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A Mixed C-VIKOR Fuzzy Approach for Material Selection during Design Phase: A Case Study in Valve Seats for High Performance Engine

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Abstract

This paper introduces an innovative simple method to manage data uncertainly based on fuzzy logic. The proposed approach perfectly integrates with the C-VIKOR algorithm used to technically ranking the candidate materials. This method aims at helping design teams to select optimal material(s) for the success of a product at the early stages of product development. When neither a material team nor a material expert is available within the company, the design team has to face autonomously with this task. A support system is thus desirable: it has to be easy to use, and not only to rank the candidate materials from a technical point of view, but also to show to the design team the confidence with which to handle this ranking. These conditions are seldom addressed by the models presented in literature, despite their importance. The few existing approaches use a complex probability logic that is tricky to manage by non-expert users. An easy-to-use support system is needed because the smart use of materials is becoming a must-be for the leading industries that have understood how the materials can functionalize the product, rather than simply represent the product hardware. The successful applicability of the proposed method is reported through a case study, debating the material selection for the production of the valve seats component in a high-performance engine, showing the practical feasibility of the method itself.

Keywords: material selection method, MADM, mechanical components, design methods, valve seats, surface mechanics, coating, high performance engine.

INTRODUCTION

In the context of a growing industrial competition, the issue of material selection has become increasingly crucial [1]. The markets are continuously supplied with new products, and the only way to keep up with competitors is either to reduce the cost of the existing product, or to develop new functionalities. It is crucial for this need to review the processes of product design and development, making them leaner and more efficient [2].

With such stressful industrial trend, no longer can an optimal selection of materials be neglected, even when dealing with lower-added-value products. However, this task is not easy to accomplish, and a lot of small-medium companies do not have the necessary know-how to manage the selection problem. The usual responses to this problematic situation are to rely completely either on the opinion of external consultants, or on the indications of expert system with material database [3,4]. Both these approaches are very expensive and, more significantly, they do not allow companies to grow their own experience in the material selection. In the last decade, several approaches have been developed to computationally support the design team to select optimal materials for a project [5-14]. These approaches are based on the use of Multi Attribute Decision Making (MADM) algorithms [15-22]. First of all, the design team should collect a limited number of possible alternatives for the design. Second, a set of selection attributes should be chosen, by which the selection alternatives can be relatively prioritized. Then the team has to collect data about the performance of each of the candidate materials relatively to each of the selection attributes (using available sources: on-line database, and handbooks, datasheet from Suppliers, experimental data, etc.). The MADM algorithm use all this information to calculate the ranking of the design alternatives.

The choice of the correct selection attributes is itself not a menial task, because it demands the exact translation of the customer needs into the technical requirements, as suggested by methodologies like Axiomatic Design, which has been applied by authors in [23]. Also, is the attribution of an importance weight to each selection attribute [11-13] is crucial to the effectiveness of this approach. Indeed, not all the selection attributes have the same importance to the performances of the project. For this reason, a correct weighting strategy has to be used. Several methods have been explored to help improve performances in order to be more and more competitive on the market: the authors have investigated applications of various models, such as mathematical simulation models like Kriging [24], or tools, like TRIZ [25], to achieve performance improvement of single products. More specifically, as far as material selection is concerned, a previous work of the authors has developed a model, called Integral Aided Material Selection (IAMS) [26], that integrates the House of Quality approach and one of the most structured and reliable MADM algorithm (i.e. the Comprehensive VIKOR algorithm or C-VIKOR [27,10]). The IAMS method is able to obtain a clear selection process from the translation of the customer needs into the technical requirements, to the ranking of the design alternatives.

This paper considers an additional element concerned with the data availability, i.e. the higher or lower variability of data referred to each combination “selection alternative” versus “selection attribute”.

In fact, the usual computational approach neglects the variability of the data presented by different sources, and use an average value for these. In the case of data unavailability, the punctual value of the selection attribute can proceed by identifying a realistic value through approximation with similar known materials.

The concepts of data variability and reliability are therefore seldom managed, which therefore might be quite dangerous. Often, the design team may have selected the technically optimal alternative, but this alternative has a lot of data uncertainty. This project is inevitably not very robust.

In this paper, we present an approach useful to resolve such lack of robustness of the traditional MADM algorithms in the material selection problems due to data uncertainly.

The authors’ target has been to develop an approach that provides the design team a tool that supports their work as:

- it is easy to use;
- it can recommend the optimal material through a limited set of selection alternatives;
- it can guide the design team in understanding the confidence with which to use the result of the selection algorithm.

This guarantees the necessary innovative and creative action by each team member.

The proposed method is based on a fuzzy probabilistic logic ready to be implemented by the team material selector using a very limited number of assumptions. The proposed model will be better explained and discussed through a case study about the choice of the optimal material for the production of the valve seats component in a high-performance engine. The paper is organized as follows. Section 2 describes the proposed method; Section 3 shows a practical case study used to demonstrate the usability of this selection model; Section 4 discusses the results of the case study; Section 5 offers some closing remarks and highlights future research perspectives.

MATERIALS AND METHODS

As stated in Section 1, the aim of this method is to develop a guided approach to material selection; specifically, this paper presents an approach based on:

- HOQ to identify the criteria and to assign them a proper weight [26],
- C-VIKOR algorithm to identify the best criteria among selection of alternatives. Here we will adopt C-VIKOR developed by Jahan et al. [27,10].
- Fuzzy logic algorithm to manage data uncertainty.

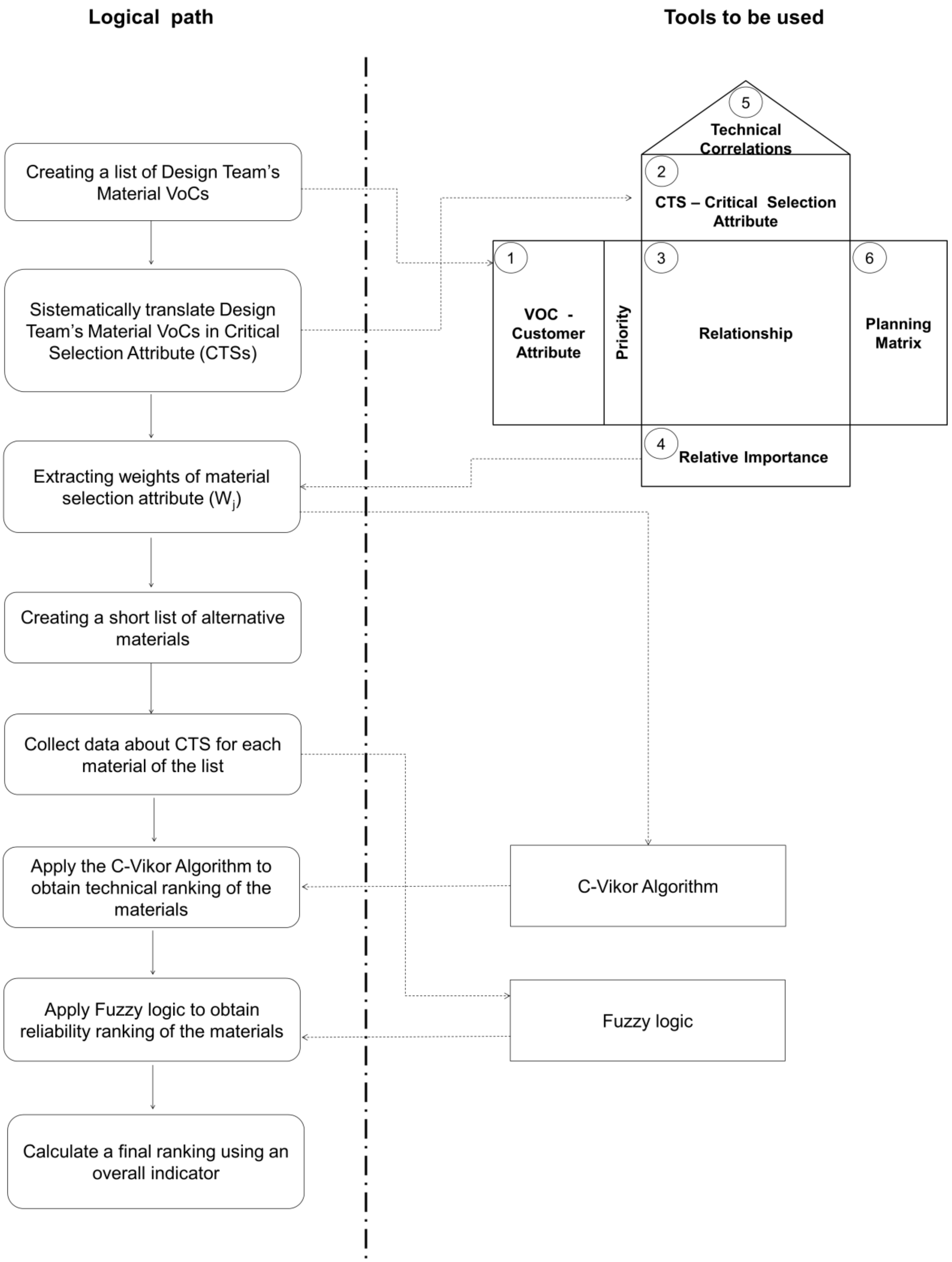

Figure 1. Scheme of the logical path and of the tools suggested in the proposed algorithm.

The flow chart of the proposed method is shown in Fig. 1 and is composed of the following activities:

1. creating a list of Design Team's Material VoCs and fill them in the room 1 of HOQ;
2. systematically translate Design Team's Material VoCs into Critical Selection Attributes (CTSs) and identify

the direction of improvement (fill the room 2 of HOQ);
3. allocate a priority value for the needs of the project, in our case using a range between 1-5, with 1 being the least important;
4. fill the room 3 (the relations matrix) using discrete factors: weak relationship to 1, 3 for average relationship, 9 for strong relationship;
5. calculate of the relative importance of each attribute selection, by summing the products of the importance of each customer need for the value of relationship between the need and the attribute (room 4);
6. extract weights of material selection attribute;
7. create a short list of alternative materials;
8. collect data about CTS for each material of the list;
9. apply the C-VIKOR Algorithm to obtain technical ranking of the materials;
10. apply Fuzzy logic to obtain reliability ranking of the materials;
11. calculate a final ranking using an overall indicator.

For more details of the House of Quality (HOQ) and the C-VIKOR algorithm (i.e. IAMS model) please refer to [27]. This section focuses on the concept of data uncertainly management (i.e. steps 8,10 and 11).

The datum used to compile the ij-cell of the selection matrix of C-VIKOR is usually the average value of the data found for the j-th selection attribute for the i-th selection alternative.

Considering the stem 8, when the design team starts to compile the selection matrix (i.e. to search the value of the selection attributes for each selection alternatives), three different types of data variability can be observed:

a) material data can be found in a single producer datasheet; in this case, data are often expressed as a minimum-maximum guaranteed values (single data source or experimental test [28-30]);
b) material data can be extrapolated from a literature survey, or from a comparison between different producers of the same material (different data sources);
c) material is well characterized, and there are probabilistic distributions for the single physical and mechanical characteristics of the produced material available.

In all these cases, the design team has to face not a single value, but a “range” of values. The concept of range appears to be general enough to be used as a useful index to evaluate data uncertainty in the process of material selection.

We define the *range* of the j-th selection attribute for the i-th selection alternative as:

1-When (case a and b) the design team has a limited value for the same physical or mechanical characteristic (in many application it is reasonable to suppose ≤ 5 different values),

$$Range_{ij} = Max_{ij} - min_{ij} \quad (1)$$

Where Max_{ij} and min_{ij} are respectively the maximum and the minimum value of the characteristic.

2- When (case c), the probabilistic distribution of the characteristics is known.

$$Range_{ij} = 6\ x\ \sigma_{ij} \quad (2)$$

where σ_{ij} is the standard deviation of the characteristic.

Therefore, the concept of range appears to be general enough to be used as a useful index to evaluate data uncertainty in the material selection process. In fact, this parameter is strongly connected with data uncertainty. The wider the range, the bigger the data uncertainty, and the lower the confidence with which to use that datum.

To simplify the calculations conducted by the proposed method, it is useful to couple this range with a simple non-dimensional parameter that the authors name *data robustness (DR)*. This parameter supports the design team in understanding the confidence with which to use the result of the selection algorithm in the proposed approach. To explain this concept, each selection alternative can be represented as a serial functional system, (see Fig. 2). The robustness of a selection alternative can be calculated as the product of data robustness and this selection alternative.

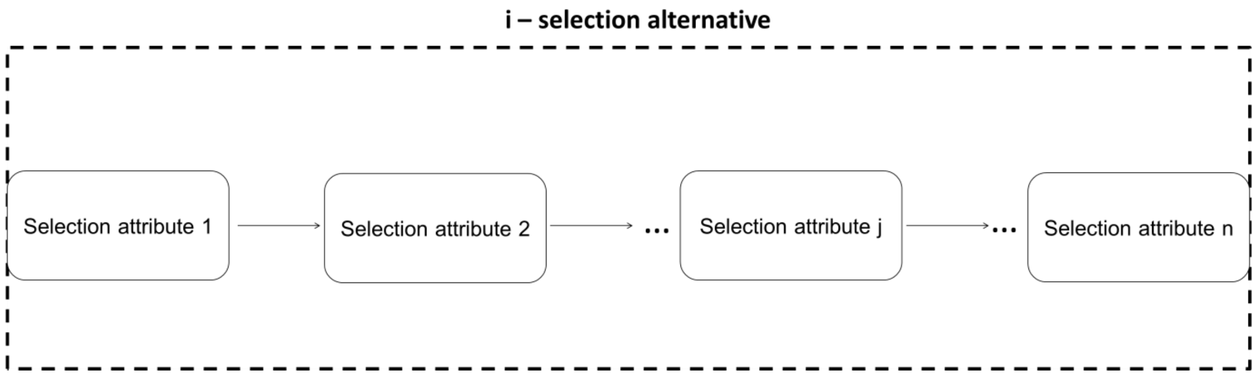

Figure 2. Graphical representation of serial functional system of a generic selection alternative.

It is very important to note that it is not reasonable to consider the same weight for the data robustness of all the selection attributes in the computation of the alternative robustness.

Indeed, two extreme cases can happen (for example for the i-th selection alternative):

a. a low importance selection attribute has high datum uncertainty (low datum robustness);
b. a high importance selection attribute has high datum uncertainty (low datum robustness).

It is easy to figure out that condition b. is far more problematic than condition a.

This is the reason why the proposed method considers different weight for the datum robustness of each selection attributes for the selection alternatives.

The fuzzy logic by which the DR for the j-selection attribute relative to the i-th selection alternative is computed is shown in Fig. 3.

With reference to the flow chart in Fig. 1, for each selection attribute a fuzzy logic linear curve is built.

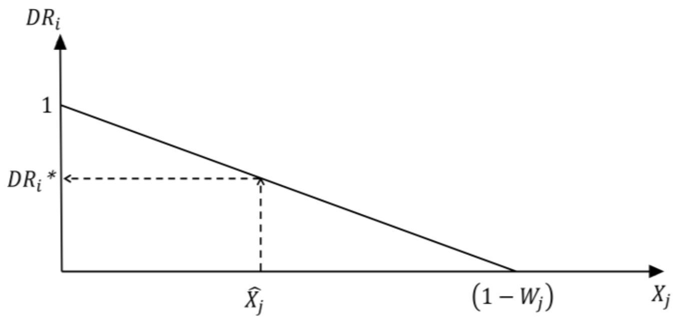

Figure 3. Fuzzy logic used to calculate datum robustness.

The slope of each of these curves is a function of the importance weight Wj of the corresponding selection attribute. The more technically important is the selection attribute, the more rapidly the curve intersects the x-axis. This strategy is clearly conservative. The logic is reasonable, because at the same value of datum dispersion, the more important the selection attribute, the lower must be the confidence with which to manage this datum (lower datum robustness).

The datum robustness is then computed as:

$$DR_{ij} = -\frac{1}{(1-W_j)}\widehat{X}_j + 1 \quad (3)$$

with $0 \leq DR_{ij} \leq 1$.

and where

$$X_j = (1 - W_j)\left(\frac{\frac{1}{2}x\ Range_{ij}}{Mean_{ij}}\right) \quad (4)$$

The DR_i (robustness of the i-th selection alternative) is finally computed as:

$$DR_i = \prod_{j=1}^{m} DR_{ij} \quad (5)$$

Where m is the total number of the selection attributes.

At this point of the method, the design team has two rankings for the set of selection alternatives:

- a technical ranking: this ranking shows (when possible) if there is a material that better responds to the customer needs;
- a data robustness ranking: this ranking signals to the design team the confidence with which each selection alternative in the technical ranking can be managed.

The design team has thus been alerted that, to maximize the market share of the developed product, pure performance is not sufficient. The product has also to be reliable and robust in its production process. This way, the team can manage the material selection using these two rankings.

Besides, a simple ranking can be obtained through the selection alternatives by the definition of the *Complete Ranking Index (CRI)*.

For the i-th selection alternative, it can be calculated as:

$$CRI_i = \left(\frac{Max(Q_i)-Q_i}{Max(Q_i)}\right) DR_i \quad (6)$$

Where Q_i is the coefficient calculated through C-VIKOR algorithm and used to create the technical ranking of the materials, and $Max(Q_i)$ is the maximum among the Q_i coefficients. The logic of the transformation is very intuitive: equation (6) normalizes the "distance" of each design alternative from the worst technical alternative (the alternative with the larger Qi as computed by the C- VIKOR). Then the distance is multiplied by Data Robustness (DR_i). Considering this logical approach, the best material is the one that has the higher value of the CRI_i.

CASE STUDY

Valve seat for high performance engine:

To validate the proposed method, a real case study is presented. The problem concerns the material selection for the production of the valve seats component in a high-performance engine (see Fig. 4). This component is critical to the engine performance for two reasons:

- it must guarantee the tightness of the combustion chamber thanks to its contact with the valve;
- through the valve seats the heat can be subtracted from the valve disk allowing to use the engine at a higher combustion temperature (maximizing the thermodynamic efficiency).

These two design aspects become even more critical when applied to engines with high specific power, the structure of which is usually made of aluminum castings, and where operating temperatures are far higher than standard motors. In the face of substantial savings in terms of the engine mass, such material is in fact absolutely not able to withstand the thermo-mechanical stresses produced by the direct contact with the sealing cone (disk) of the valve. It is therefore essential to the realization of the valve seat with a different material than the one of the cylinder head.

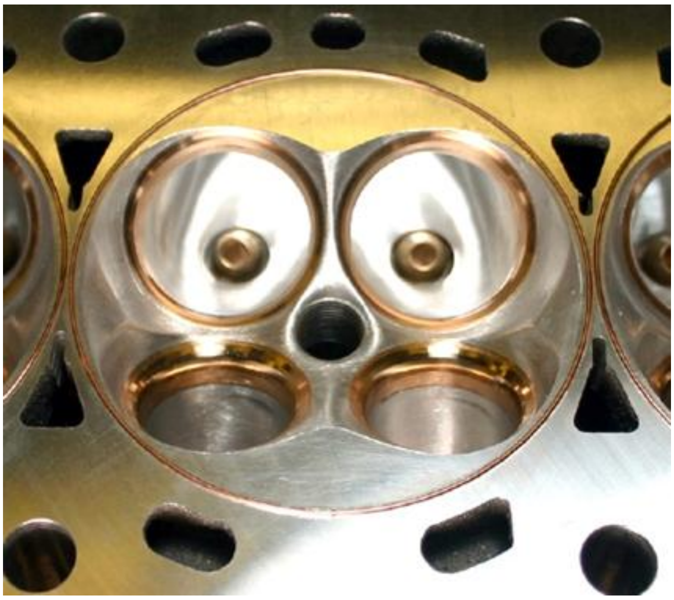

Figure 4. Typical valve seats of a high performance engine.

Construction of the HOQ

The customer needs (VOC) for this technical problem are:

- the valve seat material needs to be able to conduct efficiently the heat transmitted by the valve;
- the valve seat material needs to be able to follow the thermal deformations of the cylinder head;
- the valve seat material needs to be able to follow the mechanical deformation of the cylinder head;
- the valve seat material needs to be able to withstand repeated impacts;
- the valve seat material needs to be abrasion resistant (good tribological behavior);
- the valve seat material needs to be chemical compatible with the combustion gases;
- the mechanical strength of the valve seat material;
- the low weight of the valve seat material;
- the valve seat material to be easy to machine;
- the valve seat material to have contained material cost.

All these requirements are the input to the application of the HOQ.

Thanks to the HOQ, the VOC can be translated in a more technical language as:

- high Thermal Conductivity (K);
- thermal Expansion Coefficient (TEC) as close as possible to the thermal expansion coefficient of the cylinder head aluminum;
- young Module (E) as close as possible to the thermal expansion coefficient of the cylinder head aluminum;
- hardness (HV);
- abrasion resistance;
- hot corrosion resistance;
- rupture strength (Rm);
- density;
- machinability;
- cost.

For each of these, the critical direction of improvement has been identified: Larger-The-Better (LTB), Smaller-The-Better (STB), attributes that require a target value (Target). It is important to notice that, in this case study, nearly 30% of the attributes is of Target type, that is a proof of the importance to mathematically include this class in the selection algorithm.

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, (House of Quality in Fig. 5).

Priority	CTQ - Engineering Characteristics / VOC - Customer Attributes	K	TEC	E	HV	Abrasion resistance	Hot corrosion resistance	Rupture strength (Rm);	Density	Machinability	Cost
5	Able to conduct efficiently the heat transmitted by the valve	9									
5	Able to follow the thermal deformations of the cylinder head		9	1							
2	Able to follow the mechanical deformation of the cylinder head			9							
4	Able to withstand repeated impacts				9			3			
3	Abrasion resistant (good tribological behavior)				3	9					
4	Chemical compatible with the combustion gases						9				
4	Mechanical strength				3	3		9		3	
2	Low weight								9		
3	Easy to machine	3			3			1		9	
1	Material cost										9
	Rating of CTS	54	45	23	66	39	36	51	18	39	9
	Relative Weights % (W_j)	0.142	0.118	0.061	0.174	0.103	0.095	0.134	0.047	0.103	0.024

Figure 5. House of Quality completed.

Use of C-VIKOR algorithm

The next step of the Integral Aided Material Selection (IAMS) model [26] is the identification of a set of materials that could be used as fillers for the reinforcement of the cold- sprayed Al 7075 matrix, the list is shown below:

- CuBe (Materion Alloy 165 temper TF00);
- CuBe2;
- Alloy 3 (Materion Alloy 3 temper TF00);
- Alloy 310 (Materion Alloy 310 temper TF00);
- C18150;
- C18000;
- SS 410 martensitic stainless steel;
- 50CrV4 (AISI 6150 steel oil quenched, 540°C tempering, D=50mm);
- x38CrMoV51 (AISI Type H11).

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. To collect all the needed technical data, we have consulted numerous sources: on-line database [e.g. MatWeb], scientific papers [31-38] and handbooks (e.g. [39]), Producers and Suppliers on-line catalogues. The obtained selection matrix is shown in Tab. I and collects all the technical data about the different materials.

This data has a maximum and a minimum value, due to the dispersion through the different data sources. The criteria on the abrasion resistance, hot corrosion resistance, machinability are qualitative and have been translated into numerical terms by a simple fuzzy logic. To use the C-VIKOR algorithm the mean value of each datum is used. 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 A_j, S_i, R_i and Q_i is calculated through C-VIKOR algorithm [7]. The results are shown in Tab. II.

Fuzzy logic algorithm to manage data uncertainty.

Through the mathematical expressions (3), (4) and (5) it is possible to quantitative compute this uncertainty and understand the confidence with which the materials selector can manage the technical ranking. In Tab. III the computation is shown of the DR_{ij} parameters for each selection alternative relative to each selection attribute, and the DR_i parameters values and the data reliability ranking of each material alternative.

Results

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 technical optimality (e.g. lower Qi value means better solution). This ranking is shown in Tab. IV.

As mentioned above in the introduction chapter, to optimize the material selection process it is important to consider the data dispersion as an uncertainty indicator of selection robustness. To manage the balance between the need to maximize the technical effectiveness of the selection process, with the requirement to maximize the selection robustness, the CRI_i parameter is computed for each selection alternative. Tab. V shows the final ranking obtained.

Through the comparison of the technical ranking (Tab. IV) and the total ranking (Tab. V) it is possible to note that the selection alternative with the best technical ranking not necessarily is the best option for the project if this alternative has a low reliability index. In this case, the team can select the CuBe2 with both for technical characteristics and the confidence about the results as the best fillers for the reinforcement of the 7075 matrix Cold Sprayed. Instead, the Alloy 310 and CuBe can be seen in the second order. It is interesting to observe that the Alloy 310 and CuBe invert their position in the ranking due to a higher uncertainty about the characteristic of CuBe than of Alloy 310.

CONCLUSIONS

The material selection during design phase is usually a critical step. An important part of this criticality is due to data uncertainly about the different materials that can be selected. This paper introduces a material selection model that is able to evaluate the best material alternative considering both material characteristics and data uncertainty. The approach considers the whole process of materials selection from the definition of the customer needs, to the final materials ranking and, can consider the different reliability level of the data connected with each Engineering Characteristic. The approach integrates QFD, C-VIKOR algorithm and Fuzzy logic to create a ranking of the selection alternatives using data provided with different confidence level, as in the case of different source of the data. As shown in the case study about the material selection for the production of the valve seats component in a high-performance engine, it is of primary importance to conjugate the technical effectiveness with the material characteristics robustness to optimize the materials selection and to guarantee project functionality and reliability. In fact, the best material is the one that can combine both technical effectiveness and material characteristics robustness. This way only can the functionality and the reliability of the project be guaranteed. Such information can help the design team to better and easier identify the best design solution among a complex list of different materials and reduce the iteration in the design phase.

Table I: Completed Selection Matrix.

	K [W/mK]		**TEC** [10^{-6}/K]		**E** [GPa]		**Hardness** [HV]		**Abrasion Resistance** [null]		**Hot corrosion resistance** [null]		**Rupture strength** [MPa]		**Density** [g/cm^3]		**Machinability** [null]		**Cost** [€/kg]	
Optimization type	**LTB**		**Target**		**Target**		**Target**		**LTB**		**LTB**		**LTB**		**STB**		**LTB**		**LTB**	
Best Value			22		80		270		5		5		5				5			
Materials	min	MAX	min	MAX	min	MAX	min	MAX	min	MAX	min	MAX	min	MAX	min	MAX	min	MAX	min	MAX
1. CuBe	105	118	16.7	17	130	132	318	382	4	4	2	3	1030	1310	8.26	8.41	4	4	20.8	25.2

2. CuBe2	105	130	16.7	17	131	134	353	413	4	5	2	3	1140	1380	8.25	8.36	5	5	23.5	25.9
3. Alloy 3	240	240	17.6	17.6	138	138	195	250	2	3	3	3	690	900	8.83	8.83	3	4	21.9	24.1
4. Alloy 310$_2$	235	235	17.6	17.6	135	135	234	260	2	3	3	3	720	820	8.8	8.8	3	4	22.5	23.6
5. C18150	280	324	17	17	117	120	130	155	1	2	2	2	380	520	8.89	8.9	4	5	7.6	7.84
6. C18000	185	225	16.2	17.5	114	130	185	195	2	2	2	3	585	605	8.75	8.84	4	4	8.73	10
7. SS 410	24.9	24.9	9.9	9.9	200	200	339	410	4	5	5	5	985	1310	7.74	7.8	1	2	1	13
8. 50CrV4	46.6	46.6	12.2	12.2	205	205	309	350	4	5	3	4	1020	1145	7.83	7.85	2	3	0.7	0.8
9. x38CrMoV51	18	21	11	11.8	207	215	551	632	5	5	3	4	1835	2100	7.8	7.8	2	3	4.24	5

Table II. Selection matrix with the value of the parameters Aj, Si, Ri and Qi.

	K	**TEC** [10^{-6}/°C]	**E** [GPa]	**Hardness** [HV]	**Abrasion Resistance** [null]	**Hot corrosion resistance** [null]	**Rupture strength** [MPa]	**Density** [kg/m^3]	**Machinability** [null]	**Cost** [€/kg]			
Best Value	**302**	**22**	**80**	**270**	**5**	**5**	**1967.5**	**7.77**	**5**	**0.75**			
A_j	**282.5**	**12.1**	**131**	**449**	**3.5**	**2.5**	**1517.5**	**1.125**	**3.5**	**23.95**			
W_j	**0.142**	**0.118**	**0.061**	**0.174**	**0.103**	**0.095**	**0.134**	**0.047**	**0.103**	**0.024**			
Optimization type	**LTB**	**Target**	**Target**	**Target**	**LTB**	**LTB**	**LTB**	**STB**	**LTB**	**STB**	**S_i**	**R_i**	**Qi**
Material													
1. CuBe	0.070	0.041	0.020	0.028	0.026	0.060	0.055	0.019	0.026	0.014	**0.357**	**0.070**	**0.310**
2. CuBe2	0.068	0.041	0.020	0.039	0.014	0.060	0.050	0.018	0.000	0.015	**0.324**	**0.068**	**0.000**
3. Alloy 3	0.028	0.036	0.022	0.017	0.052	0.052	0.072	0.029	0.036	0.014	**0.359**	**0.072**	**0.399**
4. Alloy 310$_2$	0.030	0.036	0.021	0.009	0.052	0.052	0.073	0.028	0.036	0.014	**0.352**	**0.073**	**0.372**
5. C18150	0.000	0.040	0.015	0.043	0.065	0.066	0.085	0.030	0.014	0.006	**0.364**	**0.085**	**0.815**
6. C18000	0.041	0.041	0.017	0.028	0.059	0.060	0.080	0.028	0.026	0.007	**0.387**	**0.080**	**0.852**
7. SS 410	0.089	0.075	0.036	0.036	0.014	0.000	0.056	0.000	0.065	0.000	**0.371**	**0.089**	**0.991**
8. 50CrV4	0.085	0.066	0.037	0.022	0.014	0.043	0.059	0.003	0.052	0.000	**0.380**	**0.085**	**0.935**
9. x38CrMoV51	0.090	0.069	0.038	0.089	0.000	0.043	0.000	0.001	0.052	0.004	**0.386**	**0.090**	**1.140**

Table III. Computation of the DR_{ij} parameters for each selection alternative relative to each selection attribute.

	K		**TEC** [10^{-6}/°C]		**E** [GPa]		**Hardness** [HV]		**Abrasion Resistance** [null]		**Hot corrosion resistance** [null]		**Rupture strength** [MPa]		**Density** [kg/m^3]		**Machinability** [null]		**Cost** [€/kg]		
Optimization type	**LTB**		**Target**		**Target**		**Target**		**LTB**		**LTB**		**LTB**		**STB**		**LTB**		**LTB**		
Materials	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	$\widehat{X_j}$	DR_{ij}	**DR_i**
1. CuBe	0.05	0.94	0.01	0.99	0.01	0.99	0.08	0.91	0.00	1.00	0.18	0.80	0.10	0.88	0.01	0.99	0.00	1.00	0.09	0.90	**0.530**
2. CuBe2	0.09	0.89	0.01	0.99	0.01	0.99	0.06	0.92	0.10	0.89	0.18	0.80	0.08	0.90	0.01	0.99	0.00	1.00	0.05	0.95	**0.491**
3. Alloy 3	0.00	1.00	0.00	1.00	0.00	1.00	0.10	0.88	0.18	0.80	0.00	1.00	0.11	0.87	0.00	1.00	0.13	0.86	0.05	0.95	**0.497**
4. Alloy 310_2	0.00	1.00	0.00	1.00	0.00	1.00	0.04	0.95	0.18	0.80	0.00	1.00	0.06	0.94	0.00	1.00	0.13	0.86	0.02	0.98	**0.593**
5. C18150	0.06	0.93	0.00	1.00	0.01	0.99	0.07	0.91	0.30	0.67	0.00	1.00	0.13	0.84	0.00	0,99	0.10	0.89	0.02	0.98	**0.411**
6. C18000	0.08	0.90	0.03	0.96	0.06	0.93	0.02	0.97	0.00	1.00	0.18	0.80	0.01	0.98	0.00	1.00	0.00	1.00	0.07	0.93	**0.576**
7. SS 410	0.00	1.00	0.00	1.00	0.00	1.00	0.08	0.91	0.10	0.89	0.00	1.00	0.12	0.86	0.00	1.00	0.30	0.67	0.13	0.87	**0.399**
8. 50CrV4	0.00	1.00	0.00	1.00	0.00	1.00	0.05	0.94	0.10	0.89	0.13	0.86	0.05	0.94	0.00	1.00	0.18	0.80	0.07	0.93	**0.502**
9. x38CrMoV51	0.07	0.92	0.03	0.96	0.02	0.98	0.06	0.93	0.00	1.00	0.13	0.86	0.06	0.93	0.00	1.00	0.18	0.80	0.08	0.92	**0.478**

Table IV. Ranking of solution technical optimality.

Place	**Ranking based on Q_i**	**Q_i**
		LTB
1st	CuBe2	0.00
2nd	CuBe (Materion Alloy 165 temper TF00)	0.310
3th	Alloy 310 (Materion Alloy 310 temper TF00)	0.372
4th	Alloy 3 (Materion Alloy 3 temper TF00)	0.399
5th	C18150	0.815
6th	C18000	0.852
7th	50CrV4 (AISI 6150 steel oil quenched, 540°C tempering, D=50mm)	0.935
8th	SS 410 martensitic stainless steel	0.991
9th	x38CrMoV51 (AISI Type H11)	1.140

Table V. Ranking of solution technical optimality with uncertainty evaluation.

Place	**Ranking**	CRI_i
		STB
1st	CuBe2	0.491
2th	Alloy 310 (Materion Alloy 310 temper TF00)	0.399
3nd	CuBe (Materion Alloy 165 temper TF00)	0.386
4th	Alloy 3 (Materion Alloy 3 temper TF00)	0.323
5th	C18150	0.146
6th	C18000	0.117
7th	50CrV4 (AISI 6150 steel oil quenched, 540°C tempering, D=50mm)	0.090
8th	SS 410 martensitic stainless steel	0.052
9th	x38CrMoV51 (AISI Type H11)	0.000

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