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Automatically weighted high-resolution mapping of multi-criteria decision analysis for sustainable manufacturing systems

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ABSTRACT

A common feature of Multi-Criteria Decision Analysis (MCDA) to evaluate sustainable manufacturing is the participation (to various extents) of Decision Makers (DMs) or experts (e.g. to define the importance, or "weight", of each criterion). This is an undesirable requirement that can be time consuming and complex, but it can also lead to disagreement between multiple DMs. Another drawback of typical MCDA methods is the limited scope of weight sensitivity analyses that are usually performed for one criterion at the time or on an arbitrary basis, struggling to show the "big picture" of the decision making space that can be complex in many real-world cases.

This work removes all the mentioned shortcomings implementing automatic weighting through an ordinal combinatorial ranking of criteria objectively set by four pre-defined weight distributions. Such solution provides the DM not only with a fast, rational and systematic method, but also with a broader and more accurate insight into the decision making space considered. Additionally, the entropy of information in the criteria can be used to adjust the weights and emphasise the differences between potentially close alternatives.

The proposed methodology is derived generalising a problem of material selection of automotive parts in metal casting manufacturing systems. In particular, three typical aluminium, magnesium and zinc alloys in a High-Pressure Die Casting (HPDC) process are compared using the deterministic Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) combining 18 criteria organised in 4 main categories (cost, quality, time and environmental sustainability). A detailed and systematic approach to calculate the considered criteria is also provided and it includes Life Cycle Assessment (LCA) considerations. Results show that, although in most of the cases the aluminium alloy is the best option, there are a few areas in the decision making space where magnesium and zinc alloys score better without a simple correlation to categories. This shows how valuable the proposed mapping process is to understand the complex MCDA analyses. The methodology does not make specific assumptions about metal casting and can be applied to sustainable manufacturing in general.

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1. Introduction

The ecological situation of the Earth under current trends has been considered not sustainable and cause of concern as exemplified prominently by the "imperative to act" urged by the winners of the Blue Planet Prize (Watson, 2014). In particular, it is climate change that has received considerable public attention with the agreement reached at the 21st Conference of the Parties (COP21) of the UN Climate Convention held in Paris in 2015. One of the important parts of the agreement is "holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (United Nations, 2015).

Despite its history spanning millennia (Milne et al., 2003, Chap. 1.18), metal casting continues to be a fundamental manufacturing process for some products, and it is characterised by a relatively large amount of energy consumed per unit of product (Pagone et al., 2018), making it an "energy-intensive" process. Statistics from the International Energy Agency (IEA) indicate that 36% of global carbon dioxide emissions (one of the most important greenhouse gas) were generated by the industrial sector in 2016, making it the major contributor by end-use sector before buildings and transport

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(International Energy Agency, 2018). Therefore, metal casting is one of the strategic industrial processes that could make a significant impact in tackling climate change.

Historically, the EU has been one of the political entities pioneering governmental regulations to minimise climate change. For example, in 2005 it established the world's first international emissions trading scheme with a "cap and trade" mechanism. The Emission Trading System (ETS) is aimed at reducing the emissions of carbon dioxide, nitrous oxide and perfluorocarbons (European Commission, 2016). Although local results were achieved, with a reduction of about 8% of emissions in the EU between 2013 and 2016 (European Commission, 2016), ETS are likely to have promoted de-localisation of manufacturing to countries with less stringent environmental regulations. The twofold negative outcome of this process has been a relative de-industrialisation in the EU (with its relevant economic implications) and the likely increase of emissions worldwide. An alternative policy to the ETS that may overcome these issues is the taxation (as a component of the VAT, for example) based on the emissions and resource consumption embodied by the product. In this way, more sustainable practices at a global, systemic level are promoted without affecting the competitiveness of environmentally virtuous players.

This work absorbs such considerations devising a framework for Decision Makers (DMs) to select the best material to produce automotive parts with a High Pressure Die Casting (HPDC) process combining crucial traditional criteria like cost, quality and productivity with sustainability metrics (including product life cycle concepts). The alternative materials considered are typical aluminium, magnesium and zinc based alloys used in HPDC processes. A deterministic decision-making algorithm is interfaced with an objective, automatic method to assign different criteria weights distributions and, thus, a high-resolution map of the decision-making space is generated. However, the proposed framework does not make any specific assumptions to foundries, material selection or automotive products and it can be applied to automatically map the sustainability decision-making space of any manufacturing system.

2. Multi-criteria decision analysis for sustainable metal casting

The case study presented in this work combines several themes: sustainability and energy efficiency in metal casting, material selection for automotive components, elements of product Life Cycle Assessment (LCA) and Multi-Criteria Decision Analysis (MCDA). It will be shown that the proposed approach addresses a combination of aspects currently not very much analysed in the scientific literature.

Despite the resource intensive nature that characterises metal casting, there is a limited amount of works in the scientific literature that investigates its sustainability. In this regard, energy efficiency (that is an indicator of environmental sustainability) has received more attention through different approaches. For example, Sa et al. (2015) identified the links between management practices and energy efficiency studying a Swedish foundry, with a work of classification and characterisation, whereas Carabalí et al. (2018) carried out an analysis of Colombian metal casting plants identifying virtuous technical strategies for energy efficiency. Other studies have looked into the potential to reduce consumption in energy intensive processes within the UK (Chowdhury et al., 2018) or focussing on specific alloys (cast iron) in Italy (Lazzarin and Noro, 2015) with particular attention to technological opportunities and relevant barriers. Obstacles to energy efficiency in foundries have been studied empirically for several geographical locations like Europe (Trianni et al., 2013; Thollander et al., 2013), Sweden (Rohdin et al., 2007) and Italy (Cagno et al., 2015).

However, other routes to energy efficiency in metal casting have been considered beyond empirical studies. Liu et al. (2018) proposed an on-line analysis and control system for die casting machines using the Internet of Things (IoT) paradigm and Pagone et al. (2016) developed a computer program to assess rapidly material and energy flows in the process chain. Other studies targeted energy reduction through process simulation (Mishra and Sharma, 2018) that can be integrated with numerical optimisers (Papanikolaou et al., 2019) or it can be aimed firstly at quality and cost reduction (Nyemba et al., 2018; Hodbe and Shinde, 2018) that still affect indirectly energy efficiency and environmental sustainability. In particular, the work by Pinto and Silva (2017) belongs to this last category studying the production of automotive parts, but without considering different alternative materials. Metal casting energy reductions can be achieved also modelling (and minimising) energy consumption using statistical methods (He et al., 2019) or benchmarking tools tailored to major energy consumers like compressed air production (Benedetti et al., 2018). Furthermore, waste heat recovery is another option that can improve significantly the overall energy efficiency of a metal casting plant (Børset et al., 2017).

Although these studies are valuable, it has been shown in the literature that the impact of energy efficiency or sustainability measures can be very limited or misleading if considered without including other product life phases beyond manufacturing. For example, Haraldsson and Johansson (2018) analysed energy efficiency opportunities in production-related processes of aluminium-based products spanning from pre-manufacturing to recycling and observed that many manufacturing processes are less energy demanding than raw-material electrolysis. Also Salonitis et al. (2016) included a LCA while presenting a new casting process designed to maximise energy efficiency and quality. Energy savings can be achieved also developing new materials and combining manufacturing processes reducing the consumption during the use (instead of the production) phase of the product, as showed by Krüger et al. (2019) combining casting and forging processes. Furthermore, well-established energy-efficient choices in material selection can be challenged when considered through an LCA perspective. For example, passenger vehicle engine blocks produced in heavier cast iron (under some circumstances) can be less energy demanding in comparison to lighter aluminium-based blocks, if their entire life-cycle is considered (Salonitis et al., 2019). Similarity, Pagone et al. (2019b) developed new thermodynamic metrics aimed at assessing energy efficiency in metal casting and tested them for the material selection of die cast automotive parts considering key elements of the product LCA. Such type of works (material selection of automotive parts in a sustainable LCA perspective) are not very common in the scientific literature but can be traced back to pioneering studies in the Nineties. A good example is a paper by Kar and Keoleian (1996) that compared energy, air emissions, waterborne waste, solid waste and cost of sand cast and brazed aluminium intake manifolds of light-duty vehicles over their life-cycle using energy and material flow analysis. The authors presented a framework called "life cycle design" where the mentioned sustainability criteria and multiple stakeholders are considered but no method to combine the different indicators is used, although a reference to the Analytic Hierarchy Process (AHP) is provided.

However, MCDA (like AHP) has been used to assist decisions in the manufacturing field. For example, Multi-Objective Decision Analysis (MODA), a variant of MCDA where discrete alternatives are substituted by continuous variables describing process parameters, has been used to optimise Electro-Discharge Machining (EDM) operations considering five DMs and the sensitivity of their choices

in a full factorial analysis (Dewangan et al., 2015). However, no LCA considerations are evaluated in this study as well as in other MODA works aimed at improving the quality of continuous casting of steel (Filipič et al., 2015) or Wire Electrode Discharge Machining (WEDM) with aluminium hybrid composite (Muniappan et al., 2018). Favi et al. (2016) combined a MODA approach with MCDA in the early stages of product design to select the best options according to five attributes (i.e. assembly, materials, processes, cost and time) and illustrated the methodology with a case study. The authors used the MCDA Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with a discrete rating scale pointing out that a sensitivity analysis is necessary to compensate for the subjectivity of values and weights considered. The ordinal combinatorial ranking of criteria presented in this paper addresses this common shortcoming in an original way.

Furthermore, studies on MCDA applied to metal casting (without necessarily considering sustainability aspects) are, as well, not widespread in the scientific literature. Chakraborty et al. (2005) applied AHP to reduce the number of die casting vendors in a geographically defined area in India, based on five criteria (cost, quality, tardiness, flexibility and cooperation), whereas the work by Singh et al. (2006) combined lean tools (Value Stream Mapping), fuzzy logic and MCDA to identify waste (according to the lean thinking principle) in a die casting factory (pressure and gravity die casting processes) using a Multi-Attribute Utility Function (MAUF) and considering multiple DMs. Pal and Ravi (2007) used Quality Function Deployment (QFD) with Analytic Network Process (ANP) techniques to select, among twenty alternatives, the best process to produce patterns for sand and investment casting, based on the specifications of the casting engineer and a database. When one process is selected, the most similar process plan in a database is retrieved using Case-Based Reasoning (CBR) to estimate time and cost. The combined QFD-ANP technique is used to calculate weights of the tooling attributes through pair-wise comparisons that become quickly a time-consuming task with the increase of the attributes cardinality. Such inconvenience is common for a few MCDA techniques (e.g. AHP and ANP) and it is avoided by the proposed automatic mapping approach.

Neto et al. (2008) presented a method to identify the main sources of pollution in the process steps of an aluminium pressure die casting plant producing car parts. This approach combined LCA, environmental systems management and a sum-based MCDA algorithm with four different weighting distributions. Furthermore, selected changes to process parameters to reduce the environmental impact and total cost were considered in an additional sensitivity study. Although the selected weight distributions provided some insight, such method failed to provide a high-resolution picture of the entire decision making space extracting some arbitrarily located, isolated samples.

Material selection between steel and an aluminium alloy for manufacturing fan impellers has been carried out through AHP in a paper by Liu et al. (2012). Fourteen basic criteria were organised into five classes (i.e. time, quality, cost, environmental impact and resource consumption) and a process associated with each material was considered (i.e. stamping of a steel plate versus casting aluminium alloy ingots). MCDA has been used also in a study to identify the main indicators of quality in silica sand for casting, although no information about the specific MCDA technique was provided (Alhamdy and Ghalandary, 2014). Deshmukh and Hiremath (2018) assessed through MCDA three typical metal casting furnaces (i.e. cupola, divided blast cupola and induction) according to nine criteria in the area of sustainability and cost. However, limited information is provided about the relevant data sources. This is a common problem with other literature sources where it is sometimes unclear what calculation procedure have been carried out or what specific references have been consulted. In this study, this issue has been addressed providing a detailed explanation of the calculation procedure adopted and specific citations for the sources of data.

Furthermore, Bairagi et al. (2014) compared three different fuzzy MCDA approaches and a Complex PRoportional ASsessment method coupled with Grey systems theory (COPRAS-G) to select robots for foundry operations. The fuzzy weights were estimated by a fuzzy AHP method that required time consuming pair-wise comparisons. Salonitis et al. (2015) proposed a framework combining energy audits, LCA of manufacturing processes and TOPSIS to evaluate ten alternative process plans combining six criteria in the area of cost, time, quality and environmental impact. The tool is demonstrated considering a high pressure ceramics casting plant where criteria weighting was ranked by the production manager of the facility. Such approach may be unsuitable when multiple DMs disagree on the criteria ranking and does not provide information about the sensitivity to the chosen weight distribution. This is demonstrated in a paper where a committee of twenty DMs evaluated the level of danger in foundries, weighting and combining three main criteria and ten sub-criteria with Analytic Network Process (ANP) and fuzzy logic (Ilangkumaran et al., 2015). The multiple weight distribution method proposed in this work addresses these shortcomings setting the importance of criteria automatically and objectively.

AHP and TOPSIS have been combined also in the field of metal casting international resource policy. In particular, MCDA has been used to select supplier countries for the Iranian steel industry according to four environmental sustainability indicators (CO_2 emissions, number of employees, water consumption and distance) performing a sensitivity analysis varying the weights of criteria individually (Azimifard et al., 2018). However, no information about the procedure to obtain the different sets of weights in the sensitivity analysis is provided, making the assessment opaque to the user.

Yang et al. (2017) proposed a tool to select materials for remanufacturing purposes using a fuzzy TOPSIS approach with weighting based on a mixture of entropy of information and a linguistic approach. Two case studies based on sixteen criteria were illustrated: an engine block and an intake manifold with four and three alternative materials, respectively. Although not strictly related to metal casting, this work combines MCDA with material selection of automotive products but does not include broader LCA considerations. Similarly, Paraskevas et al. (2019) proposed a stochastic decision support tool aimed at resource efficiency of the aluminium recycling chain, that contributes to understand the relevant LCA but does not include the decision making process. On the other hand, a study on aluminium alloy products for automotive or aerospace components compared additive manufacturing, machining and forming on the basis of the life cycle environmental impact (Ingarao et al., 2018). Although comprehensive and harmonised environmental indicators of the ReCiPe model (Huijbregts et al., 2017) have been used, this study does not consider economic, social and manufacturing productivity indicators in the final ranking of the alternatives; all aspects addressed by the current study.

Recent MCDA frameworks, specifically developed for sustainable manufacturing, respond to the scarcity of quantitative works in the literature comprising sustainability (Stoycheva et al., 2018). The methodology proposed by Stoycheva et al. (2018) focussed on the full sustainability spectrum in the automotive industry and was illustrated choosing among five alternative materials and 15 criteria organised according to the three pillars of sustainability (i.e. economic, environmental and social aspects) using the Weighted Sum Method (WSM) and a sensitivity analysis. Four weight

distributions, representing the point of view of pre-determined stakeholders, are considered. As previously stated, such arbitrary choices are useful in interpreting the typical interests of potential DMs but lack flexibility and scope in understanding the full decision making space. Furthermore, traditional (and important) indicators do not directly map into the sustainability dimensions (e.g. productivity) and not being able to include them in the framework might make more difficult its adoption. The choice of the WSM is another aspect that could hinder applicability when there are significant complementarities between criteria that may not be handled correctly by the method (Hwang and Yoon, 1981). The proposed MCDA automatic mapping algorithm with the choice of the TOPSIS technique resolves both these shortcomings. Also Saad et al. (2019) presented a comprehensive framework aimed at assessing sustainability in manufacturing processes. The work presented an excellent overview of the overall sustainability assessment process with a critical discussion about the major normalisation and aggregation methods, in particular. Concerning the weighting process, although one objective way to set distributions is mentioned (i.e. the established technique based on the criteria entropy of information) there is only a further generic reference to "other methods" with no other specific and systematic approach. The automatic weight distribution method presented in this work can be used to make the suggested framework complete.

According to the presented literature survey, it appears that there is a scarcity of works at the intersection of sustainable metal casting with the use of MCDA techniques to perform the material selection of automotive parts, including LCA considerations. The case study presented in this paper introduces a framework to perform such type of analysis with a clear and detailed procedure to calculate the values of indicators (another aspect sometimes not well presented in similar works). Moreover, such framework produces automatically a high-resolution map of the decision making space with an objective weighting based on the ordinal, combinatorial ranking of criteria. This feature removes important shortcomings in sustainable manufacturing MCDA: the considerable amount of input necessary by experts or DMs, the potential disagreement that can arise between them and the limited scope of pre-determined, arbitrary samples of the decision making space generated by criteria weight sensitivity. Finally, the framework does not make any specific assumption about metal casting, material selection or particular products and, thus, it is applicable to explore the sustainability of any manufacturing system.

3. A case study: Material selection for an automotive component produced with a high pressure die casting (HPDC) process

The product considered in this analysis is an automotive component produced with a HPDC process with typical materials. The volume of the product is assumed fixed and the relevant mass is obtained from the density of each alloy. A more rigorous approach would consider a tailored design driven by the specific material mechanical properties (see Section 3.2.2.2 for more details). However, such approach would lose generality and prevent the wider applicability of the method. Capitalising on the compensatory nature of TOPSIS, this approximation is (at least partially) offset including the mechanical properties in the criteria considered. The mass of the product is then used to obtain dimensional quantities from data usually available normalised by unit mass (further represented with uppercase and lowercase symbols, respectively). Another important implication arise from the comparative nature of TOPSIS in combination with the assumption of a fixed volume product: the results are independent by the specific mass considered.

3.1. Materials

The alternative materials considered are three typical alloys used in HPDC processes, all suitable for automotive parts. Namely, aluminium A380, magnesium AZ91D and zinc ZA-8 alloys. The first two are cast in a cold chamber machine whereas the last in a hot chamber one. The specifications of the facility processing aluminium alloys have been provided by an industrial contact and are based on data collected monthly for two years. The information about the magnesium and zinc alloy facilities has been collected from the open literature and is provided on a monthly basis for at least one year. The main reference for these two foundries is a report of the USA Department of Energy (Eppich, 2004). The assumption that a hot chamber machine is used to produce zinc parts implies that the maximum mass of the product in the analysis cannot exceed the volume of about 5 kg of ZA-8 (since this is the maximum capacity of hot chamber machines on the market). Besides this consideration, as explained introducing this case study, the specific mass of the product does not affect the results in this comparative analysis.

3.2. Product and process performance indicators

Eighteen metrics describing the specifications of the metal alloys during the life phases of the product have been considered. Their positive or negative impact have been assessed considering the effect of an increase of each quantity. Furthermore, the metrics have been categorised according to areas of cost, time, quality and environmental sustainability (Table 1).

3.2.1. Cost

From a broad perspective, cost estimation in metal casting can be derived from general studies in manufacturing processes. Different approaches can be identified in the literature and can be classified in the following three avenues (Keeter, 2015):

- previous experience and similarity to existing products, e.g. Duverlie and Castelain (1999),
- process mapping with relevant empirical equations, e.g. Feng et al. (1996); Ou-Yang and Lin (1997),
- geometric features of the product (Farineau et al., 2001) that can be parametrised using existing data (Fagade and Kazmer, 2000; Cavalieri et al., 2004).

More specific studies focussed on selected manufacturing processes are not equally common (Chougule and Ravi, 2006). One example is the work by Chougule and Ravi (2006), specifically developed for gravity die casting and aimed to provide a methodology suitable also for people with limited technical knowledge. Concerning HPDC, methods that estimate cost on the basis of product weight and overall foundry material efficiency are well-suited considering the typical large volumes of similar product that these plants produce (Chougule and Ravi, 2006). In general, five broad categories to identify cost in casting processes have been identified since the 1970s (Chronister, 1975): material, tooling, labour, energy and overheads.

This study applies the latter broad approach and, since TOPSIS is a comparative method with alternatives belonging to the same casting family, the cost of labour and overheads is assumed to be comparable in all cases and, thus, ignored. As a consequence, the relevant metrics used in the calculations and the final results do not estimate the actual values to produce a product but they are valid only on a comparative basis.

The final indicator to assess cost C_{cg} is the sum of the material C_M, energy C_E and tooling C_T contributions calculated according to

Table 1
Categorised selected metrics of the metal alloys to produce an automotive part with a High Pressure Die Casting process.

Quantity	Impact	Category	Product life phase
Cradle to gate Cost C_{cg}	negative	cost	LCA cradle to gate
Volumetric solidification shrinkage V_{ss}	negative	quality	manufacturing
Solid linear thermal contraction α_s	negative	quality	manufacturing
Freezing temperature range ΔT_f	negative	quality	manufacturing
Solidus temperature T_s	negative	quality	manufacturing
Tensile strength F_{tu}	positive	quality	use phase, design specification
Modulus of elasticity E_t	positive	quality	use phase, design specification
Yield strength F_y	positive	quality	use phase, design specification
Elongation to break ϵ_b	positive	quality	use phase, design specification
Fracture toughness k_{Ic}	positive	quality	use phase, design specification
Corrosion depth in atmosphere d_{ca}	negative	quality	use phase
Density ρ	negative	environmental sust and quality	use phase, design specification
Energy consumption cradle to gate E_{cg}	negative	environmental sustainability	LCA cradle to gate
Cradle to gate mass of CO_2 emitted $m_{CO2,cg}$	negative	environmental sustainability	LCA cradle to gate
Primary production specific water consumption V_{wp}	negative	environmental sustainability	pre-manufacturing
Manufacturing energy efficiency η_{om}	positive	environmental sustainability	manufacturing
Manufacturing Operational Material Efficiency OME_m	positive	environmental sustainability	manufacturing
Heat of fusion ΔH_f (proportional to machine cycle time)	negative	time	manufacturing

the "cradle to gate" Life Cycle Assessment (LCA) approach (i.e. it will include the pre-manufacturing and manufacturing phase, when relevant) for one product. However, input data (detailed below) is mostly available in terms of unit mass and, thus, C_{cg} is derived by normalised values per unit mass of product c_{cg}, c_M, c_E, c_T and its mass m_p:

$$C_{cg} = c_{cg}\, m_p = (c_M + c_E + c_T)\, m_p \tag{1}$$

Material cost. The input data of material cost per unit mass used in this study (Granta Design, 2017) $c_{M,f}$ is normalised by mass of feedstock material m_f (i.e. the amount of material purchased by the foundry)

$$c_{M,f} = \frac{C_M}{m_f} \tag{2}$$

and not by mass of final product

$$c_M = \frac{C_M}{m_p} \tag{3}$$

One would be tempted to use the Operational Material Efficiency OME_m that measures the overall yield of the manufacturing processes

$$OME_m = \frac{m_p}{m_{in}} \tag{4}$$

to obtain c_M from $c_{M,f}$, but it can be easily shown that the overall input mass of the foundry m_{in} does not necessarily coincide with the purchased feedstock mass m_f.

In fact, considering the schematic in Fig. 1, m_{in} is the sum of m_f, $m_{r,e,in}$ and $m_{r,i}$ where the last two addends are the mass recycled externally (e.g. by a subcontractor or an associated company) and internally by the foundry. Thus, the feedstock mass is only a contributor to m_{in} and OME_m is not suitable to obtain c_M from $c_{M,f}$.

Continuing to refer to Fig. 1, in this work it is assumed that the cash flows associated with externally recycled mass are negligible (i.e. $m_{r,e,in} = m_{r,e,out} = 0$) and the total mass that leaves the foundry with no added value (e.g. dross, scrap not internally recycled, swarf, etc …) is consolidated into one value m_l. Hence, the conservation of mass to the flows external to the foundry reads:

$$m_p = m_f - m_l \tag{5}$$

i.e. the mass of the product is the feedstock mass removed by the no-adding value material losses. Combining Eqs. (2), (3) and (5) yields

$$c_M = \frac{c_{M,f}\, m_f}{m_p} = \frac{c_{M,f}\, m_f}{m_f - m_l} \tag{6}$$

Factoring out m_f from the last equation, a new relationship between $c_{M,f}$ and c_M is obtained that is dependent only from factor $f_{M,l} = m_l/m_p$

$$c_M = \frac{c_{M,f}}{1 - f_{M,l}} \tag{7}$$

Assuming a suitable value of $f_{M,l}$ it is possible to calculate c_M to be substituted in Eq. (1).

Energy cost. The specific cost of energy normalised by mass of final product c_E is obtained by the available specific cost of electricity $c_{E,el}$ and natural gas $c_{E,g}$ per energy unit. In fact, in the plants considered, only these two sources of energy are used, but the following method can be generalised to any source of energy (provided that data is available). The contributions of electrical energy and the combustion of natural gas are combined considering their relevant fractions of the total energy consumption, $f_{E,el}$ and $f_{E,g}$. Multiplying their specific costs by the overall specific energy consumption of the manufacturing process e_m, yields c_E:

$$c_E = e_m \left(f_{E,el}\, c_{E,el} + f_{E,g}\, c_{E,g}\right) \tag{8}$$

Finally, c_E is substituted in Eq. (1).

Tooling cost. Another aspect that may impact the profitability of a HPDC foundry is the life of the die. This tool is usually characterised by a complex design and it is produced with expensive materials like special steels (DeGarmo et al., 2003). The alloy being cast in the die affects its life significantly (DeGarmo et al., 2003) and thus, it can be another contributor to the overall cost. However, considering that the typical order of magnitude of cycles that the die can withstand is between 10^5 and 10^6 (Schrader et al., 2000), its cost per product becomes trivial and, then, $c_T = 0$ is substituted in Eq. (1).

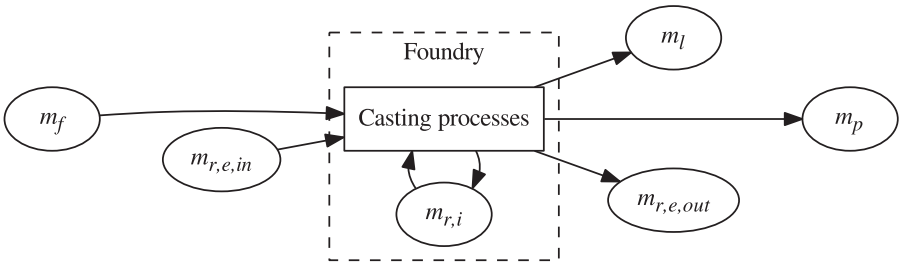


Fig. 1. Simplified material flows in a generic foundry highlighting feedstock m_f, externally $m_{r,e}$ and internally $m_{r,i}$ recycled, lost m_l and final product m_p masses.

3.2.2. Quality

Quality can be evaluated in terms of geometric and functional features (Chryssolouris, 2013) that in this work, in the context of metal casting, are loosely translated in terms of castability and mechanical properties.

Castability. Four quantities are considered to describe the castability of the alternative metal alloys as a measure of the expected manufacturing quality: volumetric solidification shrinkage V_{ss}, linear thermal contraction of the solid phase α_s, freezing temperature range ΔT_f and solidus temperature T_s.

The volumetric solidification shrinkage has been estimated from the metal elements that comprise each alloy according to the Kopp-Neumann rule applied to density (Valencia and Yu, 2002; Quested et al., 2000):

$$V_{ss} = \sum_{i=1}^{n} V_{ss,i}\, x_i \qquad \forall i \in \mathbb{N} \cap [1, n] \tag{9}$$

where an alloy of n elements with molar fraction x is considered.

Three shrinkage regimes are generally identified in metal casting processes and, in chronological order, they are: liquid contraction, solidification shrinkage and solid contraction (DeGarmo et al., 2003). In HPDC the first two are more strictly related to internal defects, whereas solid contraction mainly affects dimensional tolerances, draft angles and allowances (North American Die Casting Association, 2018). Liquid contraction is considered the least harmful of the three because most of it happens before filling the die (North American Die Casting Association, 2018) and, for this reason, it has been ignored in this analysis. Since the effects of solidification and solid-phase shrinkage on the casting quality are quite different, a separate criterion for each of them is considered. The choice to assess separately the two types of contraction permits the consideration of different ways to measure shrinkage (i.e. volumetric solidification versus linear solid-phase contraction) without affecting the correctness of the comparison (see Section 4).

Castability is significantly affected by fluidity (DeGarmo et al., 2003). For metal casting in general, it is well-established that larger freezing ranges are usually associated with reduced fluidity and, thus, relevant defects (Bastien et al., 1962). However, specific studies on the HPDC process (with Al−Si alloys) showed that in this specific case the solidus temperature dominates over freezing range to control fluidity: in particular, the lower the solidus temperature, the higher the fluidity (Han and Xu, 2005). Moreover, large freezing ranges are undesirable in HPDC because they prevent the rapid ejection of the casting from the mould increasing exposure to residual stresses (or, in the worst cases, hot tearing), while heat treatments are generally unsuitable for HPDC products (DeGarmo et al., 2003).

Mechanical properties. HPDC products are known to be easily affected by micro-porosities (Milne et al., 2003, Chap. 1.18) that reduces ductility and toughness alongside other mechanical properties (DeGarmo et al., 2003). Moreover, typical problems that can be potentially faced in material substitution are reduced corrosion resistance and reduced rigidity when thinner sections of a better performing material are designed (DeGarmo et al., 2003). For these reasons, a number of mechanical properties (tensile strength F_{tu}, modulus of elasticity E_t, yield strength F_y, elongation to break ε_b, fracture toughness k_{Ic}, corrosion depth in atmosphere d_{ca}) have been considered as additional criteria in this analysis, although the minimum values of these properties for every alloy considered must meet the minimal design requirements. Moreover, as mentioned introducing this case study, the mass of the product (used to obtain the extensive quantities from the intensive values) is calculated based on its fixed volume, ignoring the need to redesign it based on its mechanical properties. Such simplification favours unfairly lighter materials even though they might be less performing. Thus, the inclusion of these quantities in the analysis balances such intrinsic bias and expresses a measure of quality in providing an additional margin to the minimum design requirements.

Further to the above considerations, density ρ has very prominent importance among the design criteria of modern automotive parts because it affects significantly fuel economy and ride quality of the vehicles.

3.2.3. Environmental sustainability

Considering the energy-intensive nature of metal casting, an important role to apprise its environmental sustainability is energy efficiency (Pagone et al., 2019b). The “cradle to gate” specific energy consumption e_{cg} is included in the comparison of this analysis and takes into account of both the specific energy consumed during primary production of the material e_p and the specific energy of the entire manufacturing process e_m (sometimes referred to as *SEC*) through the material efficiency of the full manufacturing process OME_m. Thus, the “cradle to gate” energy consumption per product E_{cg} reads

$$E_{cg} = e_{cg}\, m_p \tag{10}$$

with

$$e_{cg} = \frac{e_p}{OME_m} + e_m \tag{11}$$

The specific carbon dioxide emissions associated with the required energy are assessed by the carbon intensity *CI*, comprising both the primary production and the manufacturing steps. The manufacturing carbon intensity has been calculated considering the fraction of electric energy and natural gas consumed together with their carbon dioxide specific emissions, in a similar way of Eq. (8) and substituting the specific cost with the carbon intensity. Thus, the “cradle to gate” mass of CO_2 emissions per product is

$$m_{CO_{2,cg}} = CI_{cg}\, m_p \tag{12}$$

This assessment does not include the energy consumed for transport of materials and the production of the HPDC machineries that are assumed to be comparable for all alternatives considered and, thus, can be ignored.

The specific energy consumption of the manufacturing process e_m provides an absolute value of the foundry overall energy efficiency, but it does not assess its performance in comparison to the ideal case for the specific alloy being processed. Thus, the definition of a manufacturing energy efficiency based on thermodynamic properties η_{om} has been proposed by Pagone et al. (2018, 2019a):

$$\eta_{om} = \frac{\Delta h_l}{e_m} \tag{13}$$

where Δh_l is the specific enthalpic rise from ambient to the liquidus temperature.

Finally, the impact of production of the primary material on water consumption V_{wp} has been included to consider also a non energy-related environmental sustainability indicator.

3.3. Time

Machine cycle time is an important contributor to the productivity of HPDC foundries (DeGarmo et al., 2003). If no plant-specific data is available, this metric can be approximated by heat of fusion of the material being processed ΔH_f that is known to be proportional to machine cycle time (Davis, 1998). Although ΔH_f is a contributor to the previously defined energy consumption E_{cg}, its impact as a component of the total allows to estimate productivity.

4. Multiple-criteria decision-making methods

Several methods have been developed in the last decades to support decision-making while considering multiple conflicting criteria. They can be classified based on the type of data that supports them as deterministic, stochastic or fuzzy. Examples of the more popular methods are the Weighted Sum Model (WSM), the Weighted Product Model (WPM), the *elimination et choix traduisant la realité* (ELECTRE), the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Several variations and improvements of the mentioned methods have been proposed. In the past years, TOPSIS (in its different forms) have seen a significant grow in popularity since it is perceived to have addressed some of the shortcomings of the other methods (e.g. compensatory tradeoff between criteria, correct comparison of criteria with significantly different scales or interdependency, mixture of qualitative and quantitative criteria). (Triantaphyllou et al., 1998).

In this work a deterministic TOPSIS analysis will be performed (Hwang and Yoon, 1981; Yoon and Hwang, 1995).

4.1. The TOPSIS method

TOPSIS was conceived in the early Eighties of the last century by Hwang and Yoon according to the principle that the best choice among a number of alternatives is the closest to the positive ideal solution A^+ and the furthest from the negative ideal solution A^-, both identified by a clearly defined number of steps (Hwang and Yoon, 1981). The technique was further developed in the subsequent decades (Hwang et al., 1993; Yoon and Hwang, 1995).

The distance between each alternative and the ideal solutions is defined according to the expression in a multi-dimensional Euclidean space. This aspect implies that the impact of all criteria is assumed to be monotonic. In this way, the scoring of each criterion can be aggregated and compensated after normalisation and appropriate weighting.

The procedure of TOPSIS algorithm (Fig. 2) is based on a decision matrix X built with the combination of n decision criteria values for m different alternative options.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{bmatrix} \tag{14}$$

The first computational step is the normalisation of each decision criterion in X to obtain matrix R as follows:

$$r_{i,j} = \frac{x_{i,j}}{\sqrt{\sum_{k=1}^{m} x_{k,j}^2}} \qquad \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \tag{15}$$

Then, a vector of n weights w so that $\sum_{j=1}^{n} w_j = 1$ is introduced to represent the importance of each criterion for the DM. Every criteria is scaled accordingly to calculate the normalised weighted matrix V:

$$v_{i,j} = r_{i,j}\, w_j \qquad \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \tag{16}$$

The ideal solutions A^+ and A^- are built combining the maximum v_i^+ or minimum v_i^- value among the m alternatives of $v_{i,j}$, considering for each criteria.

- the maximum value for A^+ and the minimum value for A^- if the criterion considered has a positive impact,
- the minimum value for A^+ and the maximum value for A^- if the criterion considered has a negative impact.

Then, the distances between each alternative and A^+ (giving d_i^+) and A^- (giving d_i^-) are calculated:

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{n} \left(v_{i,j} - v_j^+\right)^2} \qquad \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \\ d_i^- &= \sqrt{\sum_{j=1}^{n} \left(v_{i,j} - v_j^-\right)^2} \qquad \forall i,j \in \mathbb{N} : i \in [1,m], j \in [1,n] \end{aligned} \tag{17}$$

Finally, the similarity s_i^- to the worst ideal solution

$$s_i^- = \frac{d_i^-}{d_i^+ + d_i^-} \qquad \forall i \in \mathbb{N} \cap [1,m] \tag{18}$$

allows the DM to rank the alternatives and identify as the best solution the highest s_i^-.

4.2. Automatic weight distributions

As mentioned, automatic weighting addresses a number of related, typical MCDA issues.

- No time consuming and complex DMs consultation is necessary beforehand to determine the importance of criteria.
- Weighting is objectively set, avoiding disagreement between multiple DMs.
- If multiple weight distributions are considered, their scope is again objectively set and it is not restricted by the demanding process of involving DMs for defining each distribution.

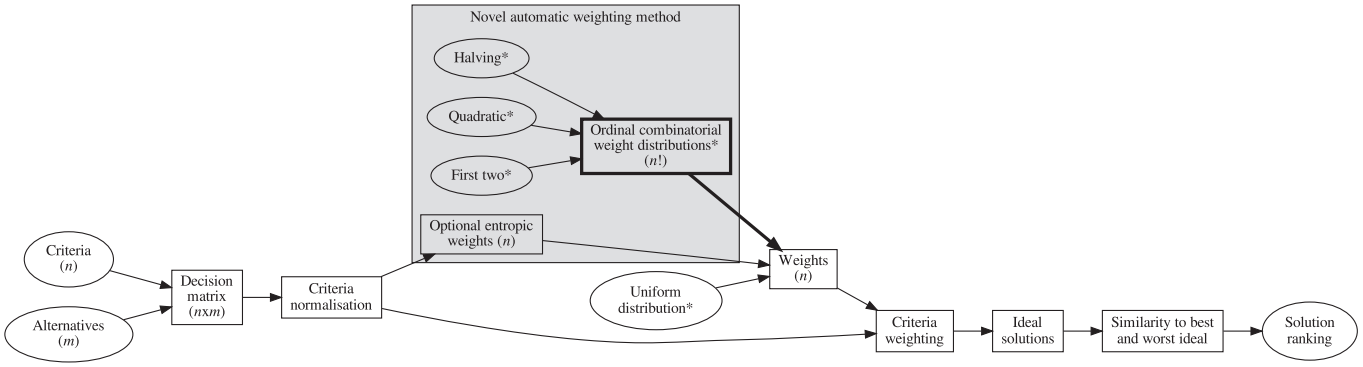


Fig. 2. Process flow of the proposed MCDA methodology combining the TOPSIS technique with automatic weighting by pre-set distributions and (optionally) using the entropy of information present in the normalised values of the criteria. Ellipses are inputs or outputs and rectangles are process steps, asterisked inputs are mutually exclusive and thicker lines suggest that multiple solutions (i.e. $n!$) are generated.

After experimentation, four pre-set weight distribution laws have been found sufficient (as the results will show) to encompass almost completely the possible DM choices for an arbitrary number of criteria. For this reason, the terms "uniform", "halving", "quadratic" and "first two" are chosen to describe the four distributions defined as follows.

The "uniform" weighting considers every criteria with equal importance whereas, in the other cases, at every successive j-th position in the ranking the weight w is reduced by a factor $f_w(j)$:

$$w(j) = \frac{1}{f_w(j)} \qquad \forall j \in \mathbb{N} \cap [1, n] \tag{19}$$

The equations that describe $f_w(j)$ in each case are the following:

- "halving"

$$\begin{aligned} f_w(1) &= 1 \\ f_w(j) &= 2\, f_w(j-1) \qquad \forall j \in \mathbb{N} \cap [2, n] \end{aligned} \tag{20}$$

- "quadratic"

$$f_w(j) = 2\, j^2 \qquad \forall j \in \mathbb{N} \cap [2, n] \tag{21}$$

- "first two"

$$\begin{aligned} f_w(1) &= f_w(2) = 1 \\ f_w(j) &= j^2 \qquad \forall j \in \mathbb{N} \cap [3, n] \end{aligned} \tag{22}$$

The distributions are exemplified graphically using the case study of Section 3 in Fig. 3 where four categories of metrics are used as main decision making criteria.

Furthermore, it is proposed to introduce optionally an additional weighting based on the entropy of information present in the values of criteria (Hwang and Yoon, 1981). This is accomplished calculating the entropy E for each of the n criteria, using the elements of the normalised decision matrix R showed in Eq. 15

$$E_i = -\frac{1}{\ln n} \sum_{i=1}^{n} r_{ij} \ln r_{ij} \qquad \forall i, j \in \mathbb{N} : i \in [1, m], j \in [1, n] \tag{23}$$

The resulting weights w_s are calculated as follows

$$w_{s,i} = \frac{|1 - E_i|}{\sum_{i=1}^{n} |1 - E_i|} \qquad \forall i \in \mathbb{N} \cap [1, n] \tag{24}$$

and, finally, combined with the weights provided by the distributions defined above w_d

$$w_i = \frac{w_{s,i}\, w_{d,i}}{\sum_{i=1}^{n} w_{s,i}\, w_{d,i}} \qquad \forall i \in \mathbb{N} \cap [1, n] \tag{25}$$

The rationale to use entropic weights is two-fold. In the first instance, it is another objective way to set weights with no intervention from the DM. Furthermore, it amplifies the importance of criteria with higher degree of divergence (i.e. with more pronounced differences) and, thus, separates them more clearly.

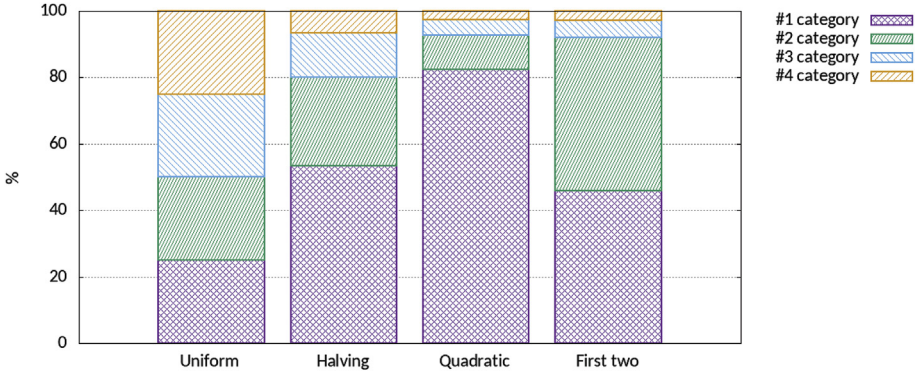


Fig. 3. Distribution of weights on a percentage basis for the pre-defined laws of the proposed MCDA methodology. Example with four categories used as criteria.

5. Results

As described in Section 3.2, some of the criteria considered for the TOPSIS analysis required additional calculations. To evaluate c_{cg}, the specific cost of each alloy normalised by the mass of the foundry feedstock $c_{M,f}$ has been taken from the database Edupack by Granta Design (2017). The fraction of the feedstock mass that leaves the foundry with no added value $f_{M,l}$ has been assumed 10% for all the materials. Unfortunately, no specific information in this regard is available except from data on melt dross of about 7% for the facility producing zinc alloy parts (Eppich, 2004). The choice to increase this value to 10% is motivated by the observation that a few other process steps will generate material losses in the foundry with no added value. On the other hand, this percentage has not been increased further because no economic value of this metal is considered in the calculations although actually between 10% and about 30% of the feedstock value can be recovered (Eppich, 2004). It is expected that the combination of these two opposite effects will bring the relevant error within the level of approximation of the entire analysis. For the calculation of the volumetric solidification shrinkage V_{ss}, the individual values for each metal element have been taken from a book by Campbell (1991) and the composition of the alloys from the online database MatWeb. The two components of the cradle to gate specific energy consumption e_{cg}, i.e. primary production e_p and manufacturing e_m have been estimated respectively using the database Edupack (Granta Design, 2017) for e_p and Eppich's report (Eppich, 2004) with direct foundry measurements (for the aluminum alloy processing plant) for e_m. These energy values have been used also to calculate c_{cg} and CI_{cg} as described in Section 3.2. Carbon intensities for the primary production have been taken from the database Edupack (Granta Design, 2017) whereas, to calculate the values of the manufacturing steps, a carbon intensity for electric energy of 76.64 g_{CO_2}/MJ (the EU28 value in 2014, European Environment Agency) and of 56.1 g_{CO_2}/MJ (Jurich, 2016) for natural gas has been used. The manufacturing energy efficiency η_{om} has been taken from a previous publication by the authors (Pagone et al., 2019a).

As explained in Section 3, considering that TOPSIS is a comparative technique, the specific mass of the product m_p used to obtain some of the extensive properties from the normalised ones does not affect the ranking of results. To a first approximation, the volume of the product has been kept constant regardless of the material considered. Since the data of the zinc alloy plant refers to a hot-chamber machine (Eppich, 2004) that is limited to parts of maximum 5 kg of mass, this is the reference value used to calculate the volume of the product from the density of zinc alloy ZA-8. A list of the values used in this analysis is provided in Table 2.

5.1. Uniformly distributed weights by category

In the first instance, the weights used for each criterion have been distributed evenly among the main categories listed in Table 1.

The quality criteria (Fig. 4) show almost always a supremacy of ZA-8 with A380 a close second, except for fracture toughness k_{Ic} where the aluminium-based alloy performs clearly better than the other two materials. When considering the effect of the entropic weighting, it is clear how corrosion resistance d_{ca} and (less markedly) the freezing temperature range ΔT_f are amplified in importance with a detrimental effect on the score of AZ91D. The corrosion resistance metric in particular, shows that alloy A380 has clearly better characteristics than its competitors.

On the other hand, looking at the environmental indicators (Fig. 5), a case where magnesium alloy AZ91D appears a winner and zinc ZA-8 is largely the least desirable alternative is the value of density ρ. This clearly confirms the efforts in the automotive industry in the past years to increase the adoption of this material to increase the fuel economy of vehicles. However, looking at the other environmental sustainability indicators, it becomes apparent how partial this conclusion is. The plant producing zinc-based ZA-8 parts is sometimes the best performer ("cradle to grave" energy consumption E_{cg} and carbon emissions $m_{CO2,cg}$), although not by a large extent when compared to the aluminium alloy plant.

It is interesting to note that the manufacturing energy efficiency of the plant η_{om} (that compares the energy performance to the theoretical maximum specific for the material being cast) shows a low value for the plant processing ZA-8 alloy. This suggests the opportunity to further improve the performance of the foundry, bringing it closer to its theoretical minimum energy consumption. This hypothesis has been verified in a previous study where it has been identified that the melting phase, in particular, can be improved with great potential benefit for the overall foundry energy performance (Pagone et al., 2019a).

Analysing the cost criterion C_{cg} (Fig. 5), it can be noticed that the choice to consider a fixed volume for the part produced favours lighter alloys. The same can be stated when looking at the productivity criterion ΔH_f although the significantly smaller latent heat of the zinc alloy makes it very close to the best performer (i.e. magnesium AZ91D). Additional weighting based on entropy shows a significant impact mainly on carbon emissions (again exacerbating the poor performance of the magnesium processing plant) and (to a smaller extent) cost.

When criteria are combined to provide a single score s^- (defined in Section 4.1), magnesium performed best with parts produced in aluminium as a close second (Fig. 6). Interestingly, the changes in weights when also entropy is considered, determine a rank reversal of the best material with almost symmetric results, favouring aluminium. In this instance, parts made of zinc ZA-8 do not seem appealing to the DM.

5.2. Combinatorial ranking of categories by importance

To better map the decision making space, three sets of analyses are considered by computing all rank permutations of categories and associating the weight distributions (with and without entropy) presented in Section 4.2:

- the weight is halved at each next position in the ranking (Fig. 7 top),
- a more aggressive reduction of the weight with the position in the ranking according to a quadratic expression (Fig. 7 middle),
- weight distribution dominated by the first two categories (Fig. 7 bottom).

In Fig. 7 the ordinal ranking of categories that dictates their importance is represented by the position of the initial letter of the relevant category in the identifier.

It can be noticed that the aluminium alloy appears usually as the best choice with magnesium as a relatively close second. The zinc alloy is negatively affected mostly by the cost criterion and in all the circumstances when this aspect becomes less important, it emerges as a strong competitor (e.g. "teqc" and "qtec" with the "halving" weight distribution, "qtec" for the "quadratic" distribution and in eight other cases in the "first two" distribution). The significant importance of the cost criterion for the zinc alloy can also be observed when comparing the cases "qcte" and "qcet" for the "quadratic" and "first two" distribution laws. In these cases a rank reversal between zinc ZA-8 and magnesium AZ91D can be observed.

The effect of entropy weighting is visible in a few circumstances. For example, in the results "tcqe" and "tceq" of "halving" weight

Table 2
Values of the criteria considered to compare different metal alloys to produce a transfer case with a High Pressure Die Casting process. A reference to the source is provided next to the values that have been not calculated or are not confidential.

Quantity	Unit of measure	Al-A380	Mg-AZ91D	Zn-ZA8
Cradle to gate cost C_{cg}	GBP	4.54	4.37	10.97
Volumetric solidification shrinkage V_{ss}	%	6.23	4.36	4.65
Solid linear thermal contraction α_s	μm/(m °C)	22 (MakeItFrom)	27 (MakeItFrom)	23 (MakeItFrom)
Freezing temperature range ΔT_f	°C	55 (MatWeb)	125 (MatWeb)	29 (MatWeb)
Solidus temperature T_s	°C	538 (MatWeb)	470 (MatWeb)	375 (MatWeb)
Tensile strength F_{tu}	MPa	340 (Granta Design, 2017)	245.5 (Granta Design, 2017)	322.5 (Granta Design, 2017)
Modulus of elasticity E_t	GPa	71 (Granta Design, 2017)	45 (Granta Design, 2017)	86 (Granta Design, 2017)
Yield strength F_y	MPa	160 (Granta Design, 2017)	155 (Granta Design, 2017)	245 (Granta Design, 2017)
Elongation to break ϵ_b	%	3.5 (MatWeb)	3 (MatWeb)	8 (MatWeb)
Fracture toughness k_{lc}	MPa $\sqrt{m}$	27.05 (Granta Design, 2017)	13 (Granta Design, 2017)	15 (Granta Design, 2017)
Corrosion depth in atmosphere d_{ca}	μm/yr	1.39 (Davis, 1998)	19.57 (Davis, 1998)	6.57 (Davis, 1998)
Density ρ	kg/l	2.74 (Granta Design, 2017)	1.81 (Granta Design, 2017)	6.3 (Granta Design, 2017)
Cradle to gate energy consumption E_{cg}	MJ	759.71	699.39	654.12
Cradle to gate mass of CO_2 emitted $m_{CO_2,cg}$	kg	27.34	100.33	21.60
Primary production specific water consumption V_{wp}	l	2294.21 (Granta Design, 2017)	1433.63 (Granta Design, 2017)	2085 (Granta Design, 2017)
Manufacturing energy efficiency η_{om}	%	6.14	3.28	1.71
Manufacturing Operational Material Efficiency OME_m	/	0.545	0.57 (Eppich, 2004)	0.52 (Eppich, 2004)
Heat of fusion ΔH_f (proportional to machine cycle time)	kJ	845.92 (MatWeb)	535.82 (MatWeb)	560 (MatWeb)

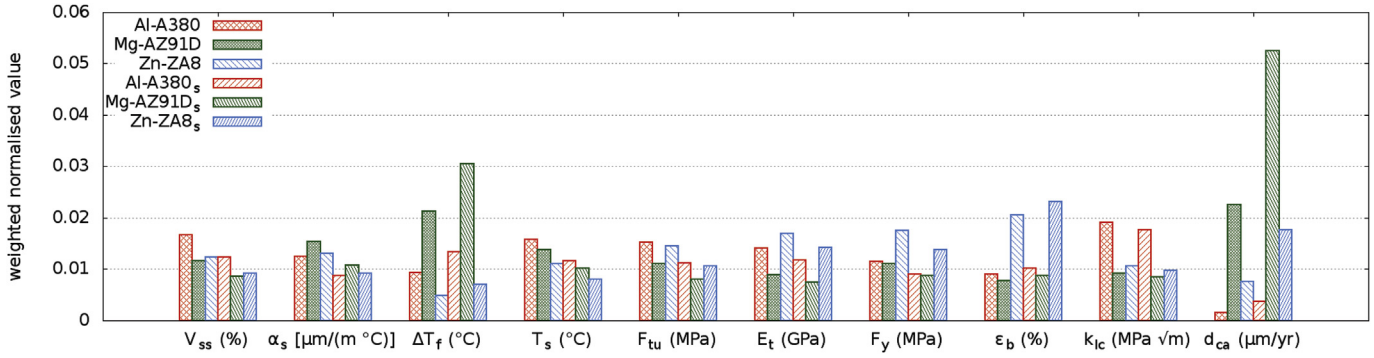


Fig. 4. Weighted and normalised values of the criteria in quality domain to compare different metal alloys to produce a product with a high pressure die casting process. The weighting modified to consider also the entropy of information in the criteria is indicated appending the subscript "s" to the name of the alloy.

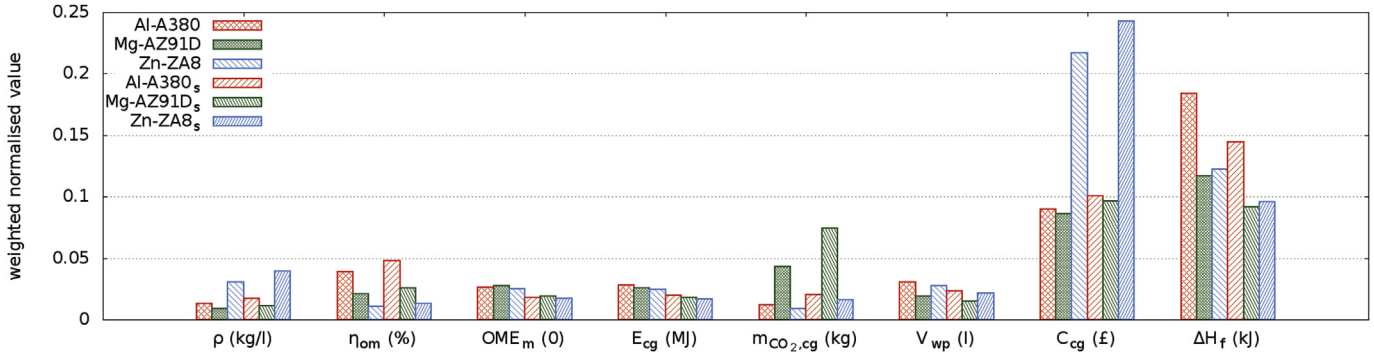


Fig. 5. Weighted and normalised values of the criteria in the environmental sustainability, cost and time domains to compare different metal alloys to produce a transfer case with a high pressure die casting process. The weighting modified to consider also the entropy of information in the criteria is indicated appending the subscript "s" to the name of the alloy.

distribution, aluminium and zinc alloys score equally in practical terms, but the use of entropy weighting favours clearly the former alternative over the latter. A similar situation can be seen in favour of aluminium A380 when looking at the results for the "quadratic" weight distribution of cases "qect" and "qetc", when the entropy weighting is factored in.

Cumulating the number of best results for each alternative in all 145 cases considered in this study (Fig. 8), aluminium alloy A380 has been the best choice most of the times, followed by magnesium alloy AZ91D with zinc ZA-8 last. The effect of entropy consolidates even more the lead of the aluminium alloy according to this classification. Alternative, more refined, ways to post-process such results might be performed on a statistical basis as suggested, for example, by Hwang and Yoon (1981). For the case to hand in this work, the presented cumulative approach is deemed sufficient.

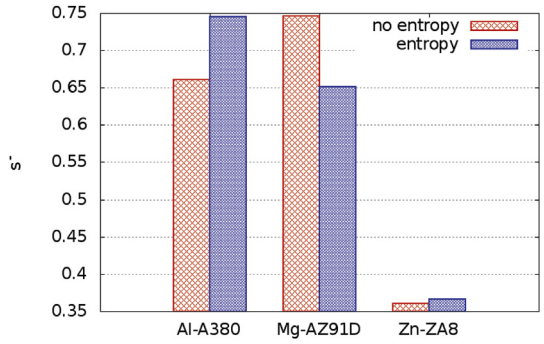


Fig. 6. Similarity index s^- to the negative ideal solution of different metal alloys to produce a transfer case with a high pressure die casting process. The best alternative has the highest score.

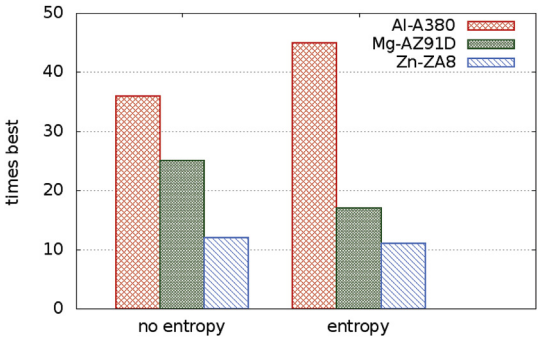


Fig. 8. Cumulative count of times when each alternative has resulted the best option for all the cases in this study.

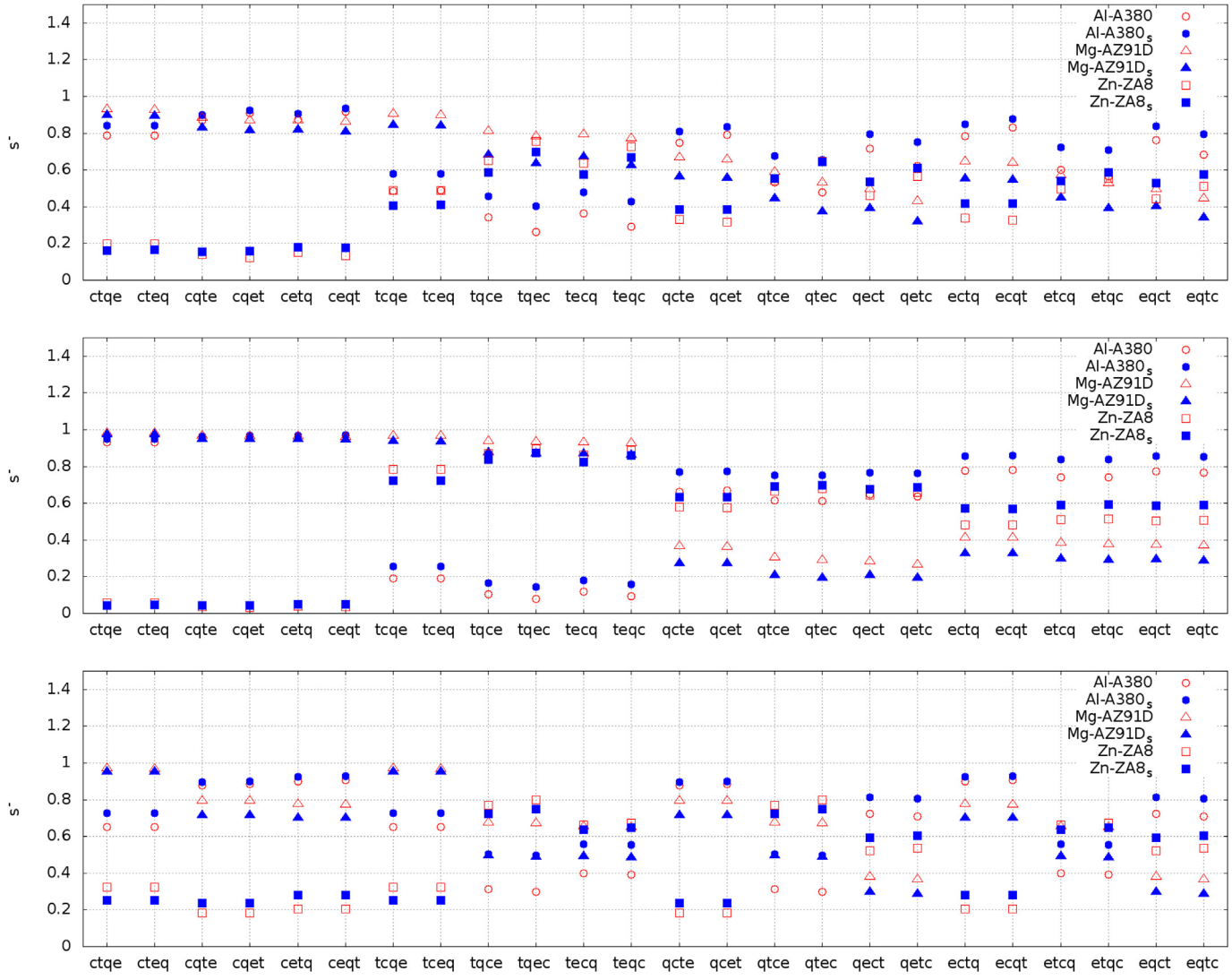


Fig. 7. Ranking of the alternative materials through the score parameter s^- with weight distributions "halving" (top), "quadratic" (middle) and "first two" (bottom) of criteria based on their ordinal position. The ranking of the four categories of criteria is shown using a sequence of their first letter (c: cost, q: quality, t: time, e: environmental sustainability). The entropic weighting is indicated by appending the subscript "s" to the name of the alternative materials.

6. Discussion

In general, decision making is a challenging task where it is difficult to weight fairly compensatory trade-offs of incommensurable metrics. Sustainability is inherently multi-disciplinary since it considers a broad variety of dimensions (i.e. environmental, economic and social) holistically and, thus, decision making that includes its instances is even more complex than usual. Attempts to support this task tried to raise awareness of such complexity, providing also a structured and objective process supported by a number MCDA methods. However, such approaches are time consuming and, although data-driven, are still highly subjective, especially when multiple DMs or stakeholders may disagree or lose confidence in the process. Attempts seen in the literature (Section 2) to interpret the typical DM interests by weighting criteria in specific ways might not be sufficiently accurate and may still fail to show a satisfactory overview of cases as illustrated by the results of the case study. In fact, the decision making map obtained combining the 144 cases of Fig. 7 with the one in Fig. 6 can be used both to satisfy specific DMs requests and also to gauge the sensitivity of the solutions to the criteria weights. Such sensitivity analysis can be considered more practical and effective than traditional approaches in manufacturing MCDA — e.g. (Stoycheva et al., 2018) — when only one criterion weight at the time is varied. Such single-dimensional approach fails to show the sensitivity to simultaneous changes of multiple attribute weights as it happens more likely in real life choices.

7. Conclusion

A methodology that includes the automatic weighting of criteria in Multi-Criteria Decision Analysis (MCDA) of sustainable manufacturing systems has been presented. Such methodology, that can be translated into a framework, has been developed from a tool used to solve a case study on sustainable metal casting. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was used to select a material between three typical materials processed in High Pressure Die Casting (HPDC) plants producing automotive components. About thirty deterministic criteria have been consolidated into eighteen indicators categorised in the areas of cost, quality, time and environmental sustainability. The procedure to calculate such quantities have been described in detail and the relevant results suggested some interesting conclusions.

- Aluminium alloy A380 has resulted the best choice for the largest number of cases investigated confirming recent industrial trends in the sector.
- The mapping of the decision making space has exposed a few cases when conventional material choices are challenged and zinc alloy ZA-8 is preferred over lighter aluminium and magnesium based alternatives. Broadly speaking, this result has been observed in a series of circumstances when the cost criterion is less important, although the mentioned map of the decision making space better describes the complex scenario.
- The contribution of entropy weighting has determined both rank reversals and better separation of close alternatives.
- No simple correlation between the importance of categories and the score of alternative materials can be generally identified and, for this reason, the high-resolution decision making map is significantly valuable.

The automatic allocation of weights is achieved objectively through an ordinal combinatorial ranking of attributes where four weight distributions are applied. The user can optionally decide to mix these weights with a contribution based on the entropy of information of the criteria. Also this optional step does not require any input from the Decision Maker (DM). Such characteristics provide some clear advantages to the user when compared to traditional approaches that are time consuming, subjective and might draw partial conclusions that can also be misleading. The presented framework is devised to minimise the subjectivity in setting up decision making investigations with a fast, rational and systematic procedure. Finally, the underlying methodology makes no specific assumption linked to the initial case study and, thus, it can be applied to assess sustainability in any manufacturing system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Emanuele Pagone: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Data curation. **Konstantinos Salonitis:** Funding acquisition, Project administration, Resources. **Mark Jolly:** Funding acquisition, Resources.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.120272.

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