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Short Communication

Integral aided method for material selection based on quality function deployment and comprehensive VIKOR algorithm

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ABSTRACT

In engineering design, the selection of material alternatives usually depends of different criteria based on the specific problem. Due to the different units of this criteria, a normalization process is needed in the selection model. A lot of normalization approach can be found in literature and at the same time many algorithms have been developed to ensure the optimal material selection for a certain industrial application. Two elements of reflection can be drawn from the analysis of these. The first is the absence of an aided support to the selection of the correct engineering criteria by whom operate the selection process. The second is the need to define a weighting method that at the same time can be user-friendly to use and representative of the project's needs. A new selection model based on the integration between House of Quality and the Comprehensive Vikor Algorithm is presented in this paper. This approach, called Integral Aided Material Selection (IAMS), can overcome the main lack of traditional material selection model and provide a real support tool to the project team. That way the project team can optimally choose the selection criteria and assign to these the correct priority coherently with the project needs. A case study is presented to illustrate and justify the proposed method. The topic of the case study concerns the identification of the best coating for the protection of an aluminum alloy substrate (Al-7075) from the effects of abrasive wear against an alternating counterpart made by a high-strength cast iron.

1. Introduction

Materials selection takes on a strategic importance to meet the highest level standard of a product/process design. The evolution of legislative, regulatory and functional needs makes this selection extremely complex as it is the result of several compromises. Otherwise chose the wrong material produce product failure, reliability problem and high costs.

Over the years various attempts have been described which aim to provide a structured support in the selection of optimum materials for the project [1]. The algorithms developed try to help in the assessing of the material performance on several critical aspects minimizing the need of high level competences.

These types of algorithms, that belong to Multi Attribute Decision Making algorithms (MADM), start considering a set of selection attributes of a multi-criteria problem. Then through many calculation they arrive to the identification of the best alternative able to better respond to the selection attributes.

It is important to observe that each of the selection attributes have usually a specific and different impact on the product quality and on the ideality of the solution so that an effective weighting method has to be adopted to consider all the attribute during the material selection process. Besides selection attributes usually have different units and the use of a normalization method is needed for a coherent comparison among all of them. There are many examples of these algorithms in the state of the art about material selection methods [2–6]. The analysis of the state of the art shows two critical issue that appears usually present in the material selection method, in particular:

- These algorithms do not explicitly consider a specific criteria for attributes that require a target value. Some study tried to supply this lack through the addition of this criteria in the VIKOR algorithm (Comprehensive Vikor algorithm, C-Vikor) [7] and in TOPSIS (Technique For Order Preference by Similarity to Ideal Situation). [8]. In the present paper we have chosen the algorithm proposed by Jahan et al. [7] that defines three different classes of selection attributes: attributes that need a maximum value optimization (called Larger-The-Better or LTB); attributes that need a minimum one (called Smaller-The-Better or STB); attributes that require a target value (called Target).
- The correct definition of the different weights for selection attributes among many alternatives is still an open topic. The various weighting methods proposed in literature have been categorized into three different groups considering their

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different level of dependence from the expertise of the designers (subjective, objective or integrated methods) [9]. Many of these methods define a precise and complete structured methodology to overcome the problems of weighting evaluation (e.g. AHP method [10]) but at the same time they appear as extremely rigid frameworks with complex procedures that usually result not sustainable for the application in the industrial environment. Also due to this rigidity and to the time consuming characteristics of these methods the most used decision making process still used in many industrial environment is a structureless approach completely based on the trust in the expertise of technicians and engineers that are members of the project team.

The aim of this paper is to introduce a preliminary tool able to increase the MADM algorithms performance through the use of the House of Quality (HOQ). It is not the first time that HOQ is used in material selection. In fact Mayyas et al. [10] used the HOQ as a direct instrument of selection but in our opinion they introduced significant calculating complications and partially lost the rational character of MADM algorithmic models. Another interesting application of QFD for material selection is proposed by Jalham [11] but he does not consider the target criteria and use a MADM algorithm similar AHP.

Anyway our proposal partially continue on his path. In fact in this paper we present an approach for material selection based on the synergic use of HOQ and C-VIKOR algorithm. In particular HOQ helps to identify and select the criteria in order to assign them a proper weight and C-VIKOR algorithm helps to operate and sort the final selection of alternatives.

The proposed model will be better shown through a case study about the choice of the optimal filler-reinforced Al matrix (CerMets) produced by Cold Spray coating technique. Finally the results achieved using the proposed approach will be compared with the results obtained using Entropy Weighting Method (EWM) [12] coupled with C-Vikor algorithm. EWM is based on the entropy assessment of the criteria and is used as a tool able to provide a rating of importance to each selection attributes. We have chosen EWM method for result comparison to emphasize the typical problem of many numeric method for weight evaluation of selection attributes, i.e. the absence of connection with project real needs. This comparison will show the different effectiveness of the two approach in the specific technical application of the case study.

2. Proposed method

2.1. HOQ

The House of Quality is one of the tools of the Quality Function Deployment (QFD).

The HOQ is a tool used to correlate in a systematic manner the customer needs (VOCs) and the design characteristics (CTQs) [13]. This tool is useful during the product (or service) development process to ensure the better match between what are the demands of the market and the characteristics that must have the product in developing. The steps necessary for its completion are as follow (referred to the scheme shown in Fig. 1):

(1) Fill the room 1 by the needs of the project.
(2) Fill the room 2 with the systematic translation of needs into CTQs – Engineering Characteristics (in the proposed approach CTQs are the selection attributes described in the introduction) and identification of the direction of improvement.

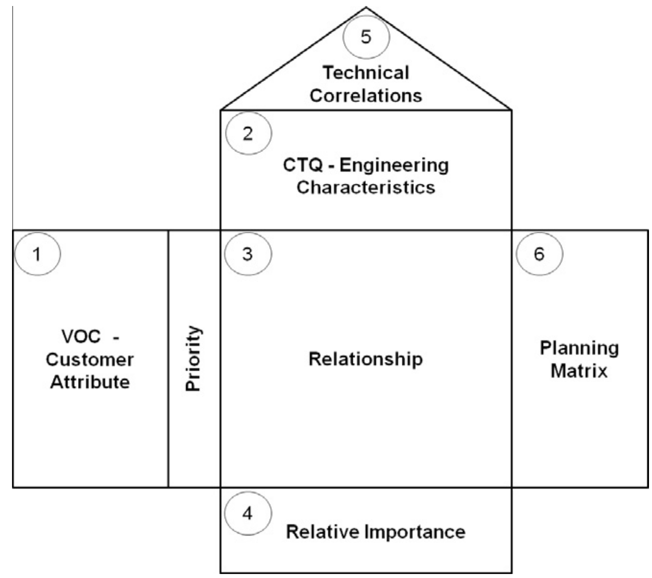

Fig. 1. HOQ scheme.

(3) Allocation of a priority value for the needs of the project, in our case using a range between 1 and 5, with 1 being least important.
(4) Fill the room 3 (the relations matrix) using the discrete factors: weak relationship to 1, 3 for average relationship, 9 for strong relationship.
(5) Fill the room 5 of the correlations indicating the presence of positive correlations (+) or negative (−) correlations.
(6) Calculation of the relative importance of each attribute selection by the sum of the products of the importance of each customer need for the value of relationship between the need and the attribute (room 4).

In the application presented in this paper, the compilation of the room 6 (the matrix in which the information on the direct competitors of the target market is collected) can be neglected. However, it is clear that where it is necessary to develop a market competing product, the availability of data about the materials used by competitors can be an interesting added value term for the model and not a limitation.

2.2. C-VIKOR

The MADM VIKOR was developed as a tool for multi-objective optimization in complex systems. This algorithm is based on the comparison between the alternatives of selection on the basis of critical attributes characterized by different units of measurement. In the VIKOR model the ranking of optimality is obtained from the analysis of what is the distance of each alternative from the ideal solution, and the concept of compromise is related to the mutual granting of the different critical attributes. Depending on the ability to consider all the three categories of attribute (LTB, STB and Target) here we will adopt the form of VIKOR developed by Jahan et al. [7], hereinafter referred to as C-VIKOR. In Fig. 2 is shown the logical process of this C-VIKOR.

The mathematical model of C-VIKOR can be found in [7].

2.3. Integration between HOQ and C-VIKOR Algorithm in guided materials selection

The C-VIKOR, shown in Fig. 2, result a good algorithm for incremental design scenario rather than disruptive/innovative application. This is due to the fact that if the project team starts

Fig. 2. Flow chart of C-VIKOR algorithm.

with a list of materials before that the selection attributes have been defined, most likely the material research will be based solely on past experience of the team, without actually exploring innovative solution in the materials domain.

Based on this observation and integrating the HOQ in the algorithm, the model called Integral Aided Material Selection (IAMS) has been developed.

From direct comparison of C-VIKOR (Fig. 2) with IAMS (Fig. 3) it should be noted that in IAMS the identification of the list of potential alternative materials is next to the identification of selection criteria. This logical change has been introduced to make as much as possible guided the selection of the materials best suited to the needs of the project. The identification of a set of alternative materials before the technical selection criteria have been explicitly formalized, seems not very consistent with the aim of a wizard for the design developed for technicians with limited experience. The integrated model proposed in this paper attempts to overcome these limitations by providing an instrument which enables the project team to better combine their previous experiences with the introduction of innovative elements in the finished product.

The research domain for the optimal set of candidate materials should be as broad as possible and not based only on historical heritage. Only the selection criteria, carefully formalized, could introduce an initial screening of materials within the domain and then allow the identification of the "best" candidates.

The usual C-VIKOR algorithm introduce two final conditions (Fig. 2), whose verification is necessary to ensure an adequate confidence level about the optimality of the option with best rating level [7,12–14]. Instead in the IAMS model the aim is not to provide the best solution to the project team. In fact in IAMS model a systematic approach that allows the team to focus his attention on a limited set of material alternatives (less than three) has to be provided to not introduce limitation in team creativity. For this reason, the use of the two conditions, C_1 and C_2 is no more needed for results validation (Fig. 3).

3. Case study and validation of the proposed method

The IAMS model is shown through the following case study. The case study concerns the development of a protective coating on a

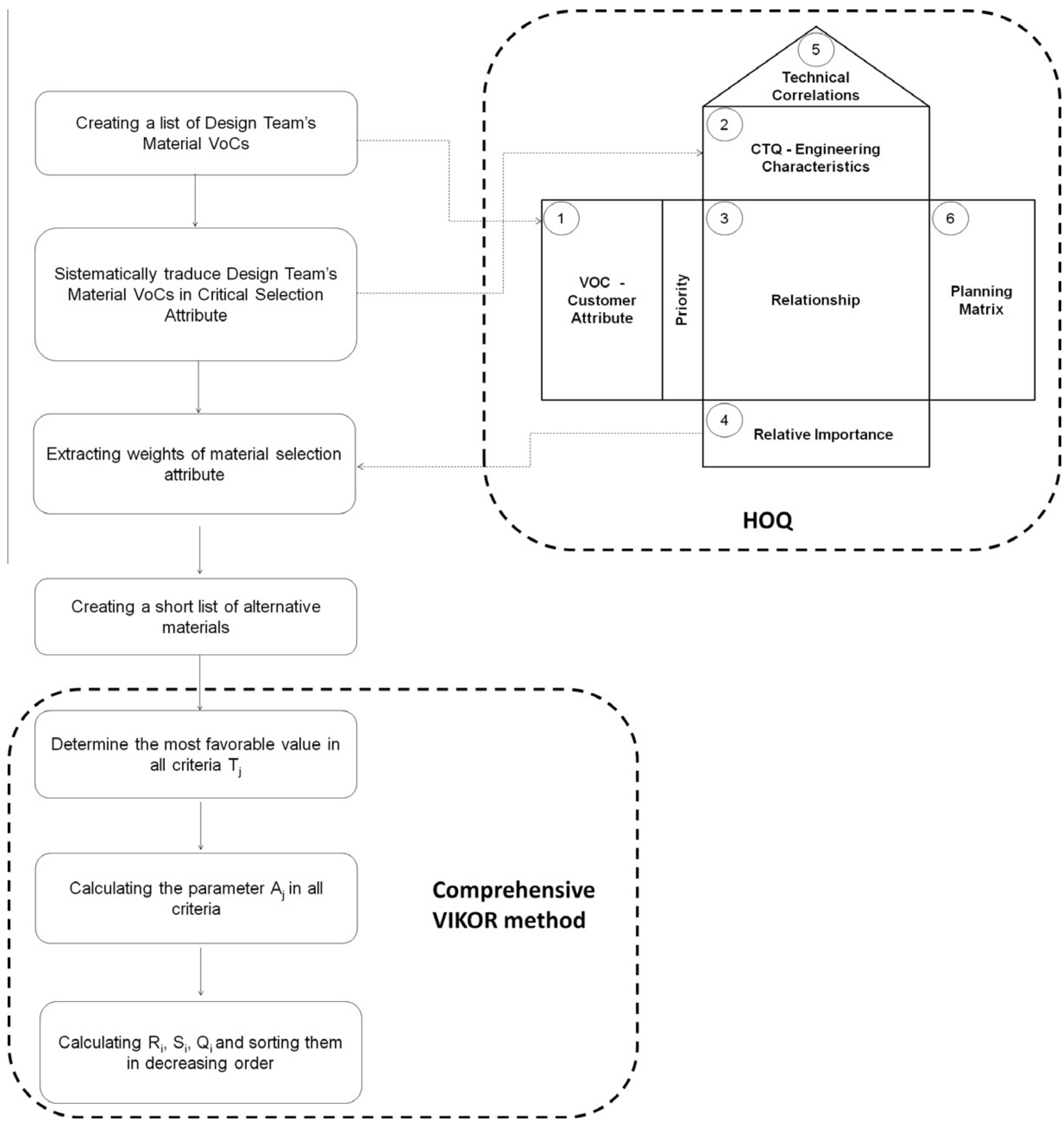

Fig. 3. Main step of the IAMS model.

aluminum alloy substrate (Al-7075, 175 HV), with the goal of protecting the substrate from the effects of abrasive wear during the sliding motion against an alternating counterpart made by a high-strength cast iron (290 HV). In the specific case it is critical to keep the surface integrity of the aluminum component, while the other part admits a limited wear of cast iron. A schematic model of the tribocouple is shown in Fig. 4. Another critical issue is the limitation in using coating technology characterized by high intrusiveness in the substrate. This limitation is necessary in order to preserve the mechanical properties of the substrate. Considering this need, it was decided to use a Cold Spray process for the deposition of a thick protective layer of ceramic particles to reinforce Al-7075 matrix.

This case study is characterized by two aspects of interest:

- The importance of being able to explicitly consider the Target criteria in the mathematical model.
- The complexity of the applications in which the choice of a material is further constrained by compatibility with other materials required.

The IAMS model is developed to drive the selection of a very limited number of candidates (2 or 3 ones), that are good solutions to strength the metal matrix.

The first step in IAMS model is the identification of the preliminary needs of the project (VOCs) (following the model shown in Fig. 3). In order to have a complete set of selection attributes, we also attributes related to the economic implications of the material selection have been consider in the model. In the case study these implications imply limitations due to the purchase costs of raw materials and technology needs that are related to production and processing subsequent to the deposition of the coating.

The VOCs identified are the following:

- Improve the substrate resistance to abrasive wear.
- Limit detrimental actions harmful to the integrity of the counterpart of the coupling (stationary part).
- Effective distribution of loads between matrix and reinforcement in the CerMet.
- The contribution to Young Module of the CerMet (E_{CM}) caused by the reinforcement is such that E_{CM} is not much different from the substrate Young Module (E_S). In a first approximation we can consider that $E_{CM} \propto E_m V_m + E_f V_f$, where E_m is the Young Module of the Al-7075 matrix (in this case study is the same of the substrate, E_S), E_f is the Young Module of the filler and V_m and V_f are, respectively, the volume fraction of the matrix and the filler.

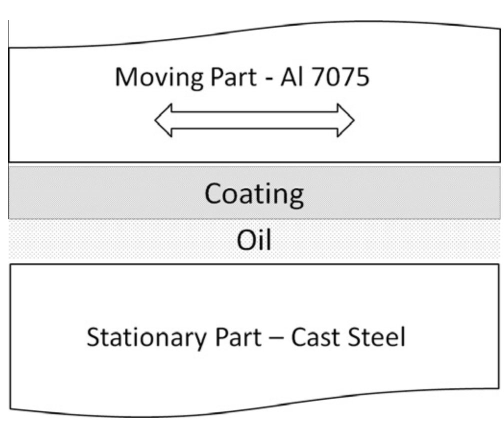

Fig. 4. Schematic model of the tribocouple.

- Do not allow differential thermal expansion between matrix and reinforcement.
- Do not allow differential thermal expansion between the CerMet and Substrate.
- Minimize the weight of the component.
- Protect the substrate from the heat.
- Build effective cohesive links between the filler and the matrix.
- Ensure the possibility of recovery of the mechanical tolerances of the workpiece.
- Reduce the cost considering both the purchase of materials and the process (machining coating).

All these requirements are the input to the application of the HOQ. Fig. 5 shows the template and then the completed HOQ. In the room 2 of the HOQ are shown the critical selection attributes obtained as technical translation of the VOCs:

– Filler hardness.
– Filler Young Module.
– Filler coefficient of thermal expansion (CTE).
– Filler density.
– Filler thermal conductivity.
– Filler wettability by the Al-7075 matrix.
– Filler workability.
– Filler cost.

For each of these the critical direction of improvement has been identified (Target, STB or LTB). It is important to notice that in this case study, nearly 40% of the attributes is of Target type, that is a proof of the importance to mathematically include this class in the selection algorithm.

A brainstorming among the members of the Project Team followed by a sensitivity analysis on the Relative Weights allowed to assign a weight to each VOC (Importance to the Project).

Depending on the relationships between the identified VOCs and the selection attributes, and considering the weights attributed to the VOCs, it is possible to calculate the relative weights % (w_j) of the different selection attributes.

The next step of IAMS model is the identification of a set of materials that could be used as fillers for the reinforcement of the 7075 matrix Cold Sprayed, the list is shown below:

(1) Al_2O_3 (94% purity).
(2) TiN (99% purity).
(3) TiC (99% purity).
(4) TiO_2 (99% purity).
(5) SiC (99% purity).
(6) SiN (99% purity).
(7) WC (99% purity).
(8) CrN (99% purity).
(9) AlN (99% purity).

This list contains two distinct categories of materials:

- The first category includes materials that are currently subjected to intense academic and industrial research to optimize their performance in cold-sprayed CerMet aluminum base coatings.
- The second category includes material that are currently difficult to be uses in industrial applications. These materials are included the list even if they are characterized by high cost of powder and extremely difficult and expensive deposition process. So this class of materials is introduced in the case study to evaluate the ability of IAMS model to evaluate the materials contained therein, and thus place them in the final ranking on the lower positions.

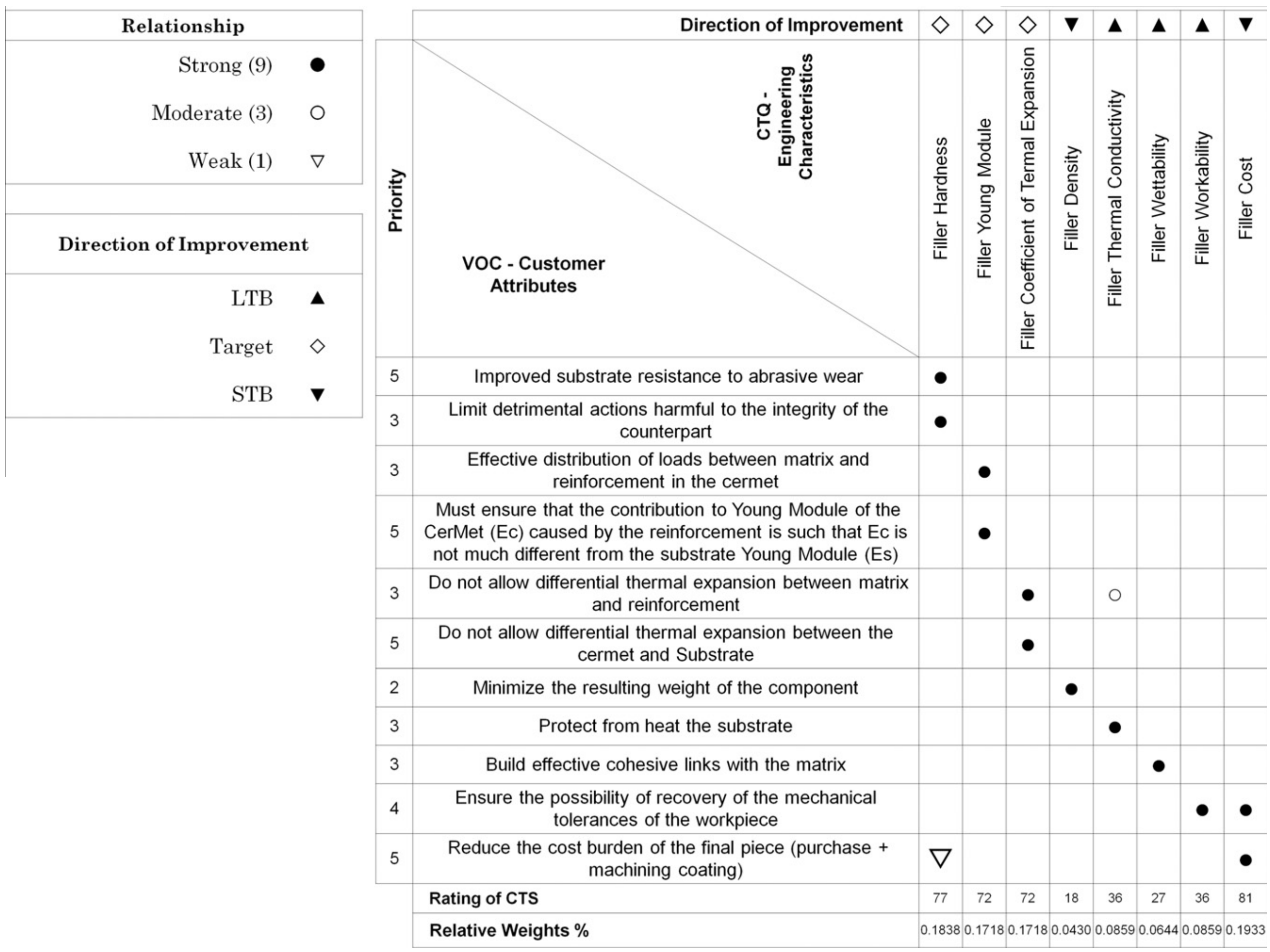

Fig. 5. HOQ completed.

Following the proposed model, we proceeded to collect data about the performance of each of the candidate materials relatively to each of the selection attributes. In this research we have used numerous sources: on-line database (i.e. MatWeb), and handbooks (i.e. Handbooks of Condensed Matter and Materials Data).

The selection matrix is shown in Table 1 and collects all the technical data about the different materials. The criteria on the wettability of the matrix and workability are qualitative and have been translated into numerical terms by a simple fuzzy logic.

Then the Selection Matrix is normalized and using the weights of different attributes of selection provided by the HOQ (w_j) the value of the parameter S_i, R_i and Q_i is calculated through C-Vikor algorithm [7]. The results are shown in Table 2.

Under the direct comparison of the value assumed by the parameter Q_i for different alternatives of selection it is possible to obtain the ranking of solution optimality. This ranking is shown in Table 4.

Then we show in Table 3 the calculation of the weights of critical attributes obtained by the traditional EWM method [12] coupled with C-Vikor MADM algorithm.

The weights obtained with the two model are compared graphically in Fig. 6. The analysis of these results shows a significant dis-

Table 1
Completed selection matrix.

Objective	Filler hardness (HV) TARGET	Filler Young Module (GPa) TARGET	Filler CTE (10–6/°C) TARGET	Filler density (gr/cc) STB	Filler thermal conductivity (W/m K) LTB	Wettability (null) LTB	Workability [null] LTB	Cost (€/kg) STB
Best value	1100	300	23	3.1	160	5	5	8.5
Materials								
1 Al_2O_3	1175	300	8.1	3.69	18	5	3	8.5
2 TiN	2500	600	9.4	5.22	19.25	4	1	38
3 TiC	2900	439	8.3	4.94	20	2	1	40
4 TiO_2	1100	230	9	4.25	11.7	4	3	22
5 SiC	2800	410	4	3.1	120	2	1	13
6 SiN	1580	310	3.3	3.3	30	4	2	33
7 WC	2300	720	3.8	15.72	84.82	2	1	17
8 CrN	1100	400	2.3	6	19.2	4	3	100
9 AlN	1100	330	4.5	3.26	160	4	3	100

Table 2
Selection matrix with the value of the parameters S_i,R_i,Q_i.

	Filler hardness (HV)	Filler Young Module (GPa)	Filler CTE (10–6/°C)	Filler density (gr/cc)	Filler thermal conductivity (W/m K)	Wettability (null)	Workability (null)	Cost (euro/kg)			
Best value	1100	300	23	3.1	160	5	5	8.5			
Aj	1800	490	20.7	12.62	148.3	3	4	91.5			
Objective	TARGET	TARGET	TARGET	STB	LTB	LTB	LTB	STB	S_i	R_i	Q_i
Material											
1 Al2O3	0.007	0.000	0.088	0.002	0.053	0.000	0.034	0.000	0.18439	0.05294	0.16011
2 TiN	0.099	0.079	0.083	0.007	0.053	0.018	0.054	0.053	0.44594	0.05266	0.62358
3 TiC	0.116	0.042	0.087	0.006	0.052	0.041	0.054	0.056	0.45564	0.05249	0.64000
4 TiO2	0.000	0.023	0.084	0.004	0.054	0.018	0.034	0.027	0.24398	0.05431	0.27276
5 SiC	0.112	0.035	0.103	0.000	0.020	0.041	0.054	0.009	0.37470	0.02031	0.33823
6 SiN	0.043	0.003	0.105	0.001	0.050	0.018	0.045	0.045	0.31183	0.05016	0.37297
7 WC	0.089	0.099	0.104	0.027	0.034	0.041	0.054	0.017	0.46572	0.03417	0.56799
8 CrN	0.000	0.032	0.109	0.009	0.053	0.018	0.034	0.122	0.37611	0.05267	0.49953
9 AlN	0.000	0.010	0.102	0.001	0.000	0.000	0.034	0.122	0.26829	0.12220	0.64911
Weight w_j	0.184	0.172	0.172	0.043	0.086	0.064	0.086	0.193	$DQ = 1/(9 - 1)=$	0.125	

Table 3
Selection matrix with adimensionalized data and weights provided by the entropy weighting method.

	Filler hardness (HV) TARGET	Filler Young Module (GPa) TARGET	Filler CTE (10–6/°C) TARGET	Filler density (gr/cc) STB	Filler thermal conductivity (W/m K) LTB	Wettability (null) LTB	Workability (null) LTB	Cost (euro/kg) STB
Materials								
1 Al_2O_3	0.0710	0.0802	0.1537	0.0746	0.0373	0.1563	0.1667	0.0229
2 TiN	0.1510	0.1605	0.1784	0.1055	0.0399	0.1250	0.0556	0.1023
3 TiC	0.1752	0.1174	0.1575	0.0998	0.0414	0.0625	0.0556	0.1077
4 TiO_2	0.0664	0.0615	0.1708	0.0859	0.0242	0.1250	0.1667	0.0592
5 SiC	0.1691	0.1097	0.0759	0.0627	0.2485	0.0625	0.0556	0.0350
6 SiN	0.0954	0.0829	0.0626	0.0667	0.0621	0.1250	0.1111	0.0888
7 WC	0.1389	0.1926	0.0721	0.3177	0.1756	0.0625	0.0556	0.0458
8 CrN	0.0664	0.1070	0.0436	0.1213	0.0398	0.1250	0.1667	0.2692
9 AlN	0.0664	0.0883	0.0854	0.0659	0.3313	0.1563	0.1667	0.2692
ej	0.9639	0.9733	0.9530	0.9217	0.8153	0.9738	0.9471	0.8679
1-ej	0.0361	0.0267	0.0470	0.0783	0.1847	0.0262	0.0529	0.1321
Weight w_j	0.0618	0.0458	0.0805	0.1340	0.3163	0.0448	0.0906	0.2261

Table 4
Rankings obtained by the IAMS and EWM models ranking based on literature.

Place	Ranking		
	IAMS	EWM	Literature
1st	Al_2O_3	SiC	Al_2O_3
2nd	TiO_2	AlN	SiC
3th	SiC	Al_2O_3	TiO_2
4th	SiN	WC	TiC
5th	CrN	SiN	TiN
6th	WC	TiO_2	SiN
7th	TiN	TiN	WC
8th	TiC	TiC	AlN
9th	AlN	CrN	CrN

crepancy between the results of the two models for weighing. In particular, we note that the method EWM, based only on the trend of data about each selection attribute, loses the sensitivity needed to understand the physical problem connected with the selection. This consideration is shown in particular observing that the model assigns to the attribute "Filler thermal conductivity" (attribute of secondary importance for the Project Team), the highest weight value among the selection attributes. On the other hand the most important mechanical properties (i.e. hardness and Young's modulus) have lower attributed weights. This important difference between the EWM and IAMS results shows clearly how the use of a direct and exclusive connection between the weights of importance and the selection criteria creates a mistake in the evaluation of real case and real project needs.

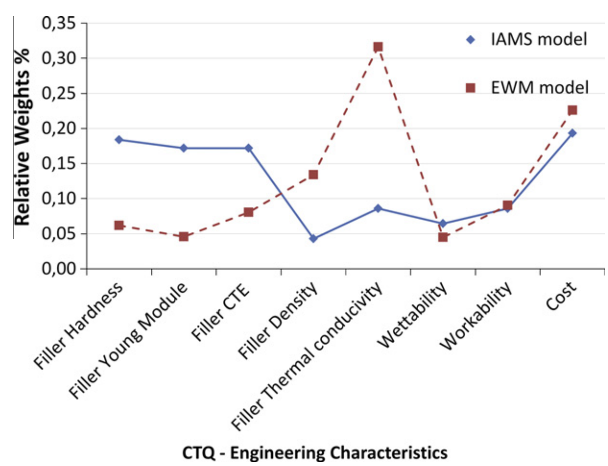

Fig. 6. Comparison of attributes weights obtained by IAMS and EWM models.

The results obtained by IAMS model and in EWM are then compared with the ranking based on the effective use of these materials obtained by a literature survey [15–20]. These three different ranking are shown in Table 4. In this Table it is clear that the distortion in the allocation of the importance weight to different selection attributes using EWM model is directly reflected on the ranking of alternatives. In particular EWM and IAMS models have generated significantly different results.

Finally the statistical Spearman Rank Coefficient (SRC) has been used to compare the two ranking of IAMS and EWM with the real ranking to verify the correctness of the conclusions proposed.

The SRC values obtained are 0.6333, when the critical value is 0.6000 considering nine alternatives and a significance level of 5%. This detects a significant statistic correlation between the results obtained with the literature based Ranking and the IAMS model results. Instead the SRC obtained considering the EWM is 0.333 that is below the threshold level of 0.6000 and confirms the low consistency of this method.

4. Conclusion

From the results derived from the case study shown in this paper, three significant conclusions can be drawn:

(1) The introduction of the HOQ has allowed to structure the basic process of identifying of the critical selection attributes. Thanks to the IAMS approach, this process appears much more guided also for the young designer and in general for the project team member who have limited experience on materials selection.
(2) The IAMS model has generated relative importance weights to the selection attributes much more consistently with the requirements of the Project. The use of an algorithmic weighting model, such as EWM, has proved its inability to really understand the project requirements.
(3) The proposed IAMS model is effective in determining the ranking of alternative materials, providing excellent compatibility with the ‘‘real ranking’’ derived from an intensive literature survey. This is an important feedback in the validation process of the IAMS model.

However an issues that has to be highlighted regards the effectiveness of the MADM model in the case of scarcity of data. In fact the availability of data concerned each Engineering Characteristic are of vital importance for the MADM ability to work. It is also very important to note that often the needed data are provided with different confidence level, as in the case of different sources for the data.

Future work will therefore concern the introduction in the IAMS model of tools capable of considering the different reliability level of the data connected with each Engineering Characteristic.

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