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Computer-Aided Design AND APPLICATIONS

Multi Criteria Material Selection for Eco-design

Marco Serafini[1], Davide Russo[2] and Caterina Rizzi[3]

[1]University of Bergamo, marco.serafini@unibg.it
[2]University of Bergamo, davide.russo@unibg.it
[3]University of Bergamo, caterina.rizzi@unibg.it

ABSTRACT

In recent years, structural optimization has changed the way we think of product development. Optimizers allow to explore every possible product shape with the aim of maximizing performance, minimizing cost and accounting for environmental factors from the early phases of the design process. Material selection plays a big role, as one of the first and most binding choices of the product development. Current material selection schemes are too generic and bound to a less shape-driven design, which doesn't take full advantage of the optimization potential. They were developed for constant or self-similar shape products and allow for a substantial degree of subjectivity, when defining weight values for non-constant shape models. This paper proposes a computer-aided material selection scheme for structurally optimized products. It aims at integrating a multi-criteria decision making approach with the product awareness of a structural optimization, in order to systematically define the ranking weight values. The procedure comprises four main steps: a) initial material screening, to obtain a list of product and process compatible materials, b) statistical analysis of the design space through a factorial DoE (Design of Experiment), to rank the effect of each material property on the environmental impact, c) Multi Criteria Decision Making, to rank materials according to each material property importance, d) structural optimization, to identify the best possible shape for the chosen material.

The methodology has been tested on a simple case study concerning the design of an environmentally friendly I-beam. The results confirm the feasibility of the proposed approach in improving material selection when a relevant number of decision criteria is involved.

Keywords: material selection, eco-design, multi criteria decision making, structural optimization.

1. INTRODUCTION

When developing a new product, or re-designing an old one, the choice of material is generally one of the most influential decisions. Material properties define a product's shape, its weight, and, most of all, its performance. More recently, user-interaction aspects such as appearance, perceptions and emotions are also considered in material selection. However, material influence is not limited to product characteristics. With the growing interest in the environmental footprint of a product, the designer has to account for the entire development, manufacture and disposal; all of which are greatly affected by the material choice, not only from an energy and cost point of view, but also from an environmental prospective [21], [24].

Yet, too often materials are chosen by trial and error or simply on the basis of what has been used before. The growing number of available materials, the large number of factors that a designer must take into account during the selection process, and the complex relationships between the different selection parameters, often make the choice of material a difficult task [11]. To help the designer, there are a series of screening and ranking tools. Screening tools narrow down the choices to a manageable number for subsequent detailed evaluation [16], while ranking methods allow the designer to rank materials from best to worst. Another possible distinction is between graphical approaches and computer-aided ones. The traditional chart method [3] cannot guarantee that the selected material is the best, because it limits the decision in material selection to only two or three criteria. As stated by [16], modern material selection for complex systems cannot be handled graphically and must be tackled with a computer-aided multi-criteria decision making approach. These systems

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offer the designer an effective way to rank all possible materials, but mostly rely on the designer knowledge in defining the importance of each objective. These problems of relative importance are old; engineers have sought methods to overcome them for at least a century. There are numerous schemes for assigning weight values [18]; all require, in varying degrees, judgment. The property judged to be most important is given the largest weight; the second most important, the second largest; and so on [2]. There's no systematic way of assigning weight values because there's little connection with the product itself and only rudimentary ways of assessing how the material is going to affect the product's shape. Thus, these methods work well for simple products with a constant shape.

On the other hand, thanks to methodologies like Eco-OptiCAD [22], the designer can structurally optimize a product shape to minimize the final environmental impact. Unlike the aforementioned material selection schemes, which lack a direct connection with the product, the optimization process is by nature product dependent. In fact, it needs a starting point; the reference product. However, material selection can only be tackled by iteration [8] and can sometimes reserve nasty surprises. A lighter product made of a more efficient material might prove to be much less environmentally friendly, due to the material eco-properties. Thus, the approach has great potential for comparing different shapes for a given material, but relies on guessing when it comes to choosing a new material.

To summarize, on the one hand there's a plethora of material ranking methods best suited to work with fixed-shape products, on the other hand, there are a set of structural optimization tools apt at evaluating all the possible shapes for the designated material.

This paper proposes a computer-aided material selection methodology which aims at integrating a multi-criteria decision making approach with the product awareness of a structural optimization, in order to systematically define the ranking weight values. This can be achieved by describing the design space (the collection of all possible material-shape combinations) through a statistical DoE (Design of Experiment), in order to identify the relative environmental importance of each material property. The result is a product dependent set of weights that can be used for multi-criteria ranking of the compatible materials.

The procedure is based on a multi variable analysis, therefore it can be applied to any product that can be parameterized through a set of material and geometry variables. In its current form, it is not suited for non-parametric models or free-form conceptual design. Non-parametric models can be optimized for eco-design with a topological or topographical approach [22], however, material selection can only be tackled iteratively.

2. STATE OF THE ART

As mentioned, when tackling a difficult material choice there are two phases: a screening phase, which narrows down the choices to a manageable number, followed by a ranking of the filtered materials. Among the available screening tools [1],[5],[10]-[12], the Ashby charts are the most commonly used, for both their ease of use and graphical presentation. Ashby's material selection charts [3], [4] are very useful for initial screening of materials, especially if combined with the CES (Cambridge Engineering Selector) software [14]. This approach is particularly effective with single objective designs where one constraint clearly stands out above the others. A typical problem would be a light-stiff beam, where the objective is to minimize weight for a prescribed stiffness. The main limit of this method, however, is that it can only work with few criteria before becoming too complicated to read. Shape is also an issue; the basic approach allows for constant or *self-similar* shapes (such that all dimensions of the cross-section change in proportion with the overall size). To account for different shapes, a shape factor is needed. Shape factors are dimensionless numbers that characterize the efficiency of use of the material in each mode of loading (bending, compression, etc..). However, the shapes into which a material can, in practice, be made are limited by manufacturing constraints and by the onset of local buckling. Thus, more empirical and analytical correlations must be included in the selection process. This is a feasible approach for a simple system, but becomes too approximate for a complex product.

Overall, the Ashby's method shines for its simplicity and graphical interpretation when tackling simple problems that can be reduced to a single mode of loading and a few decision criteria. For a true multi-criteria selection, there is the need of MCDM (Multi Criteria Decision Making) methods. After narrowing down the field of possible materials through one or more screening methods, ranking methods can be used to find the most suited materials for the product. MCDM methods can be divided in two main groups: multiple objective decision making (MODM) and multiple attribute decision making (MADM). They range from simple additive weighting methods [19], [13], to Genetic algorithms [17], Neural Networks [12],[23],[25], and Fuzzy logic [15].

This paper won't review the current multi criteria ranking methods, but there is ample literature on the subject [16]. Suffices to say that most of these require the designer to assign a weight value to each criteria and none provides a systematic and reliable way of doing so. This may be due to the fact that MCDM algorithms are meant to be as generally applicable as possible. The same approach can tackle both a complex mechanical system and a very simple decision like, "what smartphone should I buy?". This search for broad applicability brings with it an extraordinary detachment from the analyzed problem. The algorithm has all the criteria to make a decision, but no way of knowing how they influence the product characteristics. This knowledge must come from the designer in the form of weight values that assess each criteria importance. While it is often impossible to establish a direct relationship between decision criteria and product characteristics, this is not the case with material selection for mechanical applications. Thanks to CAE tools, a designer can identify how each material property affects the final product.

To bypass the problem of weight values assessment, there are a few MCDM algorithms that require no interaction with the user. Rather than using weights to assign a relative importance to each criteria, these algorithms rely on a *maximin* or *maximax* approach. The *maximin* criterion, or pessimistic approach, takes a pessimistic view, assuming that no matter which alternative is selected, the worst situation for that alternative will prevail. Therefore, the aim is to achieve the largest possible payoff by maximizing the minimum value. On the other hand the *maximax* criterion, or optimistic approach, takes an optimistic view of the situation, assuming exactly the opposite and thus trying to maximize the maximum payoff, by selecting the choice that maximizes the highest value criteria. The most well-known criterion is the Hurwicz criterion, suggested by Leonid Hurwicz in 1951, which selects the minimum and the maximum payoff to each given action. The Hurwicz criterion attempts to find a middle ground between the extremes posed by the optimist and pessimist criteria. Instead of assuming total optimism or pessimism, Hurwicz incorporates a measure of both by assigning a certain percentage weight to optimism and the balance to pessimism [20]. While useful in tackling decisions under uncertainty, these methods are even less product dependent than weight based systems. Their objective isn't finding the best solution, but rather minimizing the risk of a bad choice.

3. CASE STUDY

A simple case study will be presented alongside the detailed description of the methodology. It permits to demonstrate how the methodology works step by step and facilitate its comprehension. The case study concerns the design of an eco-friendly I-beam, manufactured by hot-metal extrusion. The beam will be fixed at one end and statically loaded at the opposite one. It will be required to withstand such a load without yielding and with a prescribed minimum stiffness. Its length is constant, but its section may vary freely, by modifying the geometric dimensions shown in Fig. 1(a) (the beam height and length are constant).

The project objective will be to minimize the environmental impact along the beam entire life cycle. In order to simplify the environmental impact analysis, we'll consider use and end of life phases impacts to be irrelevant, thus limiting the study to the pre-manufacture and manufacture phases. Another important approximation is considering the LCA (Life Cycle Analysis) a function of the product mass and material, exclusively. Therefore, the manufacturing process energy will be calculated as a factor of the processed mass and the relevant material properties (e.g. specific heat for a heat treatment process). This is a substantial approximation, as the manufacturing process energy may be influenced by the product shape. However, it is a necessary one, in order to have a single objective.

Bearing this in mind, the I-beam life cycle can be summarized in three main steps: raw material extraction, pre-process heating, and hot-metal extrusion. The environmental impact of each phase will be calculated as follows;

- Raw material extraction : $m \cdot i_{pre-man}$ (1)
- Pre-process heating : $m \cdot Cp \cdot (0.8 \cdot T_f - T_{amb}) \cdot i_{en}/\eta$ (2)
- Hot-metal extrusion : $m \cdot i_{man}$ (3)

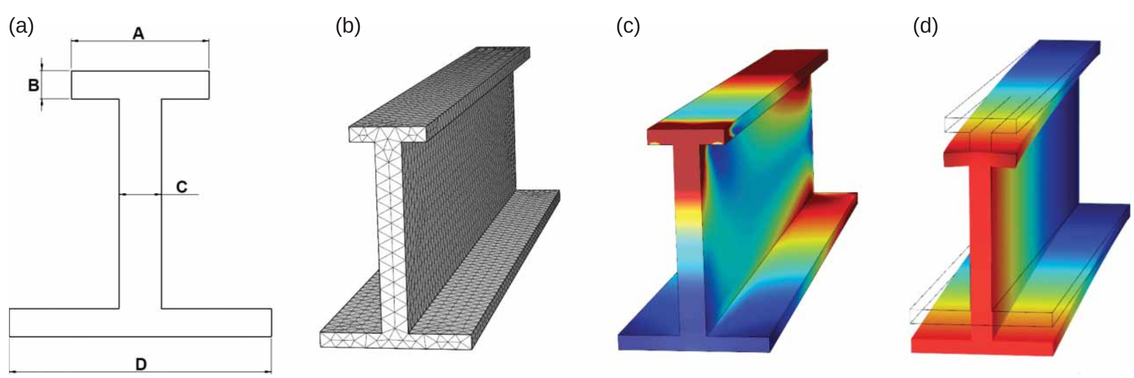


Fig. 1: (a) geometric input variables, (b) meshed model, (c) stress distribution, (d) displacement distribution and deformed shape.

Where:

m is the product mass.
η is an efficiency factor.
$i_{pre-man}$ and i_{man} are material dependent indexes for the equivalent CO_2 derived from the extraction and processing of one kilogram of material.
i_{en} is an energy index for the equivalent CO_2 of one Joule of used energy.

The project constraints are a minimum stiffness value (the maximum displacement at the loaded end of the beam), and a yield constraint. Stress and displacement values were computed using *Comsol* multi-physics software [7] (Fig. 1).

4. METHODOLOGY

From the analysis of the state of the art, it is clear that to improve current material selection schemes, the main goal should be a deeper analysis of the design space (the collection of all possible material-shape combinations). However, even with discrete geometry dimensions, the design space is made of countless combinations and it would be impossible to study each one in detail. Thus, this paper proposes a methodology based on a statistical approach, which helps the designer in determining the importance of each material property on the overall environmental impact of the product. These values can then be easily used as weights in a multi criteria decision-making process, in order to obtain a ranked list of compatible materials.

The methodology comprises four main steps (Fig. 2).

- Initial material screening to obtain a list of product and process compatible materials.
- Statistical analysis of the design space through a factorial DoE (Design of Experiment) to rank the effect of each material property on the environmental impact.
- Multi criteria decision-making to rank materials according to each material property importance.
- Structural optimization to identify the best possible shape for the chosen material.

The first three steps are devoted to the identification of the best material, while the last one is a classical optimization aimed at finding the best product shape for the chosen material. To support each step, the methodology integrates CAE tools and a DOE system. Figure 2 shows, by means of an IDEF0 diagram [6], the aforementioned activities and flows of information and data.

In the following, each phase is described in detail, followed by the case study application.

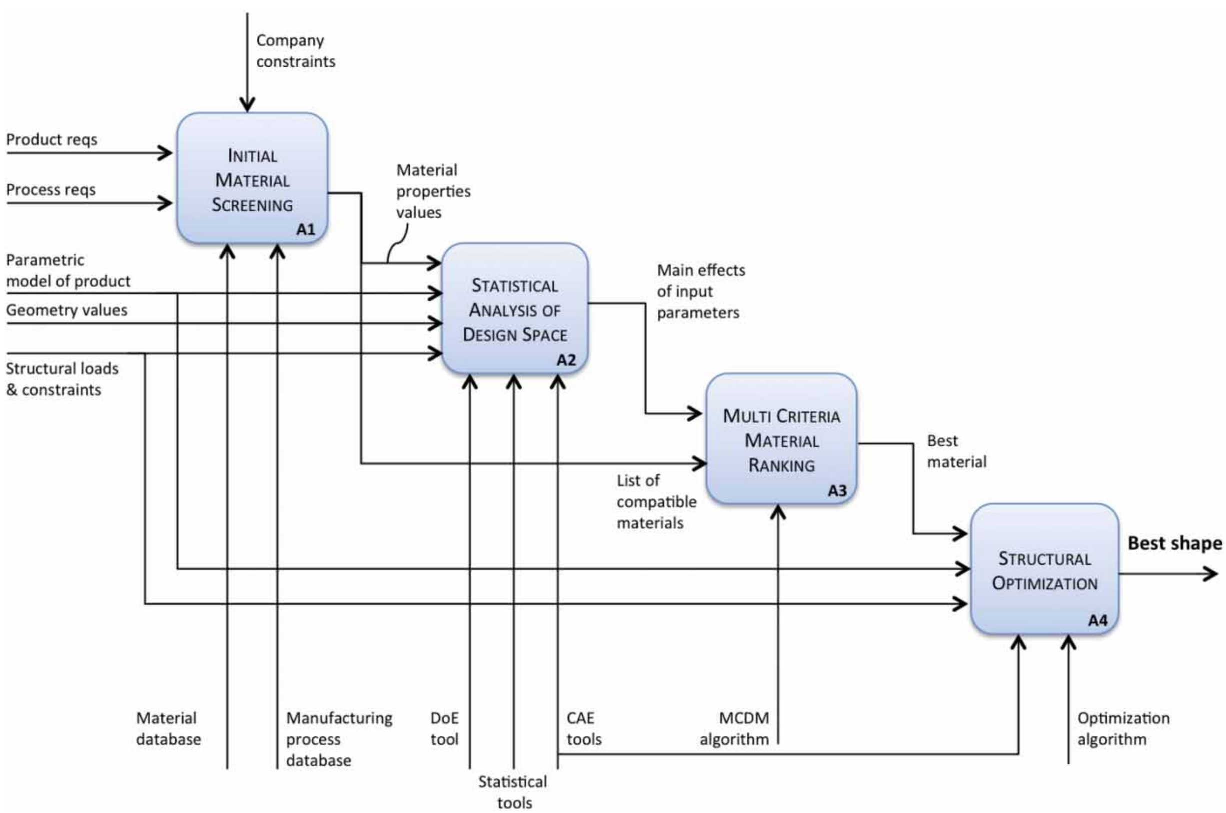


Fig. 2: Methodology workflow.

4.1. Initial Material Screening

This step guides the designer in creating a list of compatible materials, along with all relevant material properties values that will be used for the statistical analysis. Materials will be screened according to product requirements, manufacturing process requirements, and company specific constraints. To create this list, we first need to identify the material properties that influence the objective and those that represent a rigid constraint (a lower or upper limit which must be met). Only the latter can be used for screening.

When describing the design space with a factorial DoE of material properties and geometric dimensions, what mostly contributes to the DoE size is the number of input variables. To limit the analysis time and improve the statistical results, the designer should always identify what material properties should be included in the criteria for the decision making process, what properties can be defined as rigid constraints and what properties are irrelevant. As a rule of thumb, rigid constraints can be defined as *true* or *false*, while criteria variables as *better* or *worse*. The distinction is essential; the first will be used to screen a material database and create a starting list of compatible materials, while the latter will be the criteria by which to compare said materials. Examples of rigid constraints might be the maximum service temperature of a material, the compatibility with a chosen manufacturing process or the need to be fireproof. It's a requirement that must be met, but which does not need to be maximized or minimized. On the other hand, if the product needs to be light, the material density will be a deciding criterion for material selection and should be included in the analysis. It won't affect the span of the starting material list, as there's no constraint on its value. Clearly, the distinction of material properties between rigid constraints or a ranking criteria is product dependent. While fire resistance might be a requirement for a stove, it probably becomes an attribute to be maximized in a fire jacket.

Finally, a material property might define a rigid constraint, but become a ranking criterion if the constraint is also shape dependent. This is often the case of material yield strength. Resistance under loading is a requirement that depends both on geometry and the material yield strength. For a given geometry, yield strength may be used to filter all the materials that wouldn't withstand the resulting stress value, however when the geometry is also a variable, yield strength becomes a ranking criterion (materials with a higher elastic limit will be compatible with thinner shapes).

Rigid constraints used in the initial material screening can be divided into product requirements (i.e. prescribed maximum level of toxicity) and manufacturing process requirements (compliance with the selected manufacturing process). In addition, there might be company specific constraints (i.e. supplier's availability, company know-how) that can further limit the range of compatible materials. To support this phase, a comprehensive database of materials and manufacturing processes is used. The designer will be able to filter materials by properties values and by manufacturing process, obtaining a list of all the compatible materials. It is worth to note that the DoE size, and consequently the analysis times, isn't affected by the size of the materials list.

Application to case study

With regards to the I-beam, the CES software [3], [14] materials and processes database was used for a preliminary material screening. The I-beam is a simple product, mostly shape driven. Therefore, it isn't rich in non-shape dependent constraints that can be used to filter materials. Product requirements (stiffness and strength) are shape dependent, thus cannot be used for screening purposes, and there are no company specific constraints. The main screening constraint is the compatibility with the selected manufacturing process, hot-metal extrusion. Therefore, the compatible materials list will be limited to metals that can be extruded (about 800 materials ranging from Beryllium and Magnesium to all kinds of steel and aluminum alloys).

Having defined the compatible materials list, we need to identify which material properties influence the product environmental impact. These will be used as ranking criteria. For the I-beam in question, the environmental impact is a product of mass and a set of material properties, as seen in Eqn. (1–3). Clearly, these material properties will be ranking criteria, but we must also include any material property affecting the product's mass; i.e. density, yield strength, Young's module, and Poisson's ratio.

A total of eight material input variables and four geometric ones have been identified (Tab. 1), along with their respective lower and upper bounds.

4.2. Statistical Analysis of the Design Space

This step is the core of the proposed procedure. It aims at describing and analyzing the design space

Geometric dimensions	Material properties
Upper flange width	Density
Lower flange width	Yield strength
Vertical web thickness	Young's module
Flange thickness	Poisson's ratio
	Pre-manufacturing impact index
	Manufacturing impact index
	Melting point
	Specific heat

Tab. 1: Input variables affecting the I-beam environmental impact.

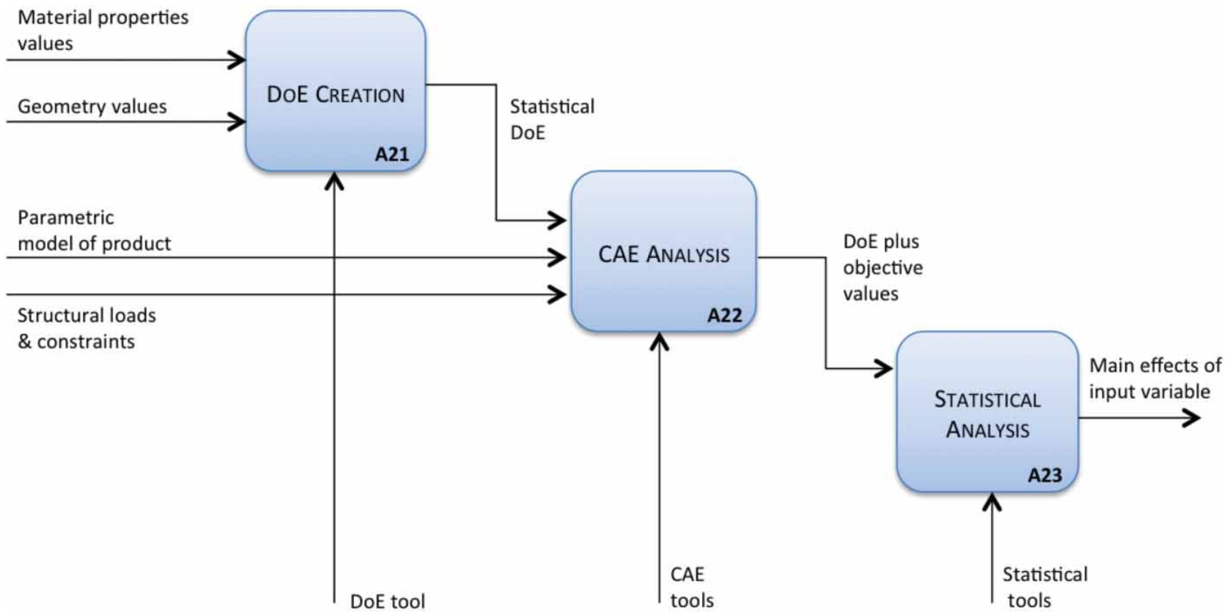


Fig. 3: Statistical analysis of the design space.

through a statistical DoE approach, in order to rank the effect of each independent variable on a given dependent variable (objective). This phase has been divided into three sub-steps (Fig. 3): the creation of a statistical DoE, CAE analysis, and statistical analysis.

4.2.1. DoE creation

A statistical DoE is a collection of input and output data designed for statistical analysis. To create such a DoE, the designer will input both geometric values and material properties values taken from the aforementioned list of compatible materials. The DoE algorithm will then automatically generate the correct set of variables combinations, to provide a stable foundation for the statistical analysis. The output of each combination will be computed in the next step (CAE analysis) and then added to the DoE.

When working with a very large, possibly infinite, sample pool (in this case, all the shape-material combinations), a DoE is the most logical approach. There are different DoE schemes for statistical analysis. All share a common goal: describing a very large sample pool by using a limited set of values. One of the simplest and most reliable forms, suitable for linear problems, is a 2-level factorial DoE which takes each variable lowest and highest value to create a set of 2^n combinations (n being the number of input variables). A factorial DoE guarantees no correlation between input variables, which is essential for reliable statistical results. A random DoE, on the other hand, always introduces a minor correlation between the inputs, making it a poor choice for a statistical analysis. However, a factorial DoE size grows exponentially with the number of input variables and can soon become unmanageable for complex systems. If this is the case, a prior sensitivity analysis might be required to identify the important system parameters and reduce the number of inputs.

While geometry variables are usually not correlated (you can change each one without affecting the others) and have a prescribed upper and lower bound, material properties are not independent variables, but come as sets; one for each material. Therefore, we must supersede the starting material list and use each property as an independent input, with its upper and lower bound defined by the lowest and highest value found in the starting material list.

The resulting DoE will be a set of combinations of the extreme values of both geometry dimensions and material properties. These represent the available range of variation of each input variable. Of course, geometry variables may freely use the entire range of variation during a structural optimization, while material properties come as rigid sets. In other words, there will be a shape with each dimension at its upper bound, but there's no one single material that can max out every material property of interest. That is precisely the reason why shape will be optimized while the material will be selected a priori with a multi criteria ranking. However, at the current stage we only seek to determine each variable effect on the objective and we may treat material properties as independent variables. Thus, the starting material list is used to determine each material property bounds, but won't be part of the statistical analysis.

Application to case study

As mentioned above, for the I-beam under analysis we have 12 input variables. Eight of these are material properties, while the remaining four are geometric dimensions, which describe the shape of the material. To create a 2-level factorial DoE, we take only the lowest and highest value of each input variable and generate all the combinations. Geometric dimensions will be limited by the overall volume limit of the product. This I-beam has a fixed length and can only vary in section geometry. Thus, each dimension lower and upper bound will be defined by the space that can be occupied at any one time by the beam and by overlapping effects within the beam section. Material properties don't have bounds per se, but they have an upper and lower value within the material list. Thus, we'll take the lowest and highest value of each property according to the materials selected in the previous step. If we think of the DoE as a table, each row will have a different combination of the 12 input data, for a total of 4096 (2^{12}) combinations.

4.2.2. *CAE analysis*

At this stage, the designer has a DoE set of 2^n combinations of input variables, made of geometric dimensions and material properties. Each combination yields a different objective value, which may be a simple function of the above, a result of CAE analysis, or a combination of the two. If the latter is the case, the designer can limit the number of CAE analysis to a subset of combinations of only the variables affecting the CAE output. These results will then be multiplied over the remaining combinations. The chosen CAE software will also be used during the optimization phase. Its role is purely as a solver, used to compute the objective value for each DoE input set.

If the output is a result of a CAE analysis, the designer will also need to set up a parametric model of the product as well as the relevant structural loads and constraints, and, depending on the DoE size, a routine to automate the process (a simple eight variables problem requires 256 analysis). The output of each DoE combination is then added to the DoE itself.

Application to case study

For the I-beam, we now have a DoE of the input variables with 4096 combinations. For each of these we have to compute the resulting stresses and displacement values (shape-dependent product requirements), and the overall environmental impact. While stress and displacement will be computed with a FEM analysis, the environmental impact is a simple product of geometry and material properties (Eqn. 1–3). Computing the stress and displacement values of each DoE entry would be a considerable effort; however, most of the selected material variables have no influence on either stress or displacement. FEM analysis may be limited to a subset of the complete DoE, made of only those variables that affect the analysis output. In this case: geometry variables, Young's module and Poisson's ratio. Thus, only 64 FEM analyses are needed (the number of possible combinations of the six variables affecting stress and displacement). The stress and displacement results can then be copied 64 times over the remaining DoE entries, where only the variables not affecting the FEM analysis will change value. The results have been computed with an automated routine, by using Esteco's *ModeFRONTIER* optimization software [9]. Every output was then added to the corresponding DoE entry, thus, each DoE row will now have 12 input and 3 output variables; the objective (environmental impact) and the constraints (stress and displacement).

4.2.3. *Statistical analysis*

The starting DoE now contains both input variables (geometric dimensions and material properties) and the analysis output (i.e. the beam mass and stiffness, in the previous example). This step aims at determining the main effect of each input on the proposed objective.

We recall the definition of main effect. It is the effect of an independent variable on a dependent variable, averaging across the levels of any other independent variable. It is relatively easy to estimate the main effect for a factor. To compute the main effect of a factor Ä, subtract the average response of all experimental runs for which A was at its low (or first) level from the average response of all experimental runs for which A was at its high (or second) level. Clearly, a 2-level factorial DoE makes the job even simpler, by splitting each variable between its upper and lower bound.

It is clear that the main effect is determined by both range of variation and the influence of the variable. For instance, the material density clearly has a direct influence on the mass (double the density, double the mass), but its effect might result null or very small if the upper and lower bounds are identical or very close. The bounds, in turn, are influenced by the starting material list; thus, if we were to choose between different aluminum alloys, all with similar density, the density would have a small effect on the mass.

Application to case study

We now wish to determine the main effects for the I-beam under analysis. It might seem that there are too many output variables, when in reality we only wish to determine the main effects on the objective. However, If we were to determine the main effects on the beam's environmental impact for the entire DoE set, we would find that the Young's module, the Poisson's ratio, and the yield strength all have zero effect. This is pretty obvious; the beam's impact is directly influenced by mass, which in turn is a product of volume and density alone. However, we must account for the fact that, in order to meet the required stiffness, a low Young's module value will limit the final product to a bulky shape, thus influencing the product mass. A similar problem arises whenever there's a constraint

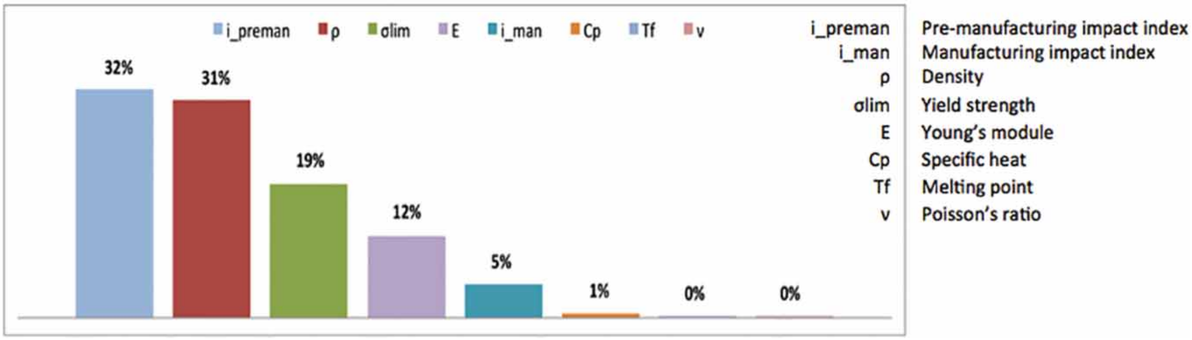


Fig. 4: Main effects of material properties on the environmental Impact of the I-beam.

dependent on both shape and material. The yield constraint depends on the stress (a function of the shape) being lower than the material yield strength. In order to calculate the effect of a material property which doesn't affect the objective directly, but rather limits its value range by imposing a constraint, the designer will choose a subset of DoE entries based on the compliance with the aforementioned constraint. For the beam, the effect of the Young's module on the environmental impact will be computed on the set of DoE entries which pass the stiffness constraint.

This leads to a non-symmetrical split between the variable lower and upper value responses and to a certain degree of correlation between the input variables. Such correlation however should involve only geometry variables and should remain close to zero for the other material properties. It is wise to check the correlation matrix; a stringent constraint might lead to high correlation and inaccurate results.

Figure 4 shows the relative main effects of the input variables on the environmental impact of the product. The effect of geometry variables has been left out, as it's of no interest toward material selection. Furthermore It is clear that the material thermal properties and Poisson's ratio have little effect on the objective. These variables will be neglected during the ranking procedure.

4.3. Multi Criteria Material Ranking

The starting material list can now be ranked by giving the correct emphasis to each material property of interest. Thus, the best material for the current product can be identified using a MCDM algorithm. Having computed the main effects of the material properties, it's a simple matter of dividing each one by their sum to find the relative effects. These, in turn, can be used as weights for the ranking process, giving more importance to material properties that have a big effect on the product objective. The result will be a ranking of the starting materials, obtained by applying one of the many commercially available weight based MCDM algorithms, with the weight factors of Figure 4.

Material	Mean ranking
Aluminum	0,746
Low alloy-steel	0,714
Magnesium	0,686
Stainless-steel	0,679
Fe-super-alloys	0,677
Carbon-Steel	0,661
Nickel	0,621
Copper	0,593
Brass	0,525
Beryllium	0,490
Cobalt alloys	0,319

Tab. 2: Mean rank value of primary material families.

Clearly, the ranking has a statistical basis; therefore, the best material is the most probable to yield the optimal result.

Application to case study
For the I-beam, we chose a genetic ranking algorithm. The ranking criteria are the selected material properties of Fig. 4, each with its relative weight. The material list obtained during the screening phase can now be ranked, from best material to worst. Table 2 shows the mean rank values of the main material families. Clearly, these have little meaning and the list should be viewed in its entirety (some high yield stainless steels outrank even low alloy steels); however, the table gives an overall idea of the ranking outcome.

4.4. Structural Optimization

The last step is a conventional optimization procedure to find the best shape for the best ranking material of the previous phase. Clearly, for the material choice to be valid, the model, loads and constraints must be the same as used in the DoE output evaluation. Furthermore, the geometric dimensions bounds should also remain untouched.

Application to case study

For the I-beam, we'll find the optimized shape and determine the environmental impact for a few materials, in order to validate the ranking results. Each optimization was performed with a *MOGAII* genetic algorithm of 56 generations.

For the sake of argument, let's suppose that the original product is made of Carbon steel (*AISI 1030*) and that its shape was structurally optimized to achieve the lowest possible weight (25.5 kg), thus the lowest environmental impact for the chosen material (132 kg of carbon dioxide). Carbon steel is a very sensible choice; it has pretty good mechanical characteristics and one of the lowest extraction indexes ($\boldsymbol{i_{pre-man}}$) of the listed materials. We now wish to change the material to improve its eco-sustainability. By applying the proposed procedure, Aluminum and Low alloy steel stand out as the best options. Low alloy steel is a logical choice. It has an even lower extraction index than Carbon steel, a slightly higher processing index ($\boldsymbol{i_{man}}$), and much better mechanical properties (a yield strength of 2000 MPa) for the same material density. We chose *AISI 9255* from the many alloys available. Its optimization yields a mass of 14.2 kg and a production of 114 kg of carbon dioxide. Clearly this was a good choice, but also a logical one, as there were few drawbacks. The same can't be said of Aluminum, the best ranking material. Its extraction index is four times that of carbon steel; it's about as impacting to process as low alloy steel; and has comparatively low values of yield strength and Young's module. It has a very low density, but there's no way of knowing if the decrease in weight will be enough to outrank Low alloy steel. Choosing Aluminum, then, is a difficult decision, without a systematic approach as the one we propose. An optimization of the best ranking material (Aluminum 7249) yields a mass of 7,3 and a production of 100 kg of carbon dioxide. Clearly, the Aluminum beam is not only the lightest of the three, as expected, but it is also the lowest impacting material-shape combination. Therefore, despite its poor environmental indexes, its low density allows for a significant decrease in mass and a resulting decrease of the overall impact.

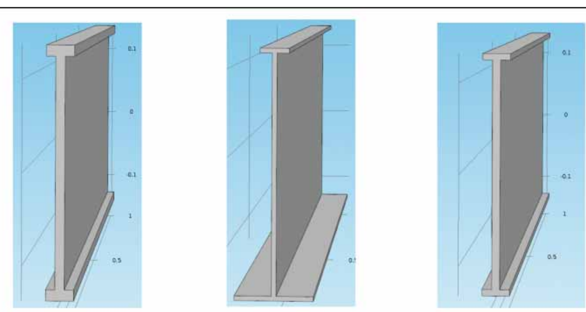
Finally, we could argue that the lightest I-beam seems to be the greenest one; however, the lowest mass (6 kg) is achieved with Beryllium, which produces 2887 kg of carbon dioxide.

A summary of the aforementioned results is presented in Figure 5.

4.5. Discussion

The case study has proven the procedure feasibility in defining objective weight values for the ranking process and determining the best material-shape combination. Results show that the selection scheme allows the designer to evaluate material choices where a complex trade-off is involved. For the I-beam, Aluminum has proven to be the best choice, thanks to it's low density, despite its poor environmental indexes.

The methodology is still in its infancy. Its main drawback is the fact that the ranking results depend on the specific list: removing one alternative from the selection can reverse the ranking of those that remain. This is a flaw already present in MCDM algorithms, but it is accentuated by the statistical analysis, which is also dependent on the starting material list. Even if the weight factors could be chosen with accuracy, the outcome depends on the population from which the choice comes. Some weight based methods are more sensitive to irrelevant alternatives than others [2]. Thus, future development should be aimed at finding or developing a MCDM algorithm to limit this intrinsic flaw.



Material	Carbon Steel	Low Alloy Steel	Aluminum
Mass	25.5	14.2	7.3
Kg CO2 eq.	132	114	100
		-14%	-24%

Fig. 5: Case study results.

Most of the procedure steps have been integrated, allowing for a fairly automated approach. However, setting up the procedure itself is still very time-consuming and requires an expert user in both CAE modeling and data management. The latter, in particular, requires a considerable effort. The lack of dedicated material databases means that the user will have to acquire and structure all relevant material properties. This might be manageable for a few materials, but becomes a daunting task when working with hundreds. We're currently developing a dedicated materials and process database, that will be integrated in the future to streamline the data collection phase. Eventually, the procedure should be integrated in a CAD environment, where FEM analysis and material databases are today well integrated.

5. CONCLUSIONS

Modern material selection can only be approached with a multi-criteria decision making method. This is due to the growing figure of available materials and the large number of factors that the designer must take into account. A very simple product, like an I-beam, can easily have 5 or more criteria for material selection. The traditional approach is that of assigning weight factors to each relevant material property, in order to rank materials by giving the correct emphasis to each decision criteria. The upside: experienced engineers can be good at assessing relative weights. The downside: the method relies on judgment. In assessing weights, judgments can differ.

The absence of an effective way to systematically define weight factors is mainly caused by lack of product awareness. While it is often impossible to establish a direct relationship between decision criteria and product characteristics, this is not the case with material selection for mechanical applications. Thanks to CAE tools, the designer can identify how input variables affect the final product, thus giving the correct emphasis to each material property.

This paper has proposed a computer-aided material selection methodology based on the integration of a multi-criteria decision making approach with structural optimization, in order to systematically define the ranking weight values. This has been achieved by describing the design space through a statistical DoE (Design of Experiment), in order to identify the relative environmental importance of each material property. The result has been a product dependent set of weights that can be used for multi-criteria ranking of the compatible materials. Any weight based ranking algorithm will work with the proposed procedure. Its own drawbacks and deficiencies, however, still apply.

The environmental aspect of a product is an exemplary application: it shows the full influence of material properties not only on product performance, but also on the entire life cycle, and it inevitably involves a trade-off between the different life cycle phases, in order to minimize the overall impact. However, the proposed approach can be applied to any number of objectives: costs, performance, etc.

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