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Sensitivity Analysis in MADM Methods: Application of Material Selection

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Material selection is a core process in design and engineering, and its effective modeling remains a key strategic concern for production economics and management. The evaluation of materials is subject to various technical and subjective criteria, which may be conflicting in nature. Nonetheless, multi attribute decision making (MADM) models facilitate the complexity in realizing engineering objectives through some form of weight of attributes (criteria) assessment procedure. This study illustrates a new approach to gain those weights based on expert judgments and then select best material using ranking-based MADM methods. Specifically, we applied the SWARA method for the criteria weight assessment of the material selection process, and subsequently prioritize the candidate materials based on WASPAS and MOORA. Sensitivity analysis is performed to assess the robustness of the solution after a comparison is made between WASPAS and MOORA in ensuring the consistency of the results. We illustrate the problem on two real material selection case studies.

Keywords: *Multi Attribute Decision Making (MADM), MOORA, WASPAS, SWARA, Material Selection.*

Introduction

A reliable engineering process requires accessible resources to comply with various process requirements. One such requirement is in the conversion of design concepts into realizable engineering and manufacturing goals, which are fraught with material challenges. Hence, material selection issues involve several decisions such as design and quality requirements. (Anojkumar *et al.*, 2014).

The traditional approach to material selection is to conduct trial by error experiments. This procedure when used extensively may deviate design engineers from the overall management goal of the firm, thus leading to cost overruns and project delays (Ashby & Cebon, 1993). Any material selection decision based on intuition without a scientific framework should not be taken as conventional wisdom, thus avoiding engineering failures (Girubha & Vinodh, 2012).

The starting point of a material selection decision is to define observable parameters of the design objectives. A decision making framework is then used to aid the assessment of reliable and appropriate material candidates (Coello Coello, C. A., & Becerra, 2009). Depending on the complexity of the decision, a hybrid structure combining two or more multi-criteria decision making method may be integrated for assessing material selection problems.

To facilitate material selection decisions, multi-attribute decision making (MADM) techniques are used due to their ability to consolidate conflicting criteria. The rest of the paper is organized as follows: Section 2 provides a brief review of MADM techniques in material selection. Section 3 explains the methodology of SWARA, MOORA and WASPAS methods. Section 4 applies those methods on the material selection cases. Section 5 concludes the paper and offers suggestions for future research work in related field.

Literature Review

Multiple criteria decision making (MCDM) is a well-established domain with a collection of methods that can be used to resolve complex decision problems incolving tradeoffs (see Behzadian *et al.,* 2010; Behzadian *et al.,* 2012; Ignatius *et al.,* 2016).

MADM is a branch of MCDM that handles the assessment of a collection of alternatives based on the level of performance of the criteria. The process of assessment includes the following features: identifying criteria and alternatives, weight each criterion, an algorithmic procedure to reach final solution by normalizing and aggregating the scores of all alternatives across each and every criterion (Yazdani *et al.,* 2016; Hu *et al.,* 2015).

In material selection, the Ashby MADM method is considered to be more popular than other techniques for screening materials (see Reddy & Gupta, 2010; Parate & Gupta, 2011; Rao, 2008 and Roth *et al.,* 1994; Chauhan & Vaish, 2012a). More recent studies in this area are listed in Table 1. Jahan & Edwards (2013) performed material evaluation by using a modified version of VIKOR. Caliskan *et al.* (2013) selected the best candidate material for a tool holder in a hard milling process by comparing the following MADM methods: TOPSIS, VIKOR, PROMETHEE II, AHP and Entropy. Anojkumar *et al.* (2014) applied VIKOR, TOPSIS, ELECTRE, PROMETHEE and Fuzzy AHP in the selection of pipe materials of the sugar industry. Yazdani & Payam (2015) solved a micro-electromechanical systems material selection decision by using the Ashby, TOPSIS and VIKOR methods. Table 1 provides a wide range of methods from AHP, TOPSIS, VIKOR, ELECTRE and PROMETHEE that has been applied to real material selection problems.

Table 1

Overview of Material Selection Studies

Author (s)	Material Selection application	Technique (s) used
Liu *et.al* (2013)	Material selection in high temperature environment	VIKOR / Induced operator weighted averaging (IOWA)
Cavallini *et.al* (2013)	Best coating for protection of an aluminum alloy	House of quality (HOQ)/VIKOR
Jahan *et.al* (2011a)	Implant material / Biomedical application	Comprehensive VIKOR
Jahan & Edwards (2013)	Biomedical implant application	New VIKOR by interval numbers
Chatterjee *et.al* (2009)	Design a flywheel / Sailing boat mast	VIKOR/ELECTRE
Chauhan & Vaish (2012b)	Soft and hard magnetic material	VIKOR/TOPSIS
Caliskan *et.al* (2013)	Selection tool holder in hard milling	TOPSIS/VIKOR/PROMETHEE II/AHP/Entropy
Chauhan & Vaish (2012a)	MEMS material selection	TOPSIS/VIKOR/Ashby approach
Jahan *et.al* (2011b)	Thermal conductor	VIKOR/TOPSIS/ELECTRE/AHP/ Comprehensive VIKOR
Rao (2008)	Metallic Bipolar plates	VIKOR/AHP
Anojkumar *et.al* (2014)	Pipe material selection in sugar industry	VIKOR/TOPSIS/ELECTRE/PROMETHEE/Fuzzy AHP
Jee & Kang (2000)	Flywheel	TOPSIS/Entropy
Shanian & Savadogo (2006)	Material selection of metallic bipolar plates	TOPSIS
Rao & Davim (2008)	Non heat-treatable cylindrical cover material/ Material for cryogenic storage tank for liquid nitrogen	TOPSIS/AHP
Rathod & Kanzaria (2011)	Selection of phase change material	AHP/TOPSIS/Fuzzy TOPSIS
Reddy & Gupta (2010)	Microelectronic Heat sink	Ashby approach
Guisbiers et.al (2010)	Radio-Frequency (RF) MEMS application	Ashby approach
Parate & Gupta (2011)	Electrostatic micro actuators	Ashby approach
Srikar & Spearing (2003)	Micro fabricated electrostatic actuators	Ashby approach
Bahraminasab & Jahan (2011)	Femoral component of total knee replacement	VIKOR/New weighting methods
Yazdani & Payam (2015)	MEMS material selection	Ashby, VIKOR, TOPSIS

It is observed that different MADM methods can generate different ranking orders. Prior to the ranking process, it is noteworthy that all MADM require each alternative to be assessed against the performance rating associated with the attributes/criteria. The attributes may take different units of measurement (e.g. meters, kilogram, liter etc). To compare the alternatives with regards to each attribute, a normalization process is performed and each method may provide its own computation in consolidating the diverse measurement units (Yoon & Hwang, 1995; Hwang & Yoon, 1981; Zavadskas & Turskis, 2008).

Therefore, the normalization procedure is a mechanism in MADM models that converts the different measurement units of performance attributes into a comparable (non-dimensional) scale. The normalized value will be a monotonically non-decreasing value, in the range of 0 and 1. Many normalization procedures are available to MADM methods (Opricovic & Tzeng, 2004).

Jahan & Edwards (2015) investigated the effects of normalization methods on the results, taking into account cost and benefit criteria and discussing the issue of rank reversal prevention and handling of negative values. Chatterjee & Chakraborty (2014) showed the normalization process used on PROMETHEE, TOPSIS and GRA for the flexible manufacturing selection problem. Zavadskas *et al*. (2006) measured the accuracy of determining the relative significance of the alternatives taking into consideration that the normalization procedure may affect the final MADM solution. They presented computational experiments for the TOPSIS method using vector and linear normalization tools. A new logarithmic normalization tool was later introduced in Zavadskas & Turskis (2008), where the LEVI.3 software supports conditions of risk and uncertainty.

While the normalization process attempts to scale the criteria values and to construct a unified comparable index, different normalization techniques may yield different solutions, and may lead provide error in recommended solutions.

In this paper the relationship between normalization methods and ranking order is investigated in a material selection problem. Namely, we study the normalization process for MOORA (Brauers & Zavadskas, 2006), WASPAS (Zavadskas *et al*. 2012) and SWARA (Kersuliene *et al.,* 2010) and provide a method for consistency evaluation of the results. The cases applied are captured from MEMS (Yazdani & Payam, 2015) and hard magnetic (Chauhan & Vaish, 2012b) material selection problems.

Methods and Materials

SWARA Method

SWARA is a method for weighing decision attributes using direct judgment of experts. The procedure for determining weights by SWARA can be stated as steps below:

***Step*1** – Should be sorted based on experts' opinion (Kendall, 1970; Zavadskas *et al.,* 2009).

***Step* 2** – From the second criterion, comparative importance of average value s_j should be done as follows: the relative importance of criterion$j$ in relation to the previous $(j-1)$ criterion (Stanujkic *et al.* 2015).

***Step* 3** - Determine the coefficient k_j

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases} \quad (1)$$

***Step* 4** - Determine weight w_j

$$w_j = \begin{cases} 1 & j = 1 \\ \frac{x_{j-1}}{k_j} & j > 1 \end{cases} \quad (2)$$

***Step* 5** – Final step in calculating the weights of the criteria

$$q_j = \frac{w_j}{\sum_{k=1}^{n} w_j} \quad (3)$$

where $q_j$denotes the relative weight of criterion j.

MOORA

The Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method was developed by Brauers & Zavadskas (2006). Gadakh (2010) applied MOORA for the milling process. Karande & Chakraborty (2012) solved material selection problems using the MOORA ration based system. Yazdani (2015) extended MOORA with intuitionistic fuzzy sets.

The MOORA procedure is as follows:

***Step 1* -** Normalize the decision matrix**.** To have comparable elements across scales in the evaluation process, the ratio system of the MOORA method computes the normalized decision matrix using the following equations; r_{kj}denotes the normalized generic element of the decision matrix

$$r_{kj} = \frac{x_{kj}}{\sum_{k=1}^{t} x_{kj}^2} \quad (4)$$

***Step 2* -** Determine the weighted normalized matrix. The kj-th element of the normalized matrix is replaced by

$$v_{kj} = r_{kj}.w_j \quad (5)$$

***Step 3* -** Compute the overall rating of benefit and cost criteria for each alternative**.** The overall rating of the k-th alternative is calculated by implementing Equations 6 and 7, respectively:

$$s_k^+ = \sum_{j \in J^{Max}} v_{kj} \quad (6)$$

$$s_k^- = \sum_{j \in J^{Min}} v_{kj} \quad (7)$$

where $J^{Max}$is the index set of beneficial criteria. Higher values indicate greater desirability. Contrastingly, J^{Min} is the index for cost criteria for which lower values are preferable.

***Step 4* -** Obtain the overall performance index of each alternative**.**

The overall performance index of the *k-th* alternative is calculated by subtracting the overall rating for beneficial and cost criteria using the following formula:

$$s_k = s_k^+ - s_k^- \quad (8)$$

***Step 5* -** Rank the alternatives**.**

The s_k values form a cardinal scale that can be used to rank the alternatives**.** The ordinal ranking of the alternatives is obtained by rearranging the s_k values in decreasing order. Higher values for $s_k$implies that the *k-th* alternative is more preferred.

Weighted Aggregated Sum Product Assessment (WASPAS)

WASPAS is a mixture between two well-known MADM approaches, i.e. the weighted sum model (WSM) and the weighted product model (WPM). Hashemkhani Zolfani *et al.* (2013) assessed shopping mall performances in Tehran, and Chakraborty & Zavadskas (2014) solved eight manufacturing decision making problems using WASPAS. The following matrix represents the decision problem:

$$\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (9)$$

where n is the number of evaluation criteria and $j = 1,2, \dots n$, x_{ij} is the performance rating of the i alternative upon the j*-th* decision criterion. This decision matrix is normalized using the following equations where the normalized generic element of the decision matrix is denoted by r_{ij}:

For benefit attributes:

$$r_{ij} = \frac{x_{ij}}{\max_i x_{ij}}, j = 1,2, \dots n, i = 1,2, \dots m \quad (10)$$

For non-benefit attributes:

$$r_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \quad j = 1,2, \dots n, i = 1,2, \dots m \quad (11)$$

To compute the weighted normalized decision matrix in WASPAS, these two actions must be performed. The first is the summarization process of WASPAS:

$$y_{ij,sum} = r_{ij}.w_j \; i = 1,2, \dots m \;, j = 1,2, \dots n \quad (12)$$

and for multiplication part;

$$y_{ij,mult} = (r_{ij})^{w_j}$$

where $= 1,2, \dots m \;, j = 1,2, \dots n$ (13)

A joint generalized criterion of weighted aggregation of additive and multiplicative methods can then be proposed as follows:

$$Q_i = 0.5 \sum_{j=1}^{n} y_{ij,sum} + 0.5 \prod_{j=1}^{n} y_{ij,mult}$$

$$i = 1,2, \dots m \;, j = 1,2, \dots n \quad (14)$$

In order to increase the ranking accuracy and effectiveness of the decision making process, a more generalized equation for determining the total relative importance of the alternatives can be employed for the WASPAS method (see Zavadskas *et al.*, 2012):

$$Q_i^{\lambda} = \lambda \sum_{j=1}^{n} y_{ij,sum} + (1-\lambda) \prod_{j=1}^{n} y_{ij,mult} \quad (15)$$

Finally, the alternatives can be ranked based on the Q - values, i.e. the best alternative would be the one having the highest Q - value. When the value of λ is 0, the WASPAS method is equivalent to WPM, whereas when $\lambda = 1$, WASPAS corresponds to WSM.

Results and Discussion

The proposed analysis presented in this paper is applied to two material selection problems.

Example 1

The first example is an application of micro-electromechanical systems (MEMS). The case focuses on material selection in the case of low electrical resistivity, i.e. high speed with low actuation voltage devices. The alternative materials and the relevant properties for this case are given in Table 3, where C_1 and C_3 are the non-benefit criteria while C_2 is the benefit criterion. Yazdani & Payam (2015) used experts' weights to rank the alternatives with the TOPSIS and VIKOR methods.

In this paper, we use the SWARA weighting method following equations 1-3. SWARA reports the weights of material criteria in Table 2 as $(q_1, q_2, q_3) = (0.339, 0.27, 0.39)$. The ranking of candidate materials is achieved by applying MOORA (using equations 4-8) and WASPAS (equations 9-15). MOORA recommends that M_1, M_6, M_2 and M_{11} are the four best options, which are consistent with the WASPAS method. Yazdani & Payam (2015) provided a similar ranking in the order of M_1, M_2, M_{11} and M_6.

Figure 1 illustrates the comparison on material ranking for case 1. The order of the material ranks is almost similar. This can be further supported by the statistically significant Spearman correlation coefficient among the four MADM methods. The highest correlation is between MOORA and TOPSIS with correlation coefficient of 0.95 at $p < 0.01$ and the lowest correlation is observed between WASPAS and VIKOR at 0.66, $p < 0.05$.

Table 2

SWARA Results for MEMS Material Ranking Problem

Material criteria	Comparative importance of average value s_j	Coefficient $k_j = 1 + s_j$	Recalculated weight w_j	Final weight q_j
C_3	-	1	1	0.39
C_1	0.15	1.15	0.87	0.339
C_2	0.25	1.25	0.696	0.271

Table 3

Material Specifications and Generated Ranking by MADM Methods

Material items	C_1	C_2	C_3	MOORA ratio system	WASPAS	TOPSIS (Yazdani & Payam, 2015)	VIKOR (Yazdani & Payam, 2015)
M_1	8.3666	5.0918	2.82E-08	1	3	1	1
M_2	9.1104	2.8129	1.59E-08	3	1	2	2
M_3	16.7033	6.2293	1.29E-07	10	9	12	12
M_4	11	3.1724	1.05E-07	9	12	8	6
M_5	12.9615	2.7986	1.05E-07	12	14	10	10
M_6	10.8167	3.6136	1.68E-08	2	2	4	4
M_7	7.0711	2.6055	1.15E-07	8	10	7	5
M_8	4	1.1878	2.08E-07	13	11	13	9
M_9	10.7703	5.0738	4.2E-07	14	13	14	14
M_{10}	13.8924	4.6562	6.99E-08	6	6	6	7
M_{11}	8.3666	1.9045	2.44E-08	4	4	3	3
M_{12}	14.4568	4.8459	6.24E-08	5	5	5	8
M_{13}	14.5258	5.1766	9.61E-08	7	8	9	11
M_{14}	20.2731	4.6207	5.28E-08	11	7	11	13

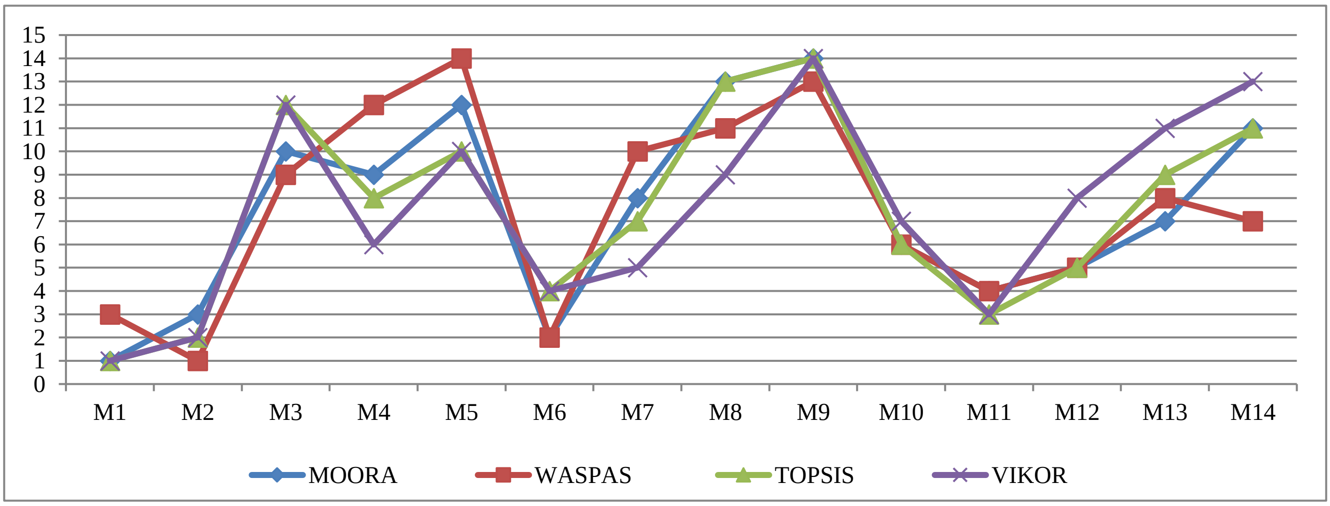

Figure 1. Ranking of Four MADM Methods for MEMS Material Problem

Example 2

This example deals with the hard magnetic material selection problems (Chauhan & Vaish, 2012b). The case considers a database with twenty four materials evaluated across five material criteria. The criteria for this study are operating temperature (C_1), remanence magnetic induction (C_2), coercive magnetic field (C_3), intrinsic coercive field (C_4) and magnetic energy (C_5). All the criteria are to be maximized (benefit) except criterion C_2. To begin the material evaluation assessment, Chauhan & Vaish (2012b) weight each criterion using the Entropy method. However, we used SWARA (equations 1-3) to obtain the weights $(w_1, w_2, w_3, w_4, w_5) = (0.124, 0.162, 0.279, 0.233, 0.202)$, see Table 4. The subsequent steps of the material selection problem are then performed by MOORA (equations 4-8) and WASPAS (equations 9-15). According to WASPAS and MOORA's ranking indices, Q_i and s_k, the prioritization for materials are identified. Table 5 lists the rank ordering using the various methods. The results show the similarity of ranking scores between MOORA and WASPAS, which is not surprising given their spearman's correlation coefficient, is 0.97. In comparison with example 1, the rank similarities are higher for example 2. In addition, WASPAS ranking is considered stabile when compared across different values of λ. Therefore, like VIKOR and TOPSIS in material selection problems (Table 1), WASPAS and MOORA can potentially be utilized by engineers.

Sensitivity analysis

Sensitivity analysis is generally an approach used to check consistency and robustness of solutions. This is achieved by parameters of factors, and observing ranking changes. One of the strategies used to test the susceptibility of the results to ranking changes is a weight adjustment method. A particular criterion will have its weight varied, while holding the other criteria constant by a decreased amount which is equally shared across remaining criteria.

Table 4

SWARA Weighting Outcomes for Case 2

Material criteria	Comparative importance of average value s_j	Coefficient $k_j = 1 + s_j$	Recalculated weight w_j	Final weight q_j
C_3	-	1	1	0.279
C_4	0.2	1.2	0.833	0.233
C_5	0.15	1.15	0.725	0.202
C_2	0.25	1.25	0.58	0.162
C_1	0.3	1.3	0.446	0.124

Table 5

Hard Magnetic Material Evaluation Table with MOORA and WASPAS

Material list	C_1	C_2	C_3	C_4	C_5	MOORA index s_k	MOORA ranking	WASPAS index Q_i	WASPAS ranking
M_1	460	0.4	175000	185000	30	0.5356	1	0.7162	1
M_2	500	1.13	640	640	240	0.1122	2	0.2065	2
M_3	250	0.92	720	1600	170	0.0716	4	0.1609	5
M_4	500	0.86	640	2000	145	0.0735	3	0.1817	3
M_5	500	0.8	535	1200	120	0.0613	5	0.1683	4
M_6	520	1.06	115	145	71.6	0.0248	6	0.1238	9
M_7	500	1.34	58	59	59.7	0.0068	13	0.1071	15
M_8	500	1.33	53	53	57.7	0.0061	15	0.1062	16
M_9	525	1.27	51	51	43.8	0.0022	23	0.1038	23
M_{10}	550	0.83	131	148	42.2	0.0193	8	0.1229	10
M_{11}	550	0.72	151	173	39.6	0.0222	7	0.1285	8
M_{12}	540	0.74	119	134	31.8	0.0167	9	0.1215	11
M_{13}	525	1.05	62	64	31	0.0037	21	0.1041	21
M_{14}	540	1.07	49	50	30	0.0031	22	0.1041	22
M_{15}	540	0.94	63	65	23.1	0.0043	17	0.1058	17
M_{16}	480	0.6	64	76	14	0.0093	12	0.1151	12
M_{17}	540	0.75	45	46	13.5	0.0063	14	0.1094	14
M_{18}	480	0.71	44	45	11.9	0.004	18	0.1047	19
M_{19}	350	0.54	44	44	12	0.0038	19	0.1054	18
M_{20}	450	0.72	37	38	11.1	0.0016	24	0.1002	24
M_{21}	480	0.7	38	39	11	0.0038	20	0.1047	20
M_{22}	590	0.535	58	62	10	0.0151	11	0.1312	7
M_{23}	590	0.52	56	61	10	0.0156	10	0.1329	6
M_{24}	540	0.67	143	161	4.5	0.0048	16	0.1128	13

This section investigates the consistency, flexibility and efficiency of material selection results in establishing a new normalization tool into both MOORA and WASPAS for each case.

The linear normalization sum-based method is as follows:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{16}$$

For benefit criteria

$$r_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}} \tag{17}$$

For cost criteria

In these formulas, r_{ij} is the normalized matrix for criteria j, and x_{ij} is the initial performance for m candidate materials. For the MOORA method, only equation 16 is taken into account, whereas equations 16 and 17 are both considered for the WASPAS algorithm. The ranking results for the original and modified version of MOORA and WASPAS are presented in Table 6. In the first case, the correlation coefficient between the original and modified MOORA (e.g. the new MOORA method which contains equation 16 for normalization) is very high (0.99). The same situation is observed for the WASPAS method (0.95). It can be concluded that the effects of normalization methods on WASPAS is higher than MOORA due to less rank order changes for the former. The eight highest ranking materials are equal across the two MOORA versions. Comparing against WASPAS, equal ranks are found for the first seven materials. Figure 2 illustrates the conformity of the results across methods.

In the second case of hard magnetic material selection, the ranking outcomes based on the different MADM models are presented in Table 7. The noteworthy point here is that that both MOORA and modified MOORA generate similar ranking in almost the first top ten materials. The same condition can be seen for the top three materials when comparing the WASPAS models.

The worst material is uncovered as (M_{24}) by both modified and original MADM methods. The correlation coefficients are acceptable for case 2 although it was not as high as case 1. Figure 3 illustrates the comparison of material ranking across the MADM methods.

Table 6

Application of New Normalization Tol on WASPAS and MOORA Ranking (Case 1)

Material	MOORA method ranking			WASPAS method ranking			C.C (M.MOORA, M.WASPAS)
	Original	Modified	C.C.	Original	Modified	C.C.	
M_1	1	1	0.99	3	3	0.95	0.83
M_2	3	3		1	1		
M_3	10	9		9	11		
M_4	9	10		12	12		
M_5	12	11		14	13		
M_6	2	2		2	2		
M_7	8	8		10	9		
M_8	13	13		11	8		
M_9	14	14		13	14		
M_{10}	6	6		6	6		
M_{11}	4	4		4	4		
M_{12}	5	5		5	5		
M_{13}	7	7		8	10		
M_{14}	11	12		7	7		

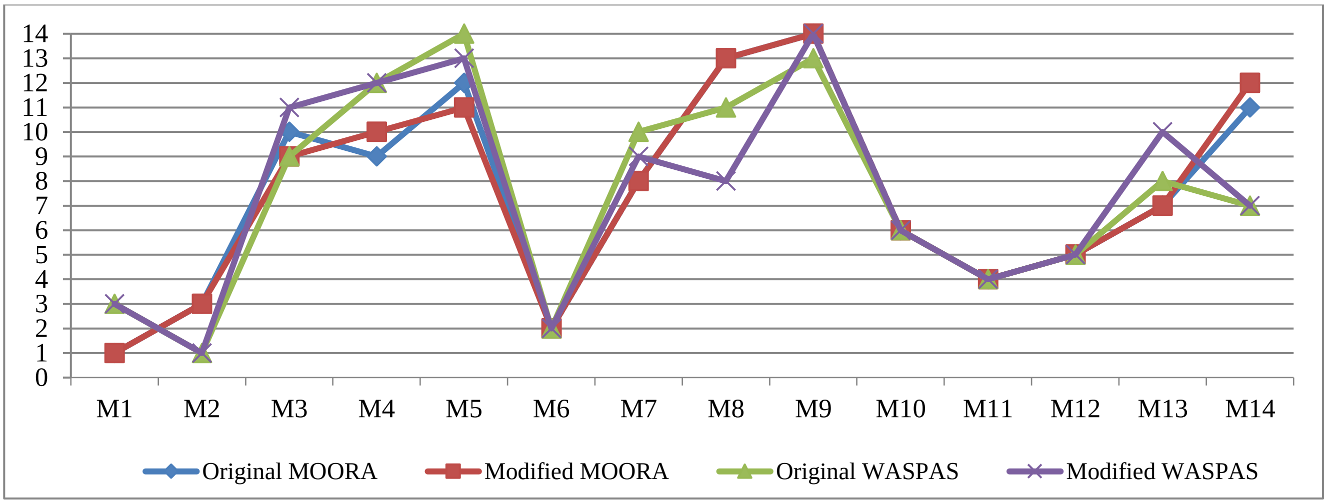

Figure 2. Different Ranking Score for Modified Version of MOORA and WASPAS (case 1)

Table 7

Application of New Normalization Tool on WASPAS and MOORA Ranking (Case 2)

Material	MOORA method ranking			WASPAS original ranking			C.C (M.MOORA, M.WASPAS)
	Original	Modified	C.C.	Original	Modified	C.C.	
M_1	1	1	0.9	1	1	0.83	0.995
M_2	2	2		2	2		
M_3	4	3		5	4		
M_4	3	4		3	3		
M_5	5	5		4	5		
M_6	6	6		9	6		
M_7	13	10		15	10		
M_8	15	11		16	11		

Material	MOORA method ranking			WASPAS original ranking			C.C (M.MOORA, M.WASPAS)
	Original	Modified		Original	Modified		
M_9	23	15		23	14		
M_{10}	8	8		10	8		
M_{11}	7	7		8	7		
M_{12}	9	9		11	9		
M_{13}	21	16		21	16		
M_{14}	22	17		22	17		
M_{15}	17	18		17	18		
M_{16}	12	14		12	15		
M_{17}	14	19		14	21		
M_{18}	18	22		19	22		
M_{19}	19	20		18	20		
M_{20}	24	24		24	24		
M_{21}	20	23		20	23		
M_{22}	11	13		7	13		
M_{23}	10	12		6	12		
M_{24}	16	21		13	19		

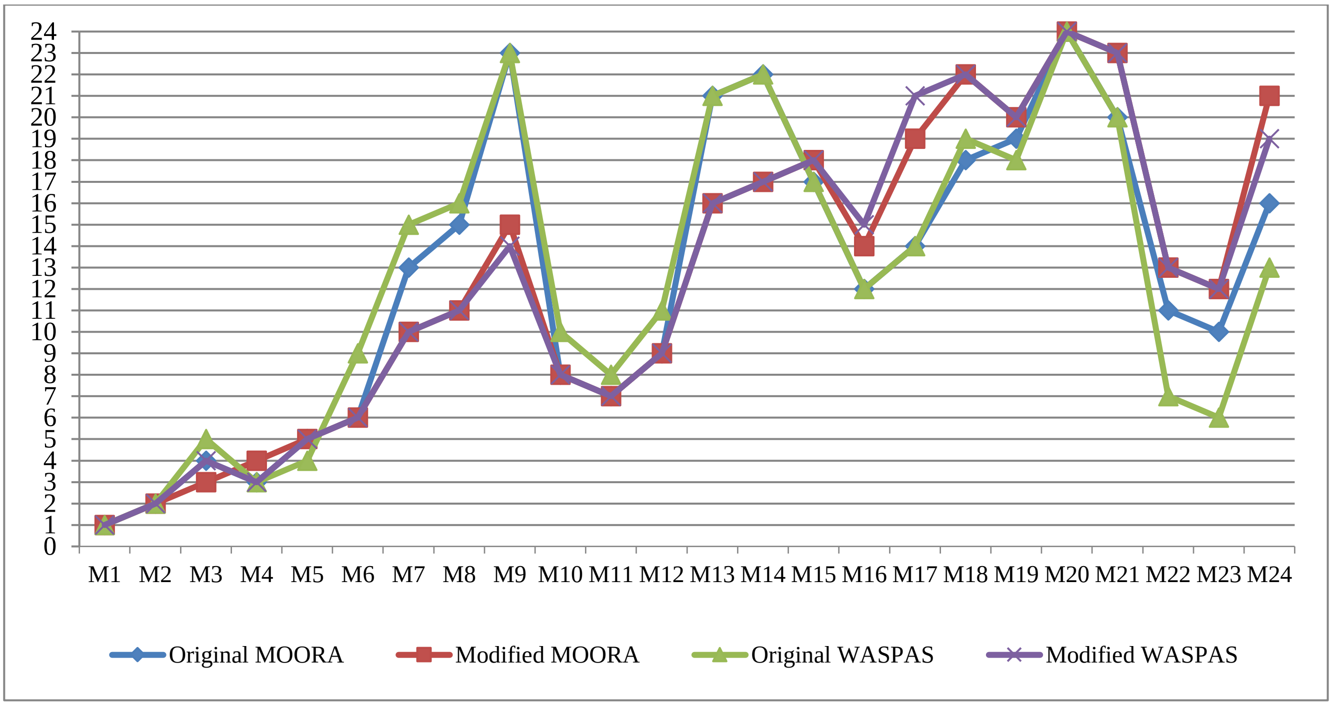

Figure 3. Comparing Different Ranking Score Modified MOORA and WASPAS (Case 2)

Conclusion

MADM techniques in material selection problems provide a transition from conventional scoring method to a more comprehensive and strategic approach. A broad volume of research articles since the past 2 decades showed the evolution of the material evaluation and selection process. Ashby, TOPSIS, AHP, VIKOR, ELECTRE and PROMETHEE have been successfully deployed in different material selection problems. Lately, methods like COPRAS, MOORA and WASPAS are gaining acceptance in decision making problems.

MADM methods in material selection problems seek to effectively outline decision procedures to enhance the quality of the final product. This aids designers and material engineers to enhance the fit between material properties and design specifications.

We provide a sensitivity analysis approach to evaluate the normalization effect on the original WASPAS and MOORA methods. This normalization process gives us the ability to appreciate how changes affect material engineer's decision. This helps engineers to embed design preferences prior to developing a new product that is supported by engineering goals. This paper could further be expanded into the domain of group decision making (see Langroudi *et al.*, 2013; Zhang et al. 2014a; Zhang *et al.*, 2014b; Zhang *et al.*, 2014c). The normalization process could be used as a hybrid methodology (see Behzadian *et al.*, 2013; Tavana *et al.*, 2016) in a decision support system (Hashemian *et al.*, 2014) or data envelopment analysis methodology (see Ghasemi *et al.*, 2014; Ghasemi *et al.*, 2015; Ignatius *et al.*, 2016). Applying other types of normalization tools in order to observe the results similarity and possible improvement can be an issue for future attempts

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