rank correlation coefficient values between the rankings of the candidate materials reached using the different MCDM approaches and those created by the proposed hybrid model, validating and comparing the rankings provided by the various.

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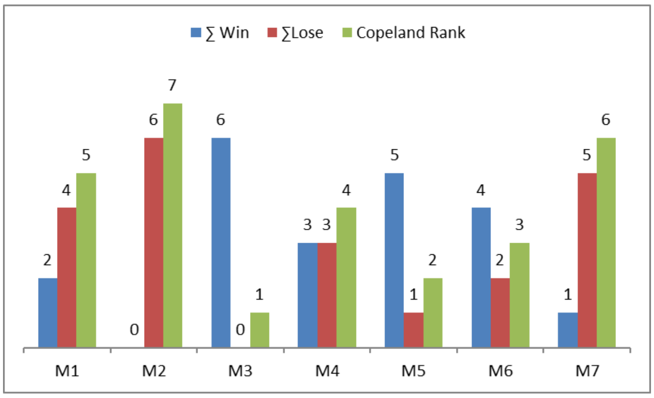

Fig. 2: Copeland's Chart

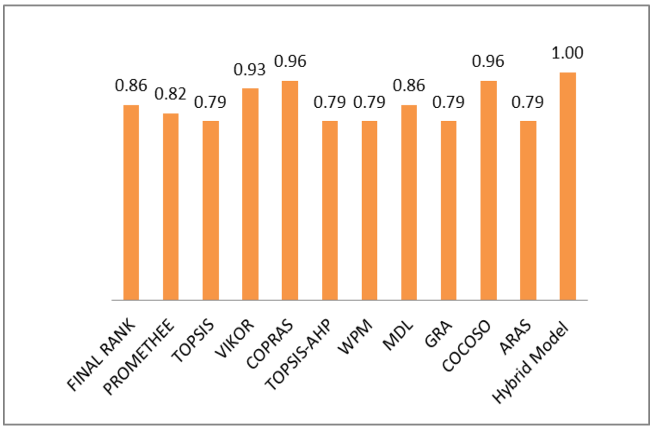

Fig. 3: Spearman's Rank Correlation Coefficient Between the Different MCDM Methods and the Proposed Hybrid Model.

We can conclude from the data that the COCOSO, COPRAS, and VIKOR methods have a perfect correlation with the proposed hybrid model rank; the MDL and PROMETHEE II methods have a moderate correlation; the ARAS, GRA, WPM, TOPSIS-AHP, and TOPSIS methods have a fair correlation; and the other methods have a fair correlation with the final rank. The results indicate the suggested hybrid model, COCOSO, COPRAS, and VIKOR techniques all perform well enough to deal with the selection problems. The rankings from the new hybrid model have a very good/strong rank correlation with the earlier MCDM techniques, as shown in Table (IX), Fig. 1, and Fig. 2. This indicates their better decision-making capacity and consistency.

V. CONCLUSIONS

In this research, we used a recently developed ARAS -TOPSIS-GRA hybrid MCDM system to assess a material selection problem, clearing the fog of previous studies. The creation of the MCDM model is the most significant contribution to the fields of manufacturing and decision theory. It also improves the efficiency and reliability of the standalone ARAS, TOPSIS, and GRA methods. According to this analysis, Material 3 (M3) is the best option out of the seven possibilities, whereas Material 7 (M7) can be completely dismissed due to its poor ranking. Important closing remarks and the most substantial contribution of this study are described below.

With the newly developed hybrid MCDM method, the best possible answer to any selection problem may be discovered rapidly and precisely. - In terms of making sound judgments, the hybrid model you constructed is second to none. All the CC values are above 0.7852, which is considered high, and they all demonstrate a strong relationship between the newly constructed hybrid model and the established methods.

Because of its ease of use, systematization, clarity, and rationality, the well-established hybrid MCDM system can be easily included in any examination of decision-making. The findings of this study may help to educate the manufacturing sector and allay some of the anxieties caused by selection problems in businesses.

Future Prospects: In the framework of upcoming studies, these concepts can be taken into account. There is flexibility in how the parameter weights are determined, and changes in relative position can be observed using different weighting methods. This paves the way for the development of cutting-edge hybrid models, which draw upon the strengths of a variety of MCDM methods.

Last but not least, this newly developed ARAS -TOPSIS -GRA hybrid MCDM system may be used in a variety of contexts, hence expanding the spectrum of problems that can be addressed by the model and revealing its full potential.

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