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A TOPSIS-based approach for the best match between manufacturing technologies and product specifications

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Abstract

The recent developments in additive manufacturing have made these technologies available not only for producing mock-ups, prototypes or small batches but also for standard mass production. Consequently, manufacturing companies are increasingly considering the use of additive manufacturing technologies for the realisation of their products. In fact, when manufacturing a part, companies must consider the specifications of its design to choose the best matching manufacturing technology in terms of product quality, production time and costs. Since all these parameters can be represented by several indicators, the problem of technology selection is configured as a real multi-criteria decision-making (MCDM) problem, which can be solved through the theory of multi-criteria decision support-systems. Although several mathematical models have been developed to solve similar problems, there is a lack of specific applications to the technology matching problem in the manufacturing sector. This study attempts to fill this gap by proposing a manufacturing-oriented model of the Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS), one of the most solid and robust MCDM methods. The solution we present, which is designed for general manufacturing processes, has been applied to the specific case of a producer of food and beverage plants and equipment that is interested in reengineering one of its products. Due to the complexity of the food and beverage industry, the case study is useful for supporting the definition of the general model and validating its applicability. Further, the results of the specific application prove the effectiveness of our model.

Keywords: Multi-criteria decision support-system; DSS; Multi-criteria decision-making; TOPSIS; Additive manufacturing; Technology selection

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Abstract

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[2] **List of abbreviations in order of appearance**
MCDM: multi-criteria decision-making
TOPSIS: Technique for Order Preference by Similarity to Ideal Solutions
AM: additive manufacturing
MAUT: Multi-Attribute Utility Theory
AHP: Analytic Hierarchy Process
DEA: Data Envelopment Analysis
SMART: Simple Multi-Attribute Rating Technique
PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluations
VIKOR: VIseKriterijumska Optimizacija I Kompromisno Resenje
CBR: Case-Based Reasoning
ELECTRE: ELimination Et Choix Traduisant la REalité
SAW: Simple Additive Weighting
F&B: food and beverage
FBC: alias of the company partner in the stud
PIS: positive ideal solution
NIS: negative ideal solution
C: cost-effectiveness drivers
T: technological drivers
C&T: cost-effectiveness and technological drivers

1. Introduction

In recent years, additive manufacturing (AM) technologies have emerged as a trend in industrial research for more than just the production of mock-ups, prototypes or stand-alone products (Gąbka & Filcek, 2018). This attention is due to the revolution that this new set of technologies has brought to industry and the fact that its potential has not yet been fully explored (Achillas, Tzetzis, & Raimondo, 2017). Hence, the progress of AM technologies suggests new approaches to manufacturing operations, such as product design, production planning and optimisation, and supply chain design (Khorram Niaki & Nonino, 2017). Some researchers (cf. Song & Zhang, 2016; Dong, Shi, & Zhang, 2017) have shown that AM technologies can have a major impact on industry by (i) reducing wastes and shortening the production cycle due to less material and information handling, (ii) allowing the manufacturing of almost all shapes and geometries, and (iii) bringing higher production capacity and flexibility to the company. In contrast, other researches (Brettel, Friederichsen, Keller, & Rosenberg, 2014; Ligon et al., 2017; Debroy et al., 2018; Westerweel, Basten, & van Houtum, 2018) have focused on following limits of AM technologies: (i) almost unknown product lifecycle costs, (ii) the need for large changes in production behaviour due to different process paradigms, (iii) the lack of compliance with specific industry norms of raw materials feeding the processes, and (iv) the mismatch between raw material properties and product's specifications. Since the early 2010s, when the first interest in AM appeared (Wohlers, 2012), AM technologies have created a world of possibilities that can lead organisations in new directions and help them to launch new businesses and business models. Nonetheless, it is well established that each company defines its own business model, as well as its own production system, in terms of management of business partners (e.g. customers and suppliers) and value chain definition (Hopp & Spearman, 2011). In this regard, it is indisputable that both the market and the industrial context have evolved and are evolving rapidly, and thus the production systems need to be updated rapidly and frequently (Yin, Stecke, & Li, 2017). The new technological revolution has led to the need to solve two major issues. From a business perspective, the first issue is whether to take the opportunities and accept the risks related to AM technologies as well as how business models should evolve to allow the company to adopt these technologies. From a manufacturing perspective, the issue is to prove whether an AM technology satisfies the product requirements in terms of design specifications and production costs.

The technology selection problem can be defined as identifying the best technology from a set of possible alternatives (Singh & Sushil, 1990). The solution of this problem can assist organizations in manufacturing and delivering more competitive products and services, by means of new solutions and more efficient processes (Melander & Tell, 2014). However, a technology selection problem must explicitly consider several characteristics, such as (i) technology specific ones, e.g. funding needs and resource prerequisites, uncertainties of technical and commercial success, and the life-cycle level of the technology (Wang, Tian, & Geng, 2014), and (ii) the interaction between diverse technologies, present and future, and the current system of the enterprise (Houseman, Tiwari, & Roy, 2004). To address the issue, it is always advisable to support the investigations with mathematical models (Hopp & Spearman, 2011). The technology selection problem can be thus regarded as a complex multi-criteria decision making (MCDM) problem (Iglesias, Del Castillo, Santos, Serrano, & Oliva, 2008), where a set of alternatives must be assessed against multiple and hierarchical evaluation criteria by means of mathematics computations (Greco, Matarazzo, & Słowiński, 2016). As an example, technology selection criteria can be classified in tangible, intangible, qualitative and quantitative categories (Sanayei & Monplaisir, 2012). Also, other categorizations have been introduced such as economic, technical, environmental, and social criteria (Muerza, de Arcocha, Larrodé, & Moreno-Jiménez, 2014).

As it emerges from a recent review of the literature on this topic, the number of published papers on the technology selection problem has been increasing extensively over the last decade. The two application domains in manufacturing field that recur more often are (i) product design and production process, and (ii) advanced manufacturing technologies, the latter being a promising application area that 'emerged or dramatically captured attentions, which seems a promising field for future research' (Hamzeh & Xu, 2019).

However, if we shift attention from the applications domain to the main technology selection methods, we note that renowned decision-making techniques such as, for example, TOPSIS and AHP (which respectively stand for Technique for Order Preference by Similarity to Ideal Solutions and Analytic Hierarchy Process, cf. section 2) have been overlooked in recent research on technology selection, despite their ease of use, especially for the selection of advanced manufacturing technologies (Hamzeh & Xu, 2019). Indeed, according to Hamzeh and Xu (2019), the Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) has never been used as a method for advanced manufacturing technology selection, despite its user-friendliness, robustness and reliability (Shih, Shyur, & Lee, 2007).

In this paper, we address the technology selection problem in both application domains of product design and production process and advanced manufacturing technologies, by considering the product characteristics while reengineering the product design and/or manufacturing process in the light of new developments in AM technologies. The problem is a multi-variable and multi-objective issue that considers: (i) technology evolution and evaluation, (ii) if and how technology is appropriate for satisfying specific requests, and (iii) the capability of the system to adapt its supply chain to the new requests making use of a specific manufacturing technology. The aim of this paper is to provide a TOPSIS-based MCDM approach for supporting a systematic analysis of existing manufacturing processes, to address the question of whether the technology in use by a company—as well as by its suppliers if the company outsources its operations—allows the best match with the product in terms of:

i. Specifications of the product to be manufactured.
ii. Company compliance to specific norms of the sector it belongs to.
iii. Company standards in a continuous improvement environment and compared to market needs.

We approach this issue through a MCDM model because of its reliability in classifying a finite number of alternatives according to a usually large number of specifications (Umm-E-habiba & Asghar, 2009). In manufacturing contexts, product and supply chain design and reengineering processes are usually carried out to optimise resource utilisation (Nicholds, Mo, & O'Rielly, 2018). Several different techniques are available to map the product's value stream and select the best manufacturing technology available, and all these techniques rely upon a deep knowledge of the product's features (Hvam, Hauksdóttir, Mortensen, & Haug, 2017). In detail, the following steps are suggested (cf. section 4):

(1) Collect detailed data concerning the product to be realised.
(2) Gather information about the available processes to realise it.
(3) Consider the criteria that summarise the information, both qualitatively and quantitatively.
(4) Rank the alternatives to identify the best solution.

This pattern is typical of an MCDM problem: MCDM can support the assessment by combining into a single index the information coming from various indexes, thus providing a more efficient and clear ranking. Hence, the selection of the most appropriate technology for manufacturing a product is an issue that can be suitably approached through MCDM.

The remainder of the paper is organised as follows. Section 2 reports a review of relevant literature on MCDM techniques, while section 3 discusses theoretical aspects of the MCDM model we propose. In section 4, the technology-selection model is first designed and then applied to our case study, and in section 5 we present and discuss the results of the specific application. Finally, in section 6 we provide conclusions and suggest future developments.

2. MCDM: a literature review

The expression ‘multiple-criteria decision making’ defines a set of techniques used to combine several evaluation indicators into an overall index to rank a list of alternatives from best to worst (Zeleny, 1982). MCDM methods, each utilising a specific approach for managing data related to the problem, determine the value function as described in equation 1.

$$f_i: [0,1]^n \rightarrow f_i \in [0,1] \quad (1)$$

The value function connects, for each alternative i, a set of both qualitative and quantitative data $x_j, j = 1,2,\ldots,n$ of the criteria vectors to a single numeric value. Each data set can be measured in its own scale, which is not necessarily consistent with other scales (Campanella & Ribeiro, 2011).

The MCDM theory relies on the assumption that, in the absence of a natural ideal solution, the best alternative would be the one that has the shortest distance from the hypothetical ideal solution, and concurrently, the farthest distance from the hypothetical worst solution (Lertprapai, 2013).

In section 2.1, we review relevant literature on MCDM methods. The present study considers only models that fit and/or have been applied in the field of product and supply chain design and reengineering. These models are: Multi-Attribute Utility Theory (MAUT), Analytic Hierarchy Process (AHP), Data Envelopment Analysis (DEA), Fuzzy Set Theory, Simple Multi-Attribute Rating Technique (SMART), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), VIKOR (acronym of the Serbian VIseKriterijumska Optimizacija I Kompromisno Resenje Serbian, meaning ‘multi-criteria optimization and compromise solution’), and Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS). Reliable methods such as Case-Based Reasoning (CBR) have not been considered due to the lack of studies in the engineering field. Other methods that do not fit with the manufacturing context include ELECTRE (acronym for French ELimination Et Choix Traduisant la REalité, meaning ‘elimination and choice expressing reality’) or Simple Additive Weighting (SAW), which are mostly used in non-manufacturing contexts due to their characteristics (Velasquez & Hester, 2013).

2.1 Literature review

2.1.1 Multi-Attribute Utility Theory (MAUT)

MAUT is an extension of multi-attribute value theory (Fishburn & Keeney, 1974) and includes risk preferences and uncertainty in the multi-criteria decision support methods (Løken, 2007). MAUT assigns utility and uncertainty to each consequence of an action in a given problem to identify its best course by calculating the best possible utility (Konidari & Mavrakis, 2007). Utility itself differentiates MAUT from other MCDM methods, with the preferences of each consequence being expressed at every step of the method. In particular, MAUT is applied in risk analysis (Canbolat, Chelst, & Garg, 2007).

MAUT may provide non-optimal results in certain cases, largely because of the need for a huge quantity of information to be processed (Velasquez & Hester, 2013).

2.1.2 Simple Multi-Attribute Rating Technique (SMART)

SMART is a declination of the MAUT method. It basically requires two assumptions: (i) utility independence and (ii) preferential independence (Chen, Okudan, & Riley, 2010). It is easy to use because it allows the development of any weight assignment technique, but it has a complex framework (Konidari & Mavrakis, 2007). It has several applications in environmental, construction, logistics, military, and manufacturing and, generally, whenever a lot of information is available (Velasquez & Hester, 2013).

2.1.3 Analytic Hierarchy Process (AHP)

The AHP method was proposed by Saaty (1980). Along with MAUT, it is one of the most popular MCDM methods. It is a hierarchical and linear method in which objectives are located on top of the model and alternatives are at lower levels (T. C. Wang, 2012). The AHP method uses pairwise comparisons to relate the alternatives, with respect to the various criteria, and then to estimate the weights of different criteria (Løken, 2007). It is applied to synthesize information related to decision-making across all production areas, from the primary sector to the tertiary one (Ambrasaite, Barfod, & Salling, 2011; Lee, Kim, Kim, & Oh, 2012; Leung, Muraoka, Nakamoto, & Pooley, 1998).

AHP is commonly used in decision-making processes due to its ease of use. Another advantage is its scalability, which means the AHP hierarchical structure can be sized up or down, although Forman (1990) limits this practice to alternatives meeting the criteria that are measured with the same absolute scale. Finally, even though it requires a large quantity of data to make pairwise comparisons, it is not data intensive. Conversely, the scientific literature suggests major limitations of AHP, such as problems of interdependence between the criteria and alternatives, inconsistencies in the judgement and ranking criteria due to the pairwise comparison approach, and the lack of reliability when alternatives are added to the model (Velasquez & Hester, 2013). Thus, several studies combine AHP with other MCDM models where appropriate (Bentes, Carneiro, da Silva, & Kimura, 2012; Lai, 1995).

A noteworthy proposal for improving AHP is the analytic network process (ANP), which is non-linear and cluster-based (Liu, Zheng, Xu, & Zhuang, 2018). However, neither AHP nor ANP are considered the best method for problems for which new alternatives are added or existing alternatives are adapted (Murphy, 1993).

2.1.4 Data Envelopment analysis (DEA)

DEA makes use of the linear programming technique to evaluate the relative efficiency of each alternative on a 0–1 judgement scale. It is useful for analysing and quantifying multiple inputs and outputs, and it uncovers relationships that other methods cannot (Thanassoulis, Kortelainen, & Allen, 2012).

While DEA can manage multiple inputs and outputs, they must be known and well established, which is not always the case (Y. M. Wang, Greatbanks, & Yang, 2005). For these reasons, DEA is typically used when there is a need to rank efficiency, and the data for doing so are precise and reliable. DEA applications are more common in infrastructure environments (Hermans, Brijs, Wets, & Vanhoof, 2009), agriculture (Chauhan, Mohapatra, & Pandey, 2006), education (Kuah & Wong, 2011), and, more generally, in business (Sowlati, Paradi, & Suld, 2005).

2.1.5 Fuzzy Set Theory

Developed by Zadeh (1965), Fuzzy Set Theory extends the classical set theory to solve problems affected by imprecise and uncertain data. This theory works with insufficient information and imprecise inputs, and it considers the evolution of available knowledge (Balmat, Lafont, Maifret, & Pessel, 2011). Hence, this model is often used when the available information and data are vague, such as in risk analysis (Khadam & Kaluarachchi, 2003), environment–resource management (Esogbue, Theologidu, & Guo, 1992), logistics, and supply chain management (Haleh & Hamidi, 2011).

The main advantages of Fuzzy Set Theory are its holistic approach and use of iterative modelling to reach convergence on a solution (Velasquez & Hester, 2013). These advantages enable the Fuzzy Set Theory method to use imprecise inputs (Velasquez & Hester, 2013).

2.1.6 Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)

PROMETHEE is an iterative method that was first introduced by Brans, Vincke, and Mareschal (1986). It is well-appreciated by decision makers because its user-friendly calculation frame (Brans & Mareschal, 2005). While the early definition of the method distinguished amongst patterns for a partial rank of the alternatives (PROMETHEE I) or a complete one (PROMETHEE II), further studies introduced judgement schemes (PROMETHEE III, PROMETHEE IV, etc.) useful for specific applications (Behzadian, Kazemzadeh, Albadvi, & Aghdasi, 2010). Due to its applicability to various cases, it has experienced considerable development for diverse specific environments, such as resource management, business and finance, chemistry, logistics, manufacturing, and production (Behzadian, Khanmohammadi Otaghsara, Yazdani, & Ignatius, 2012).

2.1.7 VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)

VIKOR was first proposed by Opricovic (1998) to solve decision problems with non-commensurable and conflicting criteria. The VIKOR method aims at finding a compromise solution by using a multi-criteria ranking index to evaluate each alternative for its closeness to the ideal solution: the goal is to determine a feasible compromise solution that is closest to the ideal one (Jati, 2012). Due to the conflicting nature of criteria, the proposed solution will be the one that achieves the best compromise (Alrababah, Gan, & Tan, 2017). VIKOR has been applied in computer science, natural science, engineering, business, and resource management.

2.1.8 Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS)

TOPSIS works in a multi-dimensional computing space to identify the alternative solution that is both closest to the ideal one and farthest from the worst one. It was introduced by Hwang and Yoon (1981) and subsequently extended (Huang, Poh, & Ang, 1995). TOPSIS is very commonly used due to its user-friendliness. Its calculation process is the same regardless of the number of alternatives (Shih, Shyur, & Lee, 2007), which enables quicker computation (Jati, 2012). For each alternative, the method concurrently considers the distance from both the best solution and the worst one (Tong, Wang, Chen, & Chen, 2004). The positive ideal solution includes all the best values of every single rank, while the negative ideal solution includes all the worst ones (Bai, Dhavale, & Sarkis, 2014).

TOPSIS is a very reliable method, even though it does not consider the correlation of attributes due to its peculiar use of Euclidean distance to assess the distance from the ideal positive and negative solutions (Velasquez & Hester, 2013). Other similar methods, such as VIKOR, directly benchmark the solution under analysis against the best and worst existing ones (Jati, 2012). Due to its reliability and robustness TOPSIS is used in several fields, such as engineering, manufacturing, resource management, business, and marketing.

Although a common trend in applying MCDM is to combine two or more methods such that each one fills the gaps of the other (Velasquez & Hester, 2013), in this paper we propose a pure TOPSIS-based approach due to its suitability to our case study.

2.2 The selected model in food and beverage context

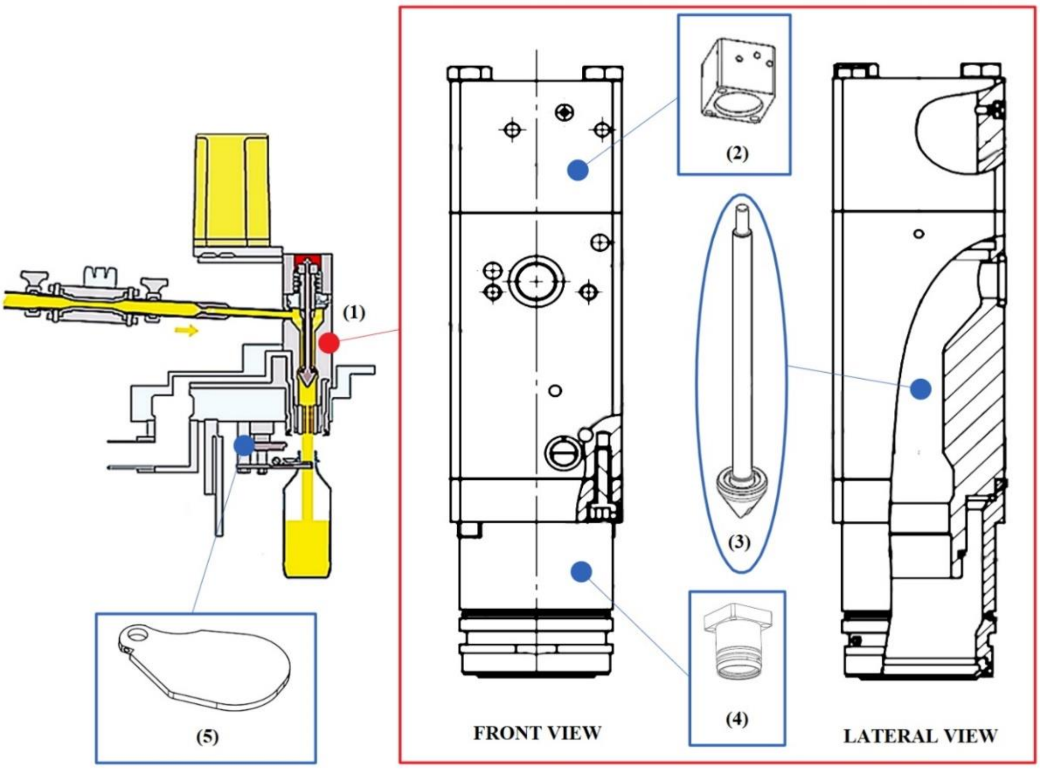
The present study was supported by a food and beverage (F&B) company, which we will refer to as FBC for reasons of confidentiality. The study started with the following question: 'Do additive manufacturing technologies fulfil the food and beverage company production requirements and marketing goals?'

Starting from this question, the research attempted to find the best match between the parts manufactured by FBC and the technologies able to manufacture them. This application is useful to the study due to the high-quality level of the F&B industry and its mandatory regulations.

The study of technology selection and/or replacement belongs to the multiple-criteria decision support system (MCDSS): the decision-making framework requires experts in the fields of design, process, and technology to tailor the framework to the specific context and apply both qualitative and quantitative judgement criteria (Gąbka & Filcek, 2018). Hence, the University of Parma and FBC scheduled a kick-off meeting to identify the framework of the investigation. The project involved two professors and one student from the university as well as cross-functional operators from FBC. The team possessed competences and skills in the following areas: operations management and manufacturing technology, product design, research and development area, purchasing and after sales (Customer Care and Regulation).

First, the team defined the product family on which to carry out the analysis: the filling valve, an assembly product of the fillers that exists in different variants depending on the machine that is fitted for and on the product to be filled (e.g. still liquids or sparkling drinks). This product family was identified for two reasons. First, due to the variety and complexity of parts composing the family. Second, because this product family, which before our analysis it was mostly manufactured within FBC using traditional subtractive technologies, was considered too expensive if compared with competitors. To illustrate the product, Figure 1 shows the main assembly parts of the object we are interested in and how it works. The liquid flows from the distribution system into the filling valve (i.e. the product analysed), and it is dispensed to the bottle (Figure 1a). The filling valve, element number (1) in the Figure 1a, is composed of three parts, shown in the exploded view in Figure 1b: the upper body (2) that both works as cover and area for positioning the control units; the central body, with the proper seat of the valve stem (3) that sets the filling regime; and the bottom body (4) that works as a manifold, and to which the shuttering 'Dummy Bottle Group' (5) joins to stop the liquid droplets.

Technologies suitable for the analysis and the drivers describing their characteristics were identified. The technologies that were investigated were different from those already in use both on the FBC shop floor and by suppliers. In particular, additive and moulding technologies were considered rather than traditional subtractive ones (e.g. lathe and mill machining). This choice was made for two reasons. First, a manufacturing company such as FBC usually has considerable experience in chip removal machining techniques, and thus it might be helpful and valuable to try and shift the focus to innovative processes. Second, we wanted to avoid the (high) risk of 'scope creep'. If a manufacturing company such as FBC was to assess the fitness of a chip removal machining technique, it is very likely that its focus will shift from assessing technology fitness to questioning process performances and parameters, causing the analysis to be greatly affected by (i) the performance of the machines and (ii) the company's standards. The full lists of technologies and drivers as well as specifications of the parts investigated at FBC are presented in section 4.



(a) (b)

Figure 1: (a) overall design of the filling system, and (b) exploded view of the filling valve main parts.

The different MCDM methods were then presented and analysed, describing their pros and cons and mapping their conceptual schemes (see section 2). The choice of the most suitable method for FBC was made by submitting a questionnaire to the company. The questionnaire summarised in a semi-structured way the theory of the user acceptance of the technology. We identified four core constructs to be evaluated: (i) perceived usefulness, (ii) ease of use, (iii) performance expectancy, and (iv) self-efficacy. These constructs were the items of the questionnaire themselves. The responses were given based on a Likert scale (1 = minimum agreement, 5 = maximum agreement) and were then weighed by the University considering the following parameters: (a) the importance of the core construct for the voluntary use of the tool, (b) the consistency of the method with the problem, (c) the reliability of the method in a manufacturing context, and finally (d) the typology of criteria that can be considered by the specific method. For the sake of conciseness, Table 1 only shows the final ranking of the survey. The overall rating scale ranged from 0 to 25. The most suitable method for FBC is TOPSIS, the theory of which is detailed in section 3.

RANK	METHOD	SCORE
1	TOPSIS	21.34
2	VIKOR	20.90
3	PROMETHEE	19.71
4	AHP	18.65
5	DEA	15.98
6	SMART	15.95
7	Fuzzy	15.53
8	MAUT	14.11

Table 1: ranking of the methods proposed by the University of Parma to FBC.

3. Theory of TOPSIS

In this section, we describe the theory behind TOPSIS. TOPSIS is a method based on MCDM theory that ranks alternatives with respect to both the shortest distance to the positive ideal solution and the farthest distance from the negative one (Alrababah et al., 2017). In doing this, TOPSIS considers two solutions: the positive and negative *ideal* answers to the problem. The former contains all the best values of the criteria in the decision matrix, while the latter contains all the worst ones (Bai et al., 2014). Both are defined as ideal solutions, as they often are non-existing (i.e. they respectively collect all the best and worst values of each criterion). The basic quantities used in the TOPSIS calculations are listed in Table 2.

Quantity	Description
n	Alternatives quantity (low bound of the set)
$A_i\ (i = 1,2,\dots,n)$	Set of the n alternatives
m	Criteria quantity (low bound of the set)
$B_j\ (j = 1,2,\dots,m)$	Set of the m criteria
X_{nxm}	Matrix Alternatives-Criteria
$x_{ij} \in X_{nxm}$	Value of criterion j for the alternative i within the matrix Alternatives-Criteria
L	Scale for judgements
W	Scale for weights
R_{nxm}	Normalised decision matrix
$r_{ij} \in R_{nxm}$	Value of criterion j for the alternative i within the normalised decision matrix $$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n}\sqrt{x_{ij}^2}}$$
w_j	Weight for the criterion j
v_j	Normalised weight for the criterion j $$v_j = \frac{w_j}{\sum_{j=1}^{m} w_j}$$
D_{nxm}	Weighted-normalised decision matrix
$t_{ij} \in D_{nxm}$	Value of criterion j for the alternative i within the weighted-normalised decision matrix $$t_{ij} = v_j r_{ij}$$ $j = 1,2,\dots,m; \qquad i = 1,2,\dots,n;$
J^+	Set of the criteria which provide the positive ideal solution
J^-	Set of the criteria which provide the negative ideal solution
A^+	Set of the positive answer to the problem $$A^+ = \{t_1^+, t_2^+, \dots, t_m^+\} = \{(\max t_{ij}\ \lvert j \in J^+), (\min t_{ij}\ \lvert j \in J^-)\}$$
A^-	Set of the negative answer to the problem $$A^- = \{t_1^-, t_2^-, \dots, t_m^-\} = \{(\min t_{ij}\ \lvert j \in J^+), (\max t_{ij}\ \lvert j \in J^-)\}$$
s_i^+	Distance between each alternative criterion element t_{ij} and the element A_j^+ $$s_i^+ = \sqrt{\sum_{j=1}^{m}(t_{ij} - t_j^+)^2}$$
s_i^-	Distance between each alternative criterion element t_{ij} and the element A_j^- $$s_i^- = \sqrt{\sum_{j=1}^{m}(t_{ij} - t_j^-)^2}$$
c_i^+	Relative closeness to the positive ideal solution $$c_i^+ = \frac{s_i^-}{(s_i^+ + s_i^-)}$$

Table 2: list of symbols and calculation in TOPSIS.

3.1 Identification of the matrix alternatives-criteria X_{nxm}

We followed the original theoretical model of TOPSIS to identify the matrix Alternatives-Criteria (Hwang & Yoon, 1981; Yoon, 1987). This model involves (i) the identification of the n alternatives of interest to the problem A_i $(i = 1,2, \dots, n)$ and (ii) the selection of the m criteria identifying the features of the alternatives and their role in solving the problem C_j $(j = 1,2, \dots, m)$. The matrix Alternatives-Criteria X_{nxm} follows these two steps, and it contains the elements x_{ij}, defining how the i^{th} alternative satisfies the j^{th} criterion. Then, the decision-maker sets the scale of judgement L for the performance of each alternative relating to each criterion. Usually, this is a scale ranging from 1 to 9.

3.2 The normalised decision matrix R_{nxm} and the weighted-normalised decision matrix D_{nxm}

As a rule, the criteria are not commensurable: TOPSIS requires the normalisation of the judgements of matrix X_{nxm} expressed by the L scale, to define how each alternative i satisfies each criterion j in a commensurable way. This computation makes use of the normalisation vector expressed in equation 2 and provides the elements r_{ij} of the normalised decision matrix R_{nxm}.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} \sqrt{x_{ij}^{2}}} \tag{2}$$

The next computational step requires allocating weights to express the relevance of each criterion in the MCDM problem definition; hence the decision-maker sets a scale of weights W, usually the same as the L scale. Also, the weights need to be normalised to solve the calculation problem, which relates to different types of measures in the decision-matrix. The linear normalisation of weights provides the normalised weights in equation 3. Equation 4, obtained by multiplying the normalised elements r_{ij} of the normalised decision matrix R_{nxm} and the normalised weights v_j, expresses the elements t_{ij} of the final weighted-normalised decision matrix D_{nxm}, reported in Table 3.

$$v_j = \frac{w_j}{\sum_{j=1}^{m} w_j} \tag{3}$$

$$t_{ij} = v_j r_{ij} \qquad j = 1,2, \dots, m; \quad i = 1,2, \dots, n. \tag{4}$$

3.3 The positive ideal solution and the negative ideal solution

In this phase, TOPSIS computes the positive and negative ideal answers to the problem, A^{+} and A^{-} respectively, to further compare each alternative to them.

CRITERIA						
c_1	$\dots$	c_j	$\dots$	c_m	D_{nxm}	**ALTERNATIVES**
t_{11}	$\dots$	t_{1j}	$\dots$	t_{1m}	a_1	
					$\dots$	
t_{i1}	$\dots$	t_{ij}	$\dots$	t_{im}	a_i	
					$\dots$	
t_{n1}	$\dots$	t_{nj}	$\dots$	t_{nm}	a_n	

Table 3: the weighted-normalised decision matrix D_{nxm}.

To compute the two ideal answers, TOPSIS differentiates the criteria according to their impact on the assessments of the alternatives. It identifies the two sets J^+ and J^-; the former contains only the s criteria positively characterising the alternatives, while the latter contains only the $m - s$ criteria characterising them negatively. Thus, the positive ideal solution (PIS) and the negative ideal solution (NIS) are identified through the two sets J^+ and J^-. The PIS contains only the values corresponding to the criteria that belong to the set J^+, i.e. those criteria that positively characterise the alternative. On the contrary, the NIS contains only values that negatively characterise the alternative and belong to the set J^-. The values of both J^+ and J^- are calculated as per equation 4 and belong to the weighted-decision matrix D_{nxm}. The optimum is a compromise solution between the PIS and the NIS. To compute this solution, once the vectors $J^{\pm}$ are defined, TOPSIS computes the positive ideal answer A^+ and the negative ideal answer A^- to the problem using equations 5 and 6.

$$A^+ = \{t_1^+, t_2^+, \dots, t_m^+\} = \{(\max t_{ij} \mid j \in J^+), (\min t_{ij} \mid j \in J^-)\} \tag{5}$$

$$A^- = \{t_1^-, t_2^-, \dots, t_m^-\} = \{(\min t_{ij} \mid j \in J^+), (\max t_{ij} \mid j \in J^-)\} \tag{6}$$

Thus, it is possible to compare alternative i to the positive and negative ideal answers and then to express a judgement to its relative closeness to the positive ideal solution c_i^+, as described in the next section 3.4.

3.4 The final rank

To define the ranking of the alternatives, TOPSIS firstly computes the distance s_i^+ between each alternative criterion t_{ij} and A_j^+, expressed by the index $t_j{}^+$. Similarly, it calculates the distance s_i^- between t_{ij} and A_j^-, namely the index t_j^-. The further step is the calculation of the distance between the index t_{ij} and the corresponding index $t_j{}^+$ of the vector of the positive ideal answer A^+, by using the Euclidean distance as in equation 7. The same applies to the distance to the index t_j^- of the negative ideal answer A^-, as indicated in equation 8.

$$s_i^+ = \sqrt{\sum_{j=1}^{m} \left(t_{ij} - t_j^+\right)^2}, \qquad i = 1, \dots, n \tag{7}$$

$$s_i^- = \sqrt{\sum_{j=1}^{m} \left(t_{ij} - t_j^-\right)^2}, \qquad i = 1, \dots, n \tag{8}$$

Whit these distances, it is possible to compute the relative closeness to the positive ideal solution c_i^+ of each alternative i, which is calculated as in equation 9.

$$c_i^+ = \frac{s_i^-}{(s_i^+ + s_i^-)} \tag{9}$$

Once the relative closeness to the positive ideal solution c_i^+ is computed for each alternative i, the alternatives can be ranked in descending order. The best-in-class solution, which as mentioned is a compromise solution between PIS and NIS, is ranked first.

4. TOPSIS application to the manufacturing technology selection

In this section we, describe how to use TOPSIS in the technology selection problem by distinguishing two main analysis. The first refers to the general technology selection problem, where the manufacturing technologies were derived from technical literature. The second refers to the design of the specific application of TOPSIS to our case study, i.e. the identification of values and weights to populate the TOPSIS matrixes and scales. Main sources of information for these analyses have been (i) the industry know-how gathered by the company sponsor of the study and (ii) workshops and visits to subcontractors and vendors. These analyses result in the definition of the alternatives suitable for manufacturing the product and the criteria of interest to the match between the same technologies and the product.

The reminder of the section is structured as follows. In section 4.1 we show how to apply TOPSIS to a technology selection problem in a manufacturing context, and then we describe the model we applied to the FBC case study. In section 4.2 we provide the technologies, whereas in section 4.3 we describe the part selected for our case study. In section 4.4 we provide the suitable criteria, which we labelled as 'drivers' in the part of the paper that concerns with the TOPSIS application. Finally, the application of the model is described in section 4.5. We introduce the symbols listed in Table 4, in addition to the standard TOPSIS items, to describe the specific application.

Quantity	Description
q	Number of products/parts of the selected product family
n^*	Total number of alternatives identified by the company for the technology selection problem
n	Number of n^* alternatives that are suitable to the specific product/part
tp_{ij}	Technology performance of the technology i relating to the driver j
ds_{hj}	Design specification of the part h relating to the driver j
X_{n*xm}	Full matrix Alternatives-Criteria
X_{nxm}	Simplified matrix Alternatives-Criteria
$x_{ij} \in R^2$	Two-element vector enabling comparison between the tp_{ij} and the ds_{hj}
$\bar{x}_{ij} \in R$	Single value obtained allocating the distance between the tp_{ij} and the ds_{hj} (through the L scale)

Table 4: list of symbols and calculation items in TOPSIS application to the manufacturing context.

4.1 Modelling TOPSIS for technology selection in manufacturing

As first stage of our framework, we set the matrix X_{nxm}. The alternatives are the n technologies under investigation, while the criteria are the m 'drivers' addressing the match between the performances of the technology and the product specifications. This criteria match introduces two preliminary steps for the definition of the matrix alternatives-criteria.

(1) The first step concerns the criteria and alternatives selection. In a manufacturing-technology selection, these criteria are the 'drivers' that describe both the characteristics of the parts belonging to the family identified and the performances of the technologies that can be used to produce them. The identification of the criteria is a consequence of the identification of the product family or, more generally, of the parts to be manufactured. However, the choice of the technologies to be considered for the study must be consistent with the product/part specifications. Issues triggering such a study may be the will to adopt (i) new technologies (e.g. AM), as well as (ii) new product/part specifications (e.g. new design), or (iii) new production requirements (e.g. the need of reducing costs, changing batch sizes, and so on). In any case, both the product family and the selected technologies contribute to define the drivers for the analysis. The framework to arrange the X_{nxm} matrix is reported in the flowchart in Figure 2, where this first phase is described in the two branches '*target*' and '*requirements*', which depart from the nodes of product reengineering and product family identification,

respectively. The dashed arrow from *technologies* to *drivers* means that the former contributes to define the latter in an indirect way. This step is described upstream of the '*benchmark*' box. The aim of the engineering/reengineering process identifies the alternative (the n^* technologies to be investigated), and the identification of the product family (q parts) along with the identified technologies settles the criteria (m drivers describing both technologies and parts).

(2) The second step concerns the identification of the element x_{ij} of the matrix alternatives-criteria X_{nxm}. Each of these elements is a vector made of two components, not necessarily numerical values, filled in by (i) the technology performance tp_{ij} of the i^{th} alternative, and (ii) the design specification ds_{hj} of the specific h^{th} part relating to the j^{th} driver (see Figure 2). Comparison of these two values results in disabling technologies that are not able to produce the part because of at least one mismatch - indeed one is already enough - between performances and specifications. The comparison is represented in the *benchmark* box in Figure 2. Thus, starting from n^* technologies, through pairwise comparison between the technology performance tp_{ij} and the design specification ds_{hj}, the number of alternatives may be reduced to $n < n^*$. This comparison in the flowchart is downstream of the decisional gate and concludes the first stage.

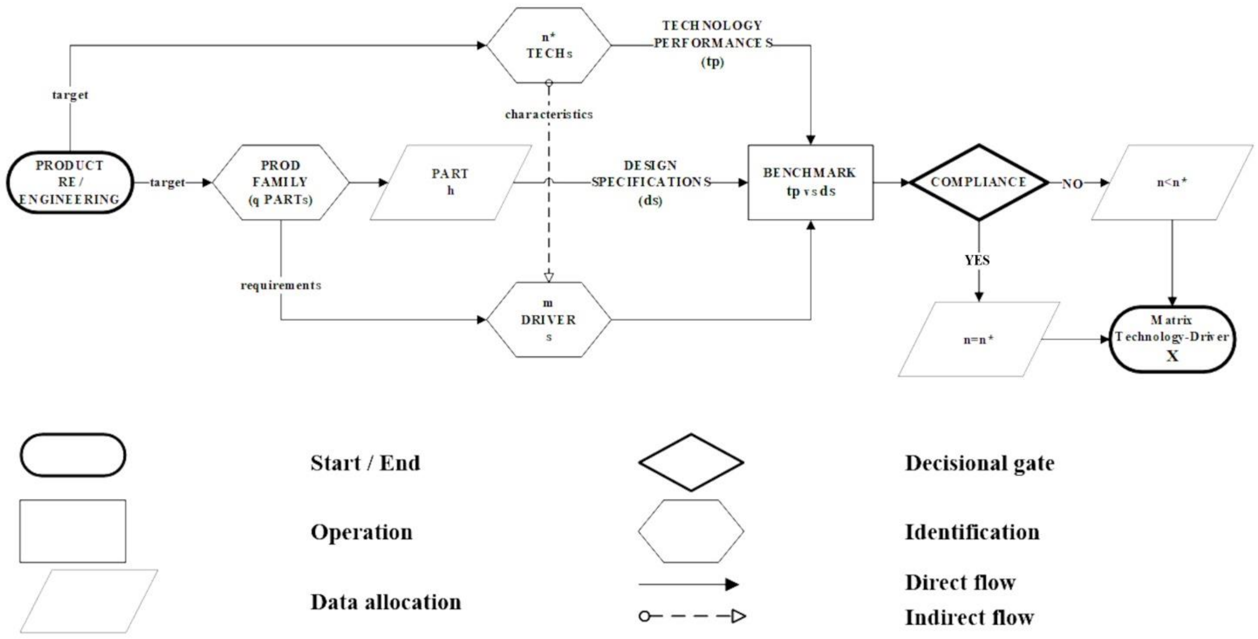


Figure 2: flowchart for the identification of the matrix alternatives-criteria in the technology selection problem.

Once the first stage is completed and the n alternatives out of the starting n^* ones are identified, the structure of the X_{nxm} matrix is defined, and the decision-maker must retrieve all data that are needed to fill its elements x_{ij} in. At the end of this step, each cell of the matrix describing every alternative is a vector of two quali-quantitative elements, and it needs to be pre-processed for TOPSIS calculation. The process for calculating the suitable single numerical value $\overline{x}_{ij}$ is depicted in Figure 3.

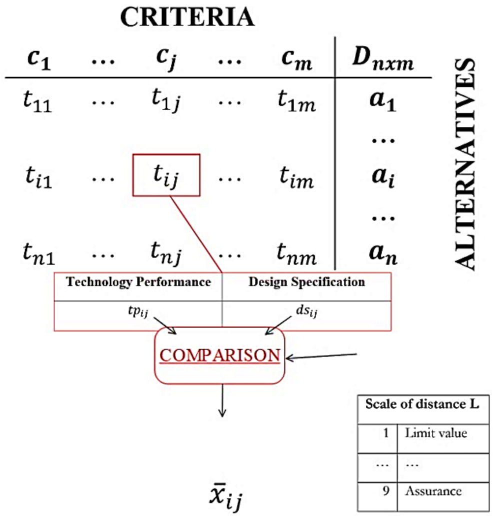


Figure 3: use of the scale of distances L to obtain a single value $\bar{x}_{ij}$.

The second stage of the framework involves the definition of a scale of judgments L, which is the scale of distances for comparing the two items tp_{ij} and ds_{ij}. We stress here that the comparison can only be done with enabled technologies. Thus, the maximum value of distance indicates the maximum probability that the technology will deliver a product that meets the requirements, while the minimum value of distance identifies the minimum probability that the technology will deliver a product that meets the requirements. At this moment, in fact, technologies whose performance cannot meet the specifications have already been excluded from the comparison, and thus the decision-maker will analyse performances of only those alternatives that are suitable. The distance between two values, specification and requirement, is the $\bar{x}_{ij}$ element of the simplified matrix Alternatives-Criteria X_{nxm}. For the sake of clarity, Table 5 recaps the framework described up to now.

Deliverable	Stage	Step	Process	OUPUT
Framework for defining the simplified-matrix Alternatives-Criteria X_{nxm}	Stage 1	Step 1	Identification of technologies and criteria	elements x_{ij} of the matrix X_{n*xm}
		Step 2	Comparison between design specification and technology performance	elements x_{ij} of the matrix X_{nxm}
	Stage 2	-	Definition of scale L to quantify alternatives consistently with TOPSIS	elements $\bar{x}_{ij}$ of the matrix X_{nxm}

Table 5: preliminary framework for solving the technology selection problem through TOPSIS

Next, we set the scale W, and equations 2 to 4 are calculated to obtain the weighted-normalised decision matrix (cf. Table 3). Another critical issue in the application of TOPSIS for the technology selection problem is the definition of two sets J^+ and J^- for the identification of the PIS and NIS. In the manufacturing context, two approaches are available to determine which drivers belong to J^+ and which belong to J^-: the former is oriented towards product quality, and the latter is oriented towards market protection. In the first approach, all the drivers that identify a high-level technological process belong to set J^+ and address the PIS in terms of assurance of a high-quality product. The set J^- addresses the NIS and it is defined complementarily to J^+. In the second approach, all the drivers that increase the final cost of the product belong to J^- and address the NIS in terms of potential loss of market shares. On the contrary, set J^+ is complementary to J^-. Once the strategy to be adopted has been defined, it is possible to compute A_i^+ and A_i^- by using equations 5 and 6, and to obtain the relative closeness to the positive ideal solution c_i^+ by applying equations 7 to 9.

4.2 The case study: product and technologies under investigation (the alternatives)

First, our case study starts with the selection of the product family to be analysed, in agreement with the cross-functional group at FBC. The choice fell upon a product characterised by high-quality requirements, relatively stringent rules to be followed for compliance with food and beverage regulations, and a high utilisation rate (i.e. many of those products are manufactured and assembled per year). We selected the filling-valves and their components, which belong to the filling machines. This product family was identified for two reasons. First, it is characterised by a wide variety of parts with high requirements (e.g. tolerances and roughness), and hence this analysis is an excellent exercise for verifying the suitability of technologies not yet known at FBC. Second, at the time of the analysis, the whole product was considered too expensive by the market, and the company aimed to reduce the production costs of the parts belonging to the family. After selecting the product family, we identified the technologies to be considered, clustering them by different technology processes (Table 6). These specific technologies were considered for the following goals: (i) investigating whether AM technologies could be used in FBC productions and (ii) achieving the best match between products and production processes. Thus, we identified the mechanical components that implement the fluid delivery mechanisms, both statics and driving. The product family and parts identification, together with the *technology scouting*, is illustrated in the flowchart reported in Figure 4.

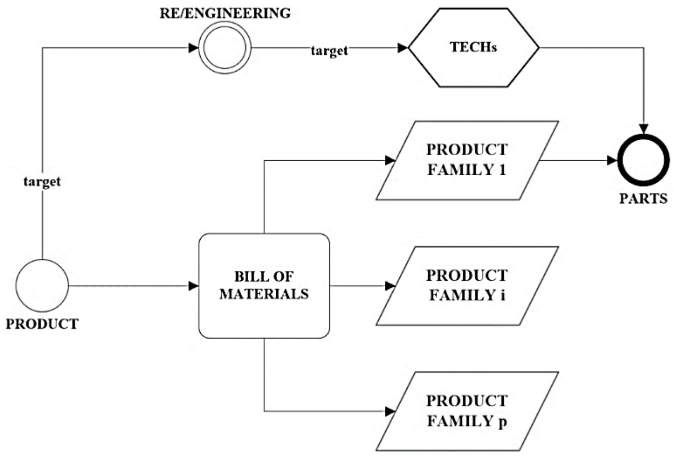


Figure 4: parts identification within the product family of the product

ID	MOULDING AND CASTING TECHs
t1	Sintering
t2	Lost wax casting
t3	Metal injection moulding
t4	Plastic injection moulding
t5	Hydroforming
t6	Cold metal moulding
t7	Forging

ID	CUTTING TECHs
t12	Laser cutting
t13	Chemical milling
t14	(Wire) electro discharge machining (WEDM)

ID	ADDITIVE MANUFACTURING
t8	Direct metal laser sintering for metal (DMLS)[3]
t9	Stereolithography for plastic (SLA)

ID	3D PRINTING
t10	Direct metal printing for metal[4]
t11	Multi-jet printing for plastic

Table 6: the technologies useful to the case study clustered in four categories depending on the process.

[3] Patented by Eos Gmbh
[4] Trademark of 3D-Systems

The technology scouting was carried out by the cross-functional team of the project, starting from the following considerations: (i) the high quality levels required by FBC standards, taking the norms and rules of the F&B sector into account, (ii) the industry inclination to accept the use of technologies differing from the subtractive ones, and (iii) the market inclination to accept material replacements (e.g. use of plastics instead of metals) and new processes, e.g. different from those traditionally used in the sector (e.g. technical specification of additive processes instead of those of chip removals).

4.3 The case study: the pilot part Dummy Bottle

The product family under investigation in the reengineering process was the filling valve of standard filling machines. The mechanical parts of this product, as per its bill of materials (BOM), have strict specifications regarding:

i. Material: stainless steel AISI 316L, not only for its mechanical characteristics (i.e. stresses and strains) but mostly for its compliance with food-contact-material regulations (e.g. EU and FDA rules).

ii. Design: although the redesign of parts is possible, constraints relating to assembly specifications (e.g. encumbrances, collisions and so on) and/or the mechanical performance of the parts themselves (e.g. stiffness, endurance and so on) must be considered.

For these reasons, replacement materials or manufacturing processes needed to fulfil both norms and technical aspects.

Although the technology replacement at FBC was carried out for all parts of the product family, in this article we only report on the pilot study of one of its parts: the '*dummy bottle*'. This part is a 5-mm-thick plate in the still-water fillers that plugs the filling valve nozzle during the appropriate phase of the operating cycle. As shown in Figure 5, it is a drop-shaped plate approximately 63 mm in width and 90 mm in length. The key issues concern the ISO H7 tolerance of the hole on the narrow side of the drop shape and the surface roughness level (i.e. Ra 1.2). We believe that this case study is particularly suitable, because it allows to apply on the field the TOPSIS operating logic in manufacturing technology selection, thus helping to understand how the general model might be applied in actual contexts. Indeed, the *dummy bottle* does not present significant limitations to the technologies, e.g. limitations on shapes, encumbrances, and materials to be used. This aspect was very important since the need to develop a wide range of possible solutions in the pilot phase allows a comprehensive and consistent TOPSIS application that can be systematically used in the whole company. In addition, FBC was open to consider minor changes to the product design to enhance its possibility to be manufactured with different technologies (e.g. small changes in product thickness and roughness level).

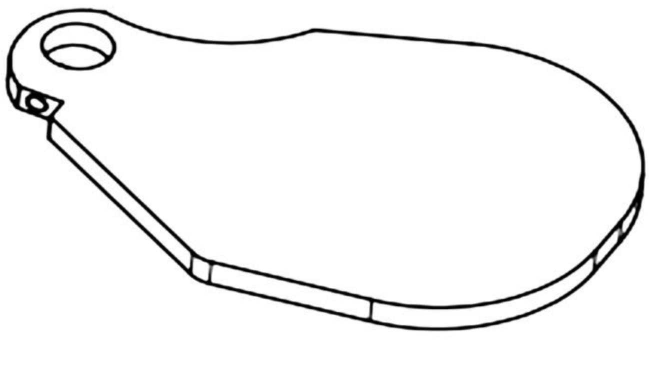


Figure 5: part identification within the product family of the product.

4.4 The case study: the allocated drivers (the criteria)

The drivers are allocated in accordance with the product family for which the technology selection is developed, i.e. the design specification of products provide preliminary criteria that must be respected when selecting the manufacturing technology. For instance, with respect to the components of the filling valve, we considered the following criteria for evaluating the technologies: (i) the desired roughness level, (ii) the thickness and the shape of the components of the final assembly, and (iii) the characteristic of the materials, with respect to both mechanical characteristics and food grade compliance. Another contribution to the definition of drivers comes from the technologies themselves. This contribution concerns (i) the machinability of the material, (ii) the encumbrance of raw materials feeding the process, and (iii) production management aspects, such as minimum order quantity, lead time, and production costs. As agreed with the management of FBC, we only focused on technological drivers, i.e. parameters to evaluate the potential of each technology, disregarding parameters linked to cost-effective performances, e.g. material and/or investment cost, direct cost breakdown and others. This choice was made for two reasons:

(1) The study started with the aim of investigating whether AM technologies meet the FBC production requirements.

(2) The technology selection was carried out to provide the best-in-class solution, based on which FBC decided which technology to use, also considering cost-effectiveness and accepting the danger of not choosing the optimal technology.

(3) Cost-effectiveness was still considered in the characterisation of the technologies when setting J^{+} and J^{-} sets, according to cost-related logics. In this case, the drivers that have a positive impact on the formulation of the product cost belong to J^{+}, while those that have a negative impact on the formulation of the product cost belong to J^{-}.

The allocated drivers are listed in Table 7.

ID	DRIVER
d1	Roughness level
d2	Tolerances
d3	Lead time for prototype
d4	Lead time for typical batch
d5	Dimension limits
d6	Weight boundaries
d7	Thicknesses
d8	Geometry specifications
d9	Other specifications
d10	Yield strength
d11	Tensile strength
d12	Young modulus for traction
d13	Density
d14	Smart shapes to be processed

Table 7: drivers allocated for the case study.

Drivers d1 and d2 refer to the lower limits of the tolerances and roughness required to process the specific product or part. Drivers d3 and d4 are related to lead times, both for prototyping and production. Drivers d5–d9 refer to the technological constraints of the process and, more specifically, consider both the upper and the lower limits (e.g. drivers d5 and d7) or just the lower limit (driver d6). Driver d8 considers process constraints related to geometry (i.e. holes, undercuts, sharp edges, and so on), while driver d9 considers process specifications and limits of applicability to the product family (e.g.

alteration of mechanical properties, ensuring surface flatness, possibility of cracking inside the material structure). It is a '*dynamic driver*', that is, a non-structured field in which to report (i) attributes that limit the technology or that strictly characterise the product and (ii) aspects that may change among different technologies. Drivers d10–d13 refer to data declared by suppliers or gathered from technical literature. Finally, d14 refers to the kind of shape that can be processed efficiently and effectively using the given technology.

The performances of every technology with respect to the drivers were obtained from (i) technical literature, (ii) company know-how, and (iii) information gathered from suppliers of the given technology or machines vendors.

4.5 The case study: TOPSIS decision support system for dummy bottle reengineering at FBC

According to Figure 2, the technology selection problem in FBC is a decision-making problem related to finding the best match between the selected $\overline{p}_h$ product dummy bottle and the $\overline{t}_i$ technology amongst $n^* = 14$ alternatives, driven by the $m = 14$ criteria / drivers. According to the theory of the method, TOPSIS was firstly used to define the simplified weighted-normalised decision matrix D_{nxm}, and then to rank the alternatives with respect to the positive ideal answer A^+. This approach consists of three phases:

(1) starting from the matrix Alternatives-Criteria X_{n^*xm}, a quali-quantitative comparison between technology performance and design specifications enables further analysis of the technologies, hence defining the simplified matrix X_{nxm}. This phase is described in section 4.5.1.

(2) Afterwards, we defined the scales and sets J^+ and J^-, as it is reported in section 4.5.2.

(3) Finally, we calculated the weighted decision matrix D_{nxm}, making use of the scales and sets produced in phase 2. This phase is presented in the section 5 devoted to the results of the study, where the final ranking of the alternatives is also computed and provided.

4.5.1 Phase 1: comparison between technology performance and design specifications

The targeted product family is the filling valve, in both version for flat and carbonated beverages. The product family was analysed by means of the bills of materials of different products, and it consists of a number of parts that will not be listed in detail and to which we refer as q for confidentiality reasons (cf. Figure 2). There are $n^* = 14$ technologies available to manufacture this product family, all that listed in Table 6. Furthermore, the product family enabled the selection of $m = 14$ technological drivers concurrently describing the performances of the $n^* = 14$ technologies and the specifications of the p_q parts (whose h^{th} is the *Dummy Bottle*). Drivers are those listed in Table 7. Each element x_{ij} of the matrix $X_{n^*xm} = X_{14x14}$ (we note that it is just a coincidence that the matrix is squared) is filled by a pairwise comparison between the performance of the i^{th} technology and the specification of the h^{th} part of the family with respect of the j^{th} criterion (see Figure 3). The comparison between the performance and specifications of this part significantly reduces the number of technologies by removing all the technologies whose process cannot satisfy the design of the specific part itself. At the end of the pairwise comparison for the *dummy bottle*, only three technologies remain out of the 14 originally considered. Hence, the simplified matrix Alternatives-Criteria is the matrix $X_{nxm} = X_{3x14}$. Three technologies enabled by the comparisons are listed in alphabetical order below.

(1) Cold metal moulding (shearing)

(2) Laser cutting

(3) WEDM

4.5.2 Phase 2: defining scales of judgement and ideal solutions' sets

First, the scale of judgement on the 14 pairwise comparisons is set: judgement is based on the distance between the performance of the technology and the required specification benchmark based on the part design. It is important to consider mandatory features of the *dummy bottle* part as well as its whole manufacturing process, paying attention to the reworks that follow the manufacturing of the raw part, which are allowed but must be kept as few as possible. We also report the scale of the weights of the drivers in the decision-making process. The scales are set so they avoid a simplistic assessment. The scales and the meaning of each value are listed in Table 8. The scales of distances are consistent with TOPSIS: the greater the distance between ds_{ij} and tp_{ij}, the more the technology i guarantees a better compliance with the product specification relating to the driver i. The weight scale, as can be easily deduced, attributes an increasing weight to the increasing importance of the specification of the driver. For instance, since the part needs to comply with food grade norms and standards, the weight for the driver d9 – Other specifications (e.g. law regulations) is $w = 9$, i.e. 'Mandatory'. More in general, all drivers concerning the part geometry (e.g. roughness level, tolerances, geometry specifications) are characterised by low-medium weights (i.e. 1 – 6) since the part is reworked within FBC, whereas drivers concerning cinematics aspects (e.g. mechanical properties) are characterised by high weights (i.e. 7-9). The same applies to the lead time drivers, since FBC works towards just in time strategy.

SCALE OF DISTANCES L

value	description
1	Limit value
2	Very close
3	Close
4	Relatively close
5	Average distance
6	Relatively harmless
7	Security
8	Very harmless
9	Assurance

SCALE OF WEIGHT W

value	description
1	Irrelevant
2	Very unimportant
3	Unimportant
4	Relatively unimportant
5	Average Importance
6	Relatively important
7	Important
8	Very important
9	Mandatory

Table 8: standard scales for weight and distance judgement.

As an example, Figure 6 reports a pairwise comparison between technology performance and design specification for the drivers $d1$ *roughness level* and $d9$ *other specification*, by analysing the alternative $t6$ *cold metal moulding*, $t1$ *sintering,* and $t4$ *plastic injection moulding*. Furthermore, the figure shows how weights w_d and distances d_t are assigned once the comparison provides positive results, namely each technology performance tp satisfies the design specification ds of the product for all the drivers. We report some considerations concerning this process in the following bullet points:

- The driver *other specification* is dynamic, and its values change among different technologies. Here, 'fg' means 'food grade material', while 'pl' means 'mandatory planarity'. Since the value of this driver is mostly qualitative and it imposes a restrictive limit on technology performance, it tends to receive the maximum weight (e.g. for cold metal moulding in the example) because once it is satisfied, it enables the specific technology.
- One single mismatch between specifications and performance is enough to disable a technology (i.e. plastic injection moulding).

- An increasing distance between ds and tp indicates a better performance of the technology, such as cold metal moulding in Figure 6 (cf. section 4.1).

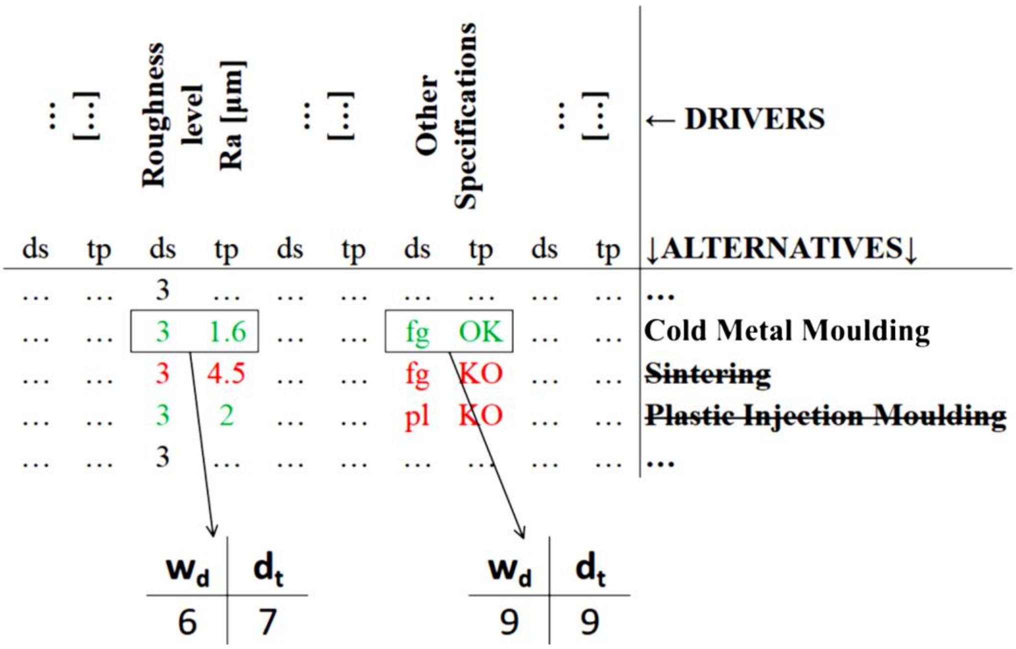


Figure 6: pairwise comparison between technology and design to enable/disable a specific technology for the analysis.

Also, weights and distances are combined to define the weighted-normalised decision matrix D_{3x14} of the problem. The results of calculations are provided in Table 9. As a last step of this phase, the J^+ and J^- sets are defined.

(d_1) Roughness level	(d_2) Tolerances	(d_3) LT for prototype	(d_4) LT for typical batch	(d_5) Dimension limits	(d_6) Weight boundaries	(d_7) Thicknesses	(d_8) Geometry specifications	(d_9) Other specifications	(d_{10}) Yeld strenght	(d_{11}) Tensile strenght	(d_{12}) Young Modulus for	(d_{13}) Density	(d_{14}) Density	D_{3x14}
0.009	0.024	0.037	0.018	0.033	0.034	0.007	0.049	0.075	0.037	0.061	0.053	0.035	0.006	**(t_1) Cold metal moulding**
0.005	0.030	0.037	0.018	0.075	0.060	0.021	0.033	0.037	0.037	0.061	0.053	0.035	0.006	**(t_2) Laser cutting**
0.001	0.048	0.075	0.088	0.042	0.060	0.057	0.016	0.037	0.075	0.031	0.053	0.035	0.006	**(t_3) Wire-cut EDM**

Table 9: weighted-normalised decision matrix D_{3x14} resulting from the TOPSIS-based design for the technology selection problem.

The J^+ set, which ideally defines the PIS, includes drivers having a positive impact on costs (i.e. cost savings). For example, if the shape of the part is compliant with shapes that are typically manufactured by the specific technology (e.g. moulding technologies avoid undercuts and prefer geometries without holes), this is likely to have a positive impact on the purchase cost of the part by the supplier, namely it addresses lower mould cost, and less controlled and therefore more cost-effective process. Conversely, the J^- set, which ideally defines the NIS, includes drivers that have a negative impact on costs. If the technology has a high-tech level or if its process is not yet well-established for specific applications (i.e. AM techs), it is likely to have a negative impact on the purchase cost. For these reasons, the sets are the following:

$$J^+ = \{d_5, d_6, d_8, d_9, d_{14}\} \quad \text{(R1)}$$

$$J^- = \{d_1, d_2, d_3, d_4, d_7, d_{10}, d_{11}, d_{12}, d_{13}\} \quad \text{(R2)}$$

This approach has been selected because, when making decisions, company management must deal with the market response, which is ultimately driven by product price. The product includes the costs and mark-up, hence cost-effectiveness considerations cannot be overlooked. Drivers $d_1 \div d_4$ as well as $d_{10} \div d_{13}$ negatively affect the final cost of the product because the higher their performances, the higher the product cost. Similarly, driver d_7 requires a high-controlled process to be satisfied at the bottom level, whereas it requires a high-consumption process, in terms of energy and materials, at the top level. Meanwhile, the match between specifications and requirements toward drivers d_9 and d_{14} clearly has a positive impact on the costs because these represent how the product fits into the technology—although this is also true for drivers d_5, d_6, and d_8. Once J^+ and J^- are defined, it is possible to calculate the positive and negative ideal answers $A^{\pm}$, according to equations 5 and 6.

5. Results and discussions

The positive and negative ideal answers A^+ and A^- in the *dummy bottle* case study, which we will refer to as 'simulation' because it entails some mathematics and it depends on the specific scenario, are two vectors $A \in R^{14}$, whose calculations are expressed in Table 10. To make it more readable, the two vectors are proposed in a A_{2X14} matrix, where the first line contains the vector A^+, and the second contains the vector A^-.

A_{2x14}	$a_1^{\pm}$	$a_2^{\pm}$	$a_3^{\pm}$	$a_4^{\pm}$	$a_5^{\pm}$	$a_6^{\pm}$	$a_7^{\pm}$	$a_8^{\pm}$	$a_9^{\pm}$	$a_{10}^{\pm}$	$a_{11}^{\pm}$	$a_{12}^{\pm}$	$a_{13}^{\pm}$	$a_{14}^{\pm}$
A^+	0.001	0.024	0.038	0.018	0.075	0.060	0.007	0.049	0.075	0.038	0.031	0.053	0.035	0.006
A^-	0.009	0.048	0.075	0.088	0.033	0.034	0.057	0.016	0.038	0.075	0.061	0.053	0.035	0.006

Table 10: The matrix containing both the positive and negative ideal solutions.

Hence, Euclidean distances from positive and negative ideal answers are calculated by equations 7 and 8, respectively, as computed in section 3.4. Finally, the relative closeness to the positive ideal solution c_i^+ for each alternative $i = (1,2,3)$ is calculated as computed in equation 9. Table 11 shows (a) the Euclidean distances and (b) the relative closeness of each alternative, sorted in decreasing order.

Distances s_i^+ and s_i^- from the best and worst condition		
Distance s_i^+	TECHNOLOGIES	Distance s_i^-
0.11550	Cold metal moulding	0.05873
0.11014	Laser cutting	0.05352
0.04231	WEDM	0.12019

(a)

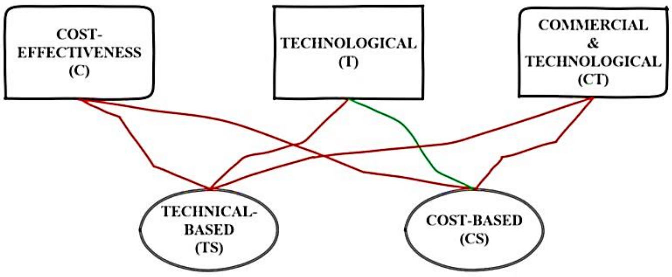
Rank	ID	TECHNOLOGIES	c_i^+
1	(2)	Laser Cutting	0.673
2	(1)	Cold Metal Moulding	0.633
3	(3)	WEDM	0.260

(b)

Table 11: (a) Euclidean distance for each alternative $\boldsymbol{i = (1, 2, 3)}$, $\boldsymbol{s_i^+}$ from the best condition and $\boldsymbol{s_i^-}$ from the worst one, (b) ranking of relative closeness to ideal solution $\boldsymbol{c_i^+}$, $\boldsymbol{i = (1, 2, 3)}$.

The result proves that all solutions are compromises because they are included between the negative ideal solution ($NIS = c^- = 0$) and the positive ideal solution ($PIS = c^+ = 1$). However, the final ranking indicates that the best solution to the specific problem is *laser cutting*, even though similar performance can be obtained from *cold metal moulding*. Meanwhile, the difference between those technologies and *wire-electro discharge machining* is significant.

In the following we propose some insights of the study. First of all, the most time-consuming stage of the simulation has been the one devoted to gather the large amount of quantitative and qualitative data on the product and the technologies, enabling the data analytics to provide clear and easy-to-read numerical information. Thus, the decision-making process has proved to be convenient, with the simple need, within the simulation, to update the technology list and the performance of the technologies, especially by adding data that will become available and/or relevant in the future, and integrate further drivers (e.g. cost-effectiveness drivers). Second, the allocation of drivers limits the simulation in two ways, because it is very specific. The first limitation concerns the driver category, which is technology-based, whereas the second concerns the setting of the J^+ and J^- sets, which are defined with respect to cost-effectiveness. Due to these two issues, the simulation is defined in a hybrid way, since it solves a technology problem through cost-effective considerations. The simulation was designed, in fact, to achieve a double result: (i) to prove which technologies were able to manufacture FBC parts and products, and (ii) which of these was the best compromise in terms of the cost–quality trade-off. It is worth noting that the limitations of the simulation relate to how it is set rather than to the general model of TOPSIS, which means that it is possible to add cost-effectiveness drivers and/or to reconsider how to arrange drivers within the two sets J^+ and J^-. Thus, it is conceivable that simulations differing from the proposed one could be developed. The number of these applications is obtained by combinatorics rules of possible options for driver categories and $J^{\pm}$ sets. This issue is a simple combination without repletion of five elements. Three are related to categories of drivers: cost-effectiveness drivers (C), technological drivers (T), and cost-effectiveness and technological drivers (C&T). The other two are related to $J^{\pm}$ sets: technical-based sets (TS) and cost-effectiveness-based sets (CS). In our opinion, a combination of TS and CS sets induces confusion, and thus it will not simplify the decision-making process. Thus, there are six possibilities (i.e. twelve pairwise combinations, each one duplicated), as showed in Figure 7. The green link indicates the developed application in FBC, while the links in red are the possible future simulations.



I/O	C-DRIVERS	T-DRIVERS	C&T-DRIVERS
TS	O	O	O
CS	O	I	O

Figure 7: Simple combination without repletion of driver-allocation options C, T, and C&T, and definition rules for $J^{\pm}$ sets.

Finally, in the proposed case study the performance of the technology is eventually analysed in terms of part and final product costs. Once the cost-effectiveness drivers are defined, it is possible to use the model in different simulations, each with its own specific goals, because (i) the model is structured, (ii) it is usable regardless of the specific application, (iii) it allows a decision-making process that is mathematics-based, and (iv) it is simple to improve by revising values and/or integrating further parameters (e.g. adding new technologies and drivers, revising judgement and distance scales depending on a further specific goal, or both concurrently). The suitability of the model we proposed and its support in making the technology selection process quicker and reproducible is also proved by the convergence of the final results of the TOPSIS-based simulation with those of a concurrent semi-structured analysis performed by FBC. Furthermore, the TOPSIS-based analysis we proposed allowed the development of robust company knowledge on the characteristics of the technologies taken into account.

6. Conclusion and future works

A general risk of manufacturing companies it to fail to understand the full potential of production technologies due to the lack of decision-making tools and knowledge. This is particularly true for advanced technologies, such as additive manufacturing, which might have completely different characteristics compared to conventional technologies. To reduce this risk, this paper provided a TOPSIS-based MCDM approach to solve the technology selection problem of advanced manufacturing technologies and product design. In particular, the TOPSIS method was selected for its ease of use, robustness and reliability, even if this method has been somehow overlooked in recent research. The model we propose combines a framework to identify the alternatives and the criteria to be considered, and the very TOPSIS method to compute values and support decision. We believe that such a model is suitable for technology selection because, in addition to its ease of use, it is reproducible and it can be used with minimum effort once the database of technology performances and the calculation tool are set. This aspect is very important for companies that have limited resources, as well as when their effort to gather information is worth the best possible solution. Also, the reliability of the approach we propose has been proven on the field with a practical application in a manufacturing case study, namely the FBC company, which still uses the model we designed for the technology selection in procurement.

Despite all the considerations reported above, the effectiveness of our model beyond the FBC application, complex as it is, requires further investigation. A first limitation of our study is that the framework to define alternatives and criteria, that is technologies and drivers, relies on knowledge and experience of the cross-functional team (i.e. FBC and university staff). Even if several norms or standards have been provided to confirm that a product, service, or system meets its specifications and fulfils its intended purpose (e.g. ISO 9000 and VVDI 2206), no comprehensive model addressing the technology selection problem exists to our knowledge. Thus, the overall goal to define a general framework for technology selection of manufacturing companies has only been partly achieved by this study.

Also, the applicability of our model could be tested in different environments. Once released from the company specificity, it would be interesting to apply our model to a few different (families of) products of some companies operating in different environments. These companies could differ in (i) the industry (e.g. sector, production system, size of enterprise), which affects how the alternatives should be considered; and (ii) the product (e.g. a part or a final assembly), which affects the allocation of the drivers and the identification of the technologies (i.e. how to compare the design specification and the technology performance).

Furthermore, our model addresses the identification of the technologies downstream of the product selection. It could also be interesting to use ‘reverse modelling’ to define a framework that starts from the technologies and further addresses the design specifications of the product. This would be useful in engineer-to-order environments and in the product design phase, regardless of the production approach (e.g. make to stock or make to order).

In addition to these technical considerations, another interesting development of our research would be providing it with a broader economic analysis. Although we have demonstrated that our model is suitable for technology selection and allows companies to make effective decision-making, we did not consider mark-up on the technology optimum. Indeed, we considered economic aspects in our study when defining PIS and NIS proximity, and we introduced a concurrent cost-out analysis, to judge the technology on the basis of the final product cost. Both those approaches, however, present some limitations. The former is a simplified approach to a broad problem, and the latter is a non-structured analysis, lacking repeatability and objectiveness. To achieve synergetic effect from both technology and economics validation, criteria (i.e.

the drivers of our analysis) need to consider both technological and economic aspects, as well as to link the one to the other, when defining the PIS and NIS. An example could be the use of optimisation algorithms to define the loss function that leads the driver selection towards the PIS and NIS.

Finally, we applied TOPSIS based on the results of the survey at FBC. However, this result was affected by FBC's attitudes regarding the MCDM methods, and by university considerations that narrowed the focus to engineering methods. This means that two different scenarios arise. The former involves a structured analysis of the MCDM methods to assess which is the best one for manufacturing contexts and to further redesign the technology selection model according to the characteristics of the specific MCDM method. However, such a problem introduces the issue of how to make the decision about the MCDM methods, which can be itself solved as a real multi-criteria decision problem. The latter scenario suggests considering just the manufacturing-oriented methods similar to TOPSIS and thus using the problem-definition to set the matrix Alternatives-Criteria, hence developing the calculations consistently with the theory of the method identified in lieu of TOPSIS. Such a framework could fit with method similar to the pure TOPSIS (Hwang & Yoon, 2012), such as (i) fuzzy TOPSIS, which includes the subjective opinion of the end-user in addition to the subjective opinion of the decision-maker (T.-C. Wang & Lee, 2009), and (ii) VIKOR, which is very similar to the pure TOPSIS (Alrababah et al., 2017).

Once (i) the framework to identify technologies and drivers is generally standardised, (ii) the criteria entail both technology and economics aspects, and (iii) the most compliant MCDM method has been identified, the model proposed would gain universality, and it could be applied regardless of the company size, industry and technology evolution. Indeed, the author are already at work on some of these topics for future research work.

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