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Comparison of multi-criteria decision-analysis methods for selecting carbon dioxide utilization products

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ABSTRACT

The paper presents several multi-criteria decision-analysis methods for the purpose of assessing carbon dioxide utilization pathways, to identify and select the most relevant processes to convert captured CO_2 from industrial gas streams into compounds of interest. This paper explores and illustrates the application of decision-analysis approaches, their associated outcomes and how these both differ and complement each other. It includes non-compensatory methods (LexiMin and LexiMax), aggregation-based methods (Weighted Sum Model and Analytic Hierarchy Process), and the elimination and choice expressing the reality approach. Nine indicators grouped into three performance criteria, involving engineering, economic, and environmental aspects, are considered to assess ten alternatives and help to identify the preference relation among them. The rankings and their tolerance to change in criterion and indicator weights are compared amongst the selected methods, highlighting the fact that some indicators are more sensitive than the others. Even though the results obtained by the aggregation methods are more decisive, the outranking method proposes more qualified conclusions, where the techno-economic and environmental aspects are complementary but not interchangeable. Low degree compensatory methods might be advised in the specific field of CO_2 utilization, as well as in the wider issue of environmental decision-making. Also, this paper discusses the limitations of the proposed methods, while providing insights and some recommendations for applications of these approaches in similar contexts. Overall, the results show that methanol, methane, and dimethyl carbonate are CO_2-based products that are the most promising to be implemented in very near future with respect to engineering, economic, and environmental performances.

1. Introduction

Global energy-related CO_2 emissions reached an historic value of 37 Gt (International Energy Agency IEA, 2019). In 2018, the Intergovernmental Panel on Climate Change (IPCC) released a report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways (Masson-Delmotte et al., 2018). Limiting global warming to 1.5 °C would require rapid, far-reaching and unprecedented changes in all aspects of society. Anthropic CO_2 is emitted by a large variety of sources, including large stationary sources and industrial facilities such as power plants, steel plants or cement plants, small-to-medium sources, such as industrial and commercial buildings, as well as smaller sources such as transportation (Muradov, 2014). In this context, Carbon Capture Utilization and Storage (CCUS) was acknowledged in almost every pathway IPCC authors used to reach the 1.5 °C (Rogelj et al., 2018). It was especially highlighted for its ability to defossilize the industrial sector, especially those with high process emissions, such as cement where the main part of CO_2 emissions comes from the decarbonation of limestone (Farfan et al., 2019). Kätelhön et al. (2019) also showed that CCUS has the technical potential to decouple chemical production from fossil resources, reducing annual greenhouse gasses emissions by up to 3.5 $GtCO_2$-eq in 2030, though it would require huge amount of low-carbon electricity.

CCUS has therefore gained significant attention from governments, the energy industry, and other important players such as the International Energy Agency (Bruhn et al., 2016). Norhasyima and Mahlia (2018) recently proposed a patent landscape review on CO_2 utilization technologies published between year 1980–2017, where more than 3000 number of patents were

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methodologically identified worldwide, including enhanced oil recovery (EOR), enhanced coal-bed methane (ECBM), and enhanced geothermal system (EGS), chemical and fuel, mineral carbonation, and biological algae cultivation. Tcvetkov et al. (2019) reviewed how CO_2 has a changing role in the transition to a circular economy, and concluded that the development of CCUS technologies will invariably lead to a change in attitudes towards CO_2, as well as the appearance of new CO_2-based markets and industries. Castillo-Castillo and Angelis-Dimakis (2019) analyzed also all European policies relevant to the development of CO_2 utilization, and outlined potential benefits of policies to foster the production and uptake of several CO_2-derived products, such as methanol, polyurethane and aggregates.

Following the capture and transport process, CO_2 can be disposed of in natural sites such as deep geological sequestration (Anwar et al., 2018; Tapia et al., 2018). CO_2 utilization is considered as a valuable complement to storage (Aldaco et al., 2019). Its potential contribution to avoid CO_2 emissions in the short term has been evaluated to 207 $MtCO_2$ per year in 2016 and is expected to reach about 332 $MtCO_2$ per year in 2030 (Aresta, 2010). Its aim to both reducing carbon dioxide emissions directly by converting CO_2 into chemicals or fuels, and reducing the dependence of fossil resource use has motivated a number of analyses. However, very few chemical processes utilizing CO_2 as feedstock are currently of industrial relevance, except for the production of urea and salicylic acid. With the emergence of a multitude of promising conversion pathways based on various chemical reactions (Alper and Yuksel Orhan, 2017; Rafiee et al., 2018), the challenge is to identify the most advanced CO_2-based technologies for short- to mid-term deployment in industries. The decision to implement such emerging technologies should be supported by multiple dimensions or criteria and involve techno-economic parameters, additionally to environmental perspectives to lower the risk of generating new CO_2 emission sources. Given that, multi-criteria approaches imply rational decision-making where there are alternative choices to be considered, that best fits with goals, objectives, values, and preferences of the decision maker to evaluate the trade-offs, in a transparent and consistent way (Cinelli et al., 2020).

Up to now, only few studies focused on a global methodology involving several criteria to assess carbon capture and utilization (CCU) options, mainly based on a simple scoring system, where scores of all criteria are summed up. Thybaud and Lebain (2010) performed a cross-sectional analysis for the French Environment and Energy Management Agency (ADEME), reviewing the different pathways of CO_2 recycling and identified the main development opportunities in France. This work was extended in 2014 by ENEA Consulting and included a preliminary assessment of the performances, advantages and drawbacks, as well as a brief analysis of the markets for several CO_2-derived compounds, including methanol, formic acid and calcium carbonates (ADEME, 2014). The Global CCS Institute (2011) investigated how CO_2 utilization would accelerate the deployment of CCU, based on a set of criteria comprising the maturity of the technology, the potential for scale-up, the value for money, the CO_2 abatement potential, as well as the environmental and social benefits. Similarly, Ampelli et al. (2015) proposed an overview of options to valorize CO_2, based on the potential developments, the economic perspectives, the external use of energy, the potential volume of use of CO_2, the time of sequestration, and other environmental impacts. An initial assessment evaluating one-hundred twenty-three reactions from the literature was also carried out by Otto et al. (2015). The reactions, representing useful CO_2 utilization options, were assessed using a scoring system to rank them. Tapia et al. (2017) proposed an approach to screen CO_2 utilization options using a hybrid Analytic Hierarchy Process- Data Envelopment Analysis method. The selection was based on attributed scores coming from a combination of quantitative data and expert judgments on qualitative criteria. They presented two case studies to illustrate their framework, involving mainly enhanced oil recovery, enhanced coal bed methane and enhanced gas recovery from shale gas as CCU options. Patricio et al. (2017) also proposed an analytical tool to facilitate the identification of potential CCU industrial symbiosis, based on the development of generic matrices for CO_2 sources and receivers. More recently, Chauvy et al. (2019) proposed a framework to select the most relevant emerging options to be implemented short- to mid-term, which included technical, economic, energetic, environmental, and market considerations, comprised in nine indicators grouped into the 3E performance criteria (Engineering-Economic-Environmental). They considered the simple Weighted Sum (WSM) approach using the Analytic Hierarchy Process (AHP) method to address the criteria and indicators weights. A ranking of emerging CO_2 utilization products was then proposed (Chauvy et al., 2019). Regarding the evaluation of carbon capture and storage (CCS), Jakobsen et al. (2013, 2014), and Roussanaly et al. (2013) developed means and tools for integrated multi-criteria assessment of the CCS value chain, involving several economic, environmental, and risk associated criteria to enable selection of most promising options for CCS. Volkart et al. (2016) carried out an interdisciplinary assessment of several power generation options with and without CCS in view of the new Swiss energy policy, showing the necessity to consider various criteria while making decision, as CO_2 storage faces sometimes adverse public opinion.

These studies consider methods that are all based on an additive score aggregation, where the alternatives with the highest total scores are selected as the most promising. However, these approaches are compensatory as they permit trade-offs between attributes. Thus, an unfavorable value in one attribute can be offset by a favorable value in other attributes. In order to avoid this, non-compensatory Multi-criteria Decision Analysis (MCDA) techniques are often applied. It is worth noting that there are also possibilities to add different levels of compensation to simple aggregation methods, i.e. if a decision maker is willing to allow that a low performance of one indicator can be compensated by another indicator fully, to a certain extent or not at all, as discussed by Gasser et al. (2020).

Following the aforementioned works and considerations, the present paper aims to test different MCDA approaches to select CO_2-based products enabling both CO_2 mitigation and replacement of fossil-derived carbon. This study is built on a case study conducted by Chauvy et al. (2019), which proposed a set of relevant criteria and indicators to assess CO_2-based products, and initially used the simple aggregation WSM approach and the AHP to elicit the weights for the selection. It then retrospectively explores and illustrates the application of several MCDA approaches, their associated outcomes and how these both differ and complement each other. Several widely used MCDA methods – elimination and choice expressing the reality (ELECTRE), LexiMin and LexiMax methods, in addition to WSM and AHP ones – are applied for the assessment of CO_2-based pathways. The rankings of the alternatives and their tolerance to change in criterion and indicator weights are compared amongst selected MCDA methods. The complementarity of these selected methods is thus explored in order to show the extent to which they add value to a decision maker's understanding, and their comparative analysis will aid them to make an informed choice of the most favorable CO_2 conversion pathways and mitigate their contribution to global warming.

2. Literature review

Proper decision-making is a very challenging task, and may be especially difficult if there are various alternatives and criteria that

Table 1
Recent literature reviews on MCDA applied in various fields. The list is not intended to be exhaustive.

Field of application	Authors	Key aspects
Civil engineering and construction	Zavadskas et al. (2016a) Zavadskas et al. (2016b)	138 studies incl. (up to 2015). Show that AHP (more used for measurement of intangible criteria when assessing sustainability or evaluating intelligent buildings), TOPSIS (technologies or structures), Fuzzy methods and ELECTRE are the most used methods.
Environment	Baumann et al. (2019)	Applied to energy storage systems. Show that AHP, partially combined with other methods (e.g., outranking approaches) are the most frequently used.
	Martins et al. (2020)	Applied to oil and gas decommissioning problems. Highlight that AHP, PROMETHEE, TOPSIS are the more frequently used.
Finance	Marqués et al. (2020)	94 studies incl. (2000–2018). Show that TOPSIS and ELECTRE models are the most popular to undertake the financial problems.
Healthcare	Adunlin et al. (2015)	66 studies incl. (1980–2013). AHP is the most used technique (50%).
Information technology	Zare et al. (2016)	42 studies incl. (2001–2015). Applied to E-learning systems. Highlight the most considered criteria in the field. Show that AHP is the most used in the field, 45% combines MCDA with fuzzy set theory. Integrated MCDA approaches such as DEMATEL[a] – ANP[b] are highly recommended.
Logistics	Chai et al. (2013)	123 studies incl. (2008–2012). Show that AHP (24%), TOPSIS (15%), ANP (12%), and ELECTRE (3%) are the most frequent methods. Highlight also the significant part of mathematical programming and artificial intelligence techniques.
	Chai and Ngai (2020)	(2013–2018). Show that ELECTRE is not reported after 2013. AHP and ANP still dominate.
Management	Mahjouri et al. (2017)	Applied to wastewater treatment. Fuzzy AHP combined with Fuzzy Delphi method to identify criteria and indicators. Show that AHP is the most applicated.
	Coban et al. (2018)	Applied to municipal solid waste management. Show that AHP and ELECTRE are mainly used in strategy and location determination; PROMETHEE is mostly preferred to identify optimal waste management strategies.
	Jones et al. (2019)	Applied to water management. Propose a framework combining life cycle assessment and MCDA and use an aggregation approach.
	Sitorus et al. (2019)	90 studies incl. (1999–2017). Applied to mine planning. Show that AHP is the most used, followed by the ELECTRE and PROMETHEE methods. Highlight a rise in application of hybrid MCDA methods (e.g., fuzzy AHP, fuzzy TOPSIS).

[a] DEMATEL – Decision Making Trial and Evaluation Laboratory.
[b] ANP – Analytic network process.

are often contradictory. MCDA methods designate a preferred alternative and/or rank alternative partially or completely in a preference order (Roy, 1996). The general procedure consists of several steps: problem and alternatives' formulation, criteria and indicators selection, criteria and indicators weighting, evaluation, and final treatment and conclusion. The problem is defined and involves different stakeholders. It identifies the goal, the assumptions and systems boundaries. The requirements imply constraints that any acceptable solution of the decision problem must fulfill. It is followed by the identification of the possible alternatives that need to meet the requirements. One of the most important part is the building of a coherent set of criteria and indicators and attributing weights, reflecting the stakeholders and decision maker. It is necessary to define discriminating criteria and indicators as objective measures. Weights can be assigned to individual criteria and indicators that give them different relative importance. Assigning weights is often perceived as subjective, depending on the approach used to determine and exploit them. One or several MCDA algorithms can then be selected and applied leading to the choice of the appropriate alternatives.

MCDA research has developed immensely. Numerous MCDA techniques are thus available, being different in the type of research questions they aim to address, the type of problem, the theoretical background, and the type of outcomes obtained (Sitorus et al., 2019), and even small variation to existing approaches may cause the creation of new research areas.

Some of literature reviews focused on the methodologies, such as Mardani et al. (2015). This study systematically reviewed a total of 393 articles published from 2000 to 2014 on methodologies of MCDA techniques and approaches. A comparative study was carried out among widely applied methods in MCDA by Kolios et al. (2016). Six methods were discussed together with the best practice implementation of each method, and included the weighted sum and weighted product methods, the analytical hierarchy process, the technique for the order of preference by similarity to the ideal solution (TOPSIS), the elimination and choice expressing the reality, and the preference ranking organization method for enrichment evaluation (PROMETHEE). More recently, Celik et al. (2019) proposed an overview of stochastic multi-criteria decision-making methods and applications, included a total of 61 papers reviewed.

Other reviews focused on applications in specific fields, as evidenced by recent literature reviews presented in Table 1. It is noticed that AHP method has strong dominance regardless of the field of MCDA applications. The method is used for criteria aggregation and final comparison. Additionally, according to the literature, the evaluation criteria most used in decision-making processes can be grouped into four main categories, namely technical, economic, environmental, and social. The strength of MCDA relies on its capacity to cope with conflicting stakeholder perspectives, and address trade-offs between economic, environmental, and social values, as discussed by Langemeyer et al. (2016). Pesce et al. (2018) also indicated the importance to involve local experts to weight the criteria, and highlighted the limit of MCDA to assess long-term performance of alternatives. Finally, it can be seen that one of the improvements to the MCDA techniques, especially to handle uncertainties, is the combination of a MCDA method with the fuzzy set theory, in order to accurately evaluate the relative importance of criteria, and the performance ratings of alternatives with respect to a criterion (see Table 1).

Prior to discussing the developed methodology, an overview of the following methods, including non-compensatory approaches (LexiMin and LexiMax), aggregation-based approaches (WSM, AHP), and the outranking method ELECTRE, is presented hereafter. They are representative of the various MCDA strategies and believed to be well suited for the purpose of this study.

2.1. LexiMin and LexiMax approaches

In LexiMin and LexiMax decision-making, a sequential elimination strategy is used until a unique solution is found (Sen, 1970). For each alternative, all scores are ordered regardless of the criteria and indicators. A sorted vector in ascending order (LexiMin) or descending order (LexiMax) is then defined. LexiMin ranks alternatives, so the decision maker is insured that the worst outcomes are avoided as much as possible. In the comparison of two alternatives, LexiMin tries to rank them on the basis of their weakest attribute. If the alternatives have the same value on their weakest attribute, this attribute is somehow discarded. Then, LexiMin tries to perform the comparison on the second weakest attribute of each alternative, and so on (Kurokawa et al., 2018). LexiMax proceeds similarly, on the basis of the strongest attribute of both alternatives.

The LexiMin and LexiMax approaches are examples of non-compensatory methods. Comparisons are made on an attribute-by-attribute basis.

2.2. Weighted sum (WSM)

The weighted sum is the most common MCDA method. If there are m alternatives and n indicators then the best alternative is the one that satisfies the following Eq. (1) (Triantaphyllou, 2000).

$$A_{WSM} = \max_j \sum_{i=1}^{n} d_{ij} w_i \tag{1}$$

where $j = 1, 2, \ldots, m$, A_{WSM} is the WSM score of the best alternative, d_{ij} is the performance value of the j^{th} alternative in terms of i^{th} indicator, and w_i is the weight allocated to the i^{th} indicator.

In this aggregation method, the weights depend on the ranges and the encoding of the scales and may be interpreted as substitution rates (Figueira et al., 2016).

2.3. Analytic hierarchy process (AHP)

The AHP approach was proposed by Saaty (1980, 1988). It is a methodology for solving decision-making problems by the prioritization of alternatives. The problem is structured in a hierarchy of different levels constituting the main criteria and indicators. On each hierarchy level, elements are compared in pairs to assess their relative preference with respect to each of the elements at the next higher level. The intensity of preference between two elements is established on the basis of Saaty's scale from 1 to 9, where assigning a numerical value of 1 means that both elements are of the same importance, and assigning a value equal to 9 indicates that one of the elements shows an extreme dominance over another. This process results in a $n \times n$ reciprocal pairwise comparison matrix format, where n is the number of elements compared. Based on the matrix, criteria weights can be calculated in some methods, such as arithmetic mean method, geometric mean method or characteristic root method (Wang et al., 2009).

After deriving the numerical weights for each element of the hierarchy, the final step of the process deals with the numerical priorities that are calculated for each of the decision alternatives, representing the alternatives' relative ability to achieve the decision goal. Thus, a $m \times n$ matrix (m alternatives and n indicators) is constructed. According to the AHP approach, the best alternative in the maximization case is indicated by a similar relationship than expression (1). The AHP method is often considered to assist decision makers to calculate the weight for each criterion used in the weighted sum.

2.4. ELECTRE (Elimination and choice expressing the reality)

The outranking methods consist of establishing a preference relation (degree of dominance) on a set of alternatives, which results in a partial preference ranking of alternatives, instead of a cardinal measure of their preference relation. They can deal with unclear and incomplete information (Penadés-Plà et al., 2016).

ELECTRE outranking methods have been developed in the mid-1960s (Roy, 1968). They aim to assess whether option a is at least as good as b. It is based on two major concepts: concordance, when an alternative a outranks an alternative b if a sufficient majority of criteria are in favor of alternative a; and non-discordance, when the concordance condition holds and none of the criteria in the minority should be opposed too strongly to the outranking of b by a. It allows to handle heterogeneous criteria, both quantitative and qualitative, where aggregation in a common scale is difficult. It prevents compensation behavior.

2.5. Summary of the MCDA methods

Table 2 presents a summary of the different MCDA methods previously briefly introduced as well as their strengths and weaknesses.

3. Methodology

The following statements are considered for the selected methods:

- $G = \{g_i\}$ is the finite set of indicators, where $i = 1, 2, \ldots n$.
- $A = \{a_j\}$ is the finite set of alternatives, where $j = 1, 2, \ldots m$.
- $g_i(a_j)$ denotes the performance of alternative a_j against indicator g_i. For the sake of simplicity, it is assumed that the higher the performance value, the better. All the performance data are gathered in the decision table $D = \{d_{ij}\}$, where $d_{ij} = g_i(a_j)$, $i = 1, 2, \ldots n$ and $j = 1, 2, \ldots m$. This way, the performances of all the alternatives against indicator g_i are read in row i of D, whereas the performances of alternative a_j against all the indicators are read in column j of D.
- $W = \{w_i\}$ is the finite set of weights eventually (i.e., depending on the algorithm) assigned to the indicators, where $i = 1, 2, \ldots n$ and $\sum_{i=1}^{n} w_i = 1$.
- The dominance relation between the alternatives is defined as follows. The alternative a_1 is said to dominate the alternative a_2 with respect to the set of indicators G, i.e. $a_1 \geq a_2$, when for all i, $g_i(a_1) \geq g_i(a_2)$.

3.1. LexiMin and LexiMax methodology

The LexiMin ordering is a simple aggregation method (Bouyssou et al., 2006), based on the lowest performance value whatever the indicator. $g^{\uparrow}(a_j)$ denotes the performance vector $g(a_j)$ when reordered in ascending order.

When two alternatives, for example, a_1 and a_2, are evaluated, the reordered vectors, $g^{\uparrow}(a_1)$ and $g^{\uparrow}(a_2)$, are built and compared as follows. All elements of both reordered vectors, from index 1 to maximum n, are compared until a difference is found, say at index value s, i.e. $g_1^{\uparrow}(a_1) = g_1^{\uparrow}(a_2); \ldots; g_{s-1}^{\uparrow}(a_1) = g_{s-1}^{\uparrow}(a_2)$. It is worth noting that the reordering for a_1 may be different than the reordering for a_2.

If $g_s^{\uparrow}(a_1) > g_s^{\uparrow}(a_2)$, a_1 is LexiMin-preferred to a_2 and the result is noted $a_1 \succ_{leximin} a_2$. In contrast, if $g_1^{\uparrow}(a_1) < g_1^{\uparrow}(a_2)$, a_2 is LexiMin-preferred to a_1 and the result is noted $a_2 \succ_{leximin} a_1$. If no difference is found over all the elements, i.e., $g_i^{\uparrow}(a_1) = g_i^{\uparrow}(a_2)$, the result is noted $a_1 \sim_{leximin} a_2$.

The commensurability of the scales is crucial for this method as the performances against different indicators need to be compared. For example, if 3 and 4 are two performance values against criteria g_1 and g_2, respectively, then the decision maker must consider 4 as better than 3, regardless of the indicators.

As shown by the algorithm, the LexiMin method lies on a worst-performance basis, irrespective of the indicators considered. The LexiMax method is similar to the LexiMin one, however lies on a best-performance basis. Selecting one method or the other depends on the decision maker's objectives.

Table 2
Summary of the MCDA methods considered in this paper.
Adapted from Kumar et al. (2017).

Methods	Steps	Strength	Weakness	Ref.
LexiMin/ LexiMax	Define sorted vector in ascending order (LexiMin) or descending order (LexiMax). Compare then each component.	Simple aggregation method.	Performances must be able to be compared on different criteria.	Bouyssou et al. (2006)
Weighted Sum Method (**WSM**)	Develop evaluation matrix Set the weights for each criterion. Calculate weighted score of each alternative by multiplying each criterion value by its corresponding weight. Aggregate.	Does not involve complex mathematics; Easily adaptable.	Difficulty when applied to multi-dimensional decision-making problems; High sensitivity to changes in scale.	Mulliner et al. (2016)
Analytical hierarchy process (**AHP**)	Define objective into a hierarchical model. Determine weights for each criterion. Calculate score of each alternative considering criteria. Calculate overall score of each alternative. Determine the consistency index and consistency ratio.	Adaptable; Evaluate the consistency of the decision matrix.	Interdependency between objectives and alternatives leading sometimes to hazardous results.	Saaty (1980, 1988) Penadés-Plà et al. (2016)
Elimination and choice (**ELECTRE**)	Determine the threshold function. Determine the Concordance index. Determine the Discordance index. Determine the Outranking relations. Assign rank.	Deals with both quantitative and qualitative features of criteria; Deals with heterogeneous scales; Less sensitive to any changes in data.	Not suitable to calculate an overall score; Requires an additional threshold to be introduced: no “correct value”.	Pohekar and Ramachandran (2004) Papadopoulos and Karagiannidis (2008) Bottero et al. (2015) Penadés-Plà et al. (2016)

3.2. AHP methodology

Once the decision problem is structured and indicators defined, the AHP approach comprises mainly two steps to first define the weights of the indicators, and then obtain an overall score for each option leading to the optimum alternatives.

Weighting the indicators is not a trivial task and, among several weighting methods, the AHP method has been considered here. Let first note that the indicators, denoted g_1, g_2,... g_n, can be grouped in sets based on their technical affinity, which leads to higher-level criteria. This way, the calculation of the scores, thus the ranking of the alternatives can be achieved according to two hierarchical levels of the indicators/criteria.

At the lower level, the weighting factors $w^{(ind)}$ were determined using the AHP method described by Saaty (1980, 1988) and from the initial case study proposed by Chauvy et al. (2019). In this method, the criteria are compared two by two, each pair being given a comparison value according to the following linear scale: 1: Equal importance; 3: Weak importance; 5: Essential or strong importance; 7: Very strong or demonstrated importance; 9: Absolute importance. For example, giving pair (g_1,g_2) a value of 7 means that g_1 exhibits a ‘very strong or demonstrated importance’ with respect to g_2. The intermediate values 2, 4, 6 and 8 are used in particular compromising situations (Saaty, 1980). At the higher level, the weighting factors $w^{(crit)}$ were determined similarly.

Let describe how the weights are computed whatever the hierarchical level h (i.e., indicators $w^{(ind)}$ and criteria $w^{(crit)}$) and the number n of indicators or criteria.

The pairwise comparison and evaluation process allows the building of the $n \times n$ matrix $B^{(h)}$.

$$B^{(h)} = \begin{bmatrix} 1 & b_{12} & \dots b_{1n} \\ b_{21} & 1 & \dots b_{2n} \\ \vdots & \vdots & \ddots \ \vdots \\ b_{n1} & b_{n2} & \dots \ 1 \end{bmatrix} \tag{2}$$

More exactly, when comparing two elements k and l, the comparison value of the linear scale is given to element b_{kl}, if element k is better than element l; and to b_{lk} otherwise. Then the other elements are computed according to constraint $b_{kl} . b_{lk} = 1$. Diagonal elements are obviously equal to 1.

The weight vectors ${w_k}^{(h)}$ are computed from matrix $B^{(h)}$ using the approximate eigenvector method from Saaty (1980) (see Eq. (3)).

$${w_k}^{(h)} = \frac{\sqrt[n]{\prod_{i=1}^{n} b_{ik}}}{\sum_{k=1}^{n} \sqrt[n]{\prod_{i=1}^{n} b_{ik}}} \tag{3}$$

The computation of the weight vector $w^{(h)}$ guarantees that the weighting constraint $\sum_{k=1}^{n} {w_k}^{(h)} = 1$ is verified. To this extent, for each group of indicators (corresponding to a criterion), a weight vector v is derived by multiplying the local weight vector $w^{(ind)}$ by the corresponding criterion weight element in $w^{(crit)}$. The global weight vector is obtained by concatenation of the three v weight vectors.

When many pairwise comparisons are performed, inconsistencies may typically arise. An important feature of the AHP method is to guarantee overall consistency.

Consistency is measured by the Consistency Ratio (CR), which is defined in Eq. (4):

$$CR = \frac{CI}{RI} \tag{4}$$

where CI is the consistency index of the matrix, and RI the consistency index of a reference, random-like matrix.

CI is estimated using Eqs. (5) and (6), the closer the ε_{max} to n, the more consistent the computed weights.

$$CI = \frac{\varepsilon_{max} - n}{n - 1} \tag{5}$$

Table 3
Values of the Random Index (*RI*) (Saaty, 1980).

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

$$\varepsilon_{max} = \frac{1}{n}\sum_{k=1}^{n}\frac{\left(B^{(h)}w^{(h)}\right)_k}{w_k} \tag{6}$$

Reference *RI* values have been provided by Saaty (1980) for different values of n, as shown in Table 3.

An overall consistency ratio integrating both hierarchy levels, i.e. criterion and indicator levels, is defined as the ratio of a weighted consistency index (*CI*) to a weighted random consistency index (*RI*). If the consistency ratio is greater than 0.10, it is necessary to revise the judgments in order to identify the cause of the inconsistency (Saaty, 1980).

The next step in the AHP method is to evaluate the alternatives with respect to the criteria. A real $n \times m$ score matrix $S = \{s_{ij}\}$ is defined, where each entry s_{ij} represents the score of the j^{th} alternative with respect to the i^{th} indicator. To compute the scores, a pairwise comparison $m \times m$ matrix $R^{(i)}$ is built for each indicator g_i separately, where m is the number of alternatives evaluated. Each element ${r_{jj'}}^{(i)}$ of $R^{(i)}$ represents the evaluation of the j^{th} alternative compared to the $j'^{\,th}$ alternative, with respect to the i^{th} indicator. The elements ${r_{jj'}}^{(i)}$ and ${r_{j'j}}^{(i)}$ satisfy the constraint ${r_{jj'}}^{(i)}.{r_{j'j}}^{(i)} = 1$, and ${r_{jj}}^{(i)} = 1$. An evaluation scale similar to the one previously introduced is used to translate the decision table D to the comparison matrix $R^{(i)}$, according to a predefined translation table, T.

The procedure described for the pairwise comparison $B^{(h)}$ is applied to each matrix $R^{(i)}$. Score vectors $s^{(i)}$ are computed similarly to ${w_k}^{(h)}$, with $i = 1 \ldots n$. Hence, the vector $s^{(i)}$ contains the scores of the evaluated alternatives, with respect to the i^{th} indicator, defining the table S.

Finally, the best alternative is the one that has the greatest global score (Eq. (7)):

$$AHP_j = \sum_{i=1}^{n} s_{ij}\ w_i \tag{7}$$

where AHP_j is the global score of the alternative a_j, and where w_i, s_{ij}, and n are defined as above.

3.3. Integrated multi–criteria decision-making AHP–WSM methodology

In this method, for each alternative, a score is computed as the weighted sum of the performances against the indicators, as expressed in Eq. (8):

$$s(a_j) = \sum_{i=1}^{n} d_{ij}\ w_i \tag{8}$$

where $j = 1,\ 2, \ldots,\ M$, d_{ij} is the performance value of the alternative a_j against indicator g_i, and w_i is the weight allocated to indicator g_i. The weights determined by the first step of the AHP method may be used, ensuring that they correspond to what the decision maker mean, i.e. the relative importance placed on each indicator, by comparing for instance alternatives with similar attributes. Then the alternatives are ranked according to the scores, e.g., in decreasing order.

It is worth noting that the weighted sum method is a compensatory method, where a bad performance on criterion g_1 can be compensated by a good performance on criterion g_2. Non-compensatory method might be more desirable when comparison across criteria are difficult.

3.4. ELECTRE methodology

ELECTRE is a set of non-compensatory methods allowing in the end for preference modeling of alternatives (Figueira et al., 2016). The preference model is based on an outranking binary relation between alternatives, noted S. For example, relation a_1Sa_2 means "a_1 is at least as good as a_2 over a sufficient subset of the set G of the indicators", and its validation conditions are explained later in this section.

The preference concept is defined based on the outranking occurrences between alternatives a_1 and a_2, and graphical representation of the outranking relations is given in Table 4.

- a_1Sa_2 and not a_2Sa_1: a_1Pa_2 (a_1 is strictly preferred to a_2)
- a_2Sa_1 and not a_1Sa_2: $a_1P^{-}a_2$ (a_2 is strictly preferred to a_1, or $a_1$is inversely preferred to a_2)
- a_1Sa_2 and a_2Sa_1: a_1Ia_2 ($a_1$is indifferent to a_2); implying a_2Ia_1
- Not a_1Sa_2 and not a_2Sa_1: a_1Ra_2 ($a_1$is incomparable to a_2); implying a_2Ra_1

The outranking relation a_1Sa_2 is true if a sufficient majority of criteria are in favor of it (concordance) and if none of the criteria of the minority oppose too strongly (non-discordance or non-veto). Concordance and discordance are evaluated by using appropriate indices and threshold values.

Concordance. The strength of the concordant coalition is measured by a concordance index $C(a_1Sa_2)$, which is defined by Eq. (9). In this general definition, the weights w_i allow to adjust the importance of the indicators. The index is compared to a concordance level c^*, which is generally selected within the range $[0.5,\ 1 - min_i\ w_i]$, calculated by Eq. (10)

.

$$C(a_1Sa_2) = \sum_{i\in IC'} w_i \tag{9}$$

where $IC' = \{i : g_i(a_1) \geq g_i(a_2)\}$, i.e., the index set of criteria in favor of a_1Sa_2 (at least as good as).

$$c^* = \frac{\sum_{a_1}^{m}\sum_{a_2}^{m} C(a_1Sa_2)}{m(1-m)} \tag{10}$$

where m is the number of alternatives.

The coalition is considered to be strong enough if Eq. (11) holds:

$$C(a_1Sa_2) \geq c^* \tag{11}$$

Discordance. Discordance to relation a_1Sa_2 is concretely defined here by Eq. (12) i.e., discordance is established as soon a_2 is sufficiently better than a_1 for some indicator.

$$D(a_1Sa_2) = \begin{cases} 1 \text{ iff } \exists\ j:\ \ g_i(a_2) \geq g_i(a_1) + \delta_i \\ \quad\quad 0 \end{cases} \tag{12}$$

Table 4
Graphical representation of the outranking relations.

Outranking relation	Graphical representation
a_1Pa_2	$a_1 \longrightarrow a_2$
$a_1P^{-}a_2$	$a_1 \longleftarrow a_2$
a_1Ia_2	$a_1 \longleftrightarrow a_2$
a_1Ra_2	$a_1 \quad a_2$

Table 5
Values of the weights (Ω) to estimate weighted distance of Kendall's tau (K_Ω) (Kumar and Vassilvitskii, 2010).

Position j	1	2	3	4	5	6	7	8	9	10
(Ω_j)	0.488	0.146	0.089	0.066	0.051	0.041	0.033	0.029	0.027	0.027

where δ_i is a positive veto threshold, which is defined for each indicator $g_i \in G$ (Vincke, 1989).

To summarize, the outranking relation a_1Sa_2 holds as defined by Eq. (13):

$$a_1Sa_2 \text{ iff } \begin{cases} C(a_1, a_2) \geq c^* \\ \quad \text{and} \\ D(a_1Sa_2) = 0 \end{cases} \tag{13}$$

This outranking relation is usually not a weak order (i.e., a ranking) and a complementary analysis is often necessary, using for example the kernel (Bouyssou et al., 2006).

A Graph Kernel is used to identify the best alternatives. A kernel of a graph $K \subset A$ is defined as:

- $\forall a_1 \in K, \nexists a_2$: a_1Sa_2: no alternative a_1 inside the kernel K is better than any other alternative a_2 inside K
- $\forall a_1,\ a_2 \in K$: a_1Ra_2: within the kernel K, a_1 is incomparable to a_2
- $\forall a_3 \notin K, \exists a_1 \in K$: a_1Sa_3: each alternative a_3 outside of the kernel K is worse than at least one alternative inside K.

The kernel is unique if the graph has no cycle. In case of cycle, each cycle can be replaced by a single node. The kernel K of a set A forms a set of preferred alternatives.

To represent a finite partially ordered set, in the form of a drawing of the transitive reduction of Graph Kernels, the Hasse Graph is preferably considered, based on this axiom of transitivity:

- a_1Sa_2 and a_2Sa_3 implies a_1Sa_3.

Beside the Graph Kernel, the Net Flow Score (NFS) procedure (Bouyssou et al., 2006; Szeląg et al., 2014) is used to order the alternatives, for example in decreasing order of preference strength. For each alternative a_j, it accounts for the number of other alternatives that it outranks and for the number of those that do outrank it. Concretely, assuming that the outranking relation $a_jSa_{j'}$ is equal to 1 when it is true and to 0 otherwise, Eq. (14) can be used to calculate the net flow score of a_j:

$$NFS(a_j) = \sum_{a_j \in A} \left[\left(a_{j'}Sa_j \right) - \left(a_jSa_{j'} \right) \right] \tag{14}$$

The alternatives are then ranked in decreasing order of NFS.

3.5. Comparative analysis of alternative rankings using different MCDA methods

The different MCDA methods do not necessarily provide the same ranking among the alternatives. To compare the rankings, one can use either the Kendall rank correlation coefficient, the Kendall's tau distance or a weighted analogue.

The Kendall rank correlation coefficient (τ), as it is defined by Eq. (15), was chosen to measure the correlation between the ranking methods. Values of τ range from -1 (100% negative association, or perfect inversion) to $+1$ (100% positive association, or perfect agreement). A value of zero indicates the absence of association.

$$\tau = \frac{C - D}{C(M, 2)} \tag{15}$$

where C is the number of concordant pairs, D the number of discordant pairs, and $C(M, 2)$ is the total number of distinct alternative pairs (number of combinations of two elements in a set of M elements).

Let x and y refer to two ranking methods, j and j' refer to two alternative indices, therefore x_j, y_j, $x_{j'}$, and $y_{j'}$ refer to the corresponding ranks. Concordance holds if ($x_j > x_{j'}$ and $y_j > y_{j'}$) or ($x_j < x_{j'}$ and $y_j < y_{j'}$); discordance holds if ($x_j > x_{j'}$ and $y_j < y_{j'}$) or ($x_j < x_{j'}$ and $y_j > y_{j'}$); Neither (i.e., tied) if $x_j = x_{j'}$ or $y_j = y_{j'}$. If there are no ties, then $C(M, 2) = C + D$.

The higher the Kendall's tau (τ), the better is the similarity between the two compared rankings.

Complementarily, the Kendall's tau distance counts the number of pairwise disagreements between two ranking lists (see Eq. (16)) (Kumar and Vassilvitskii, 2010). The larger the distance, the more dissimilar the two ranks are.

$$K_\tau = \sum_{(j,j'):\ j>j'} \left[y_j < y_{j'} \right] \tag{16}$$

However, both Kendall's rank correlation coefficient τ and Kendall's tau distance K_τ penalize equally inversions near the head and near the tail of a rank. To this extent, the weighted distance of Kendall's tau (K_Ω) is estimated by Eq. (17) (Kumar and Vassilvitskii, 2010). It penalizes each inversion proportionally to the product of the weights (Ω) of the two elements being inverted. Eq. (17) applies when alternatives are sorted according to the rank in x.

$$K_\Omega = \sum_{(j,j'):\ j>j'} \Omega_j \Omega_{j'} \left[y_j < y_{j'} \right] \tag{17}$$

The higher the weighted distance K_Ω, the stronger are the dissimilarities between the two compared rankings, with respect to the weights Ω.

The weights (Ω) considered are presented in Table 5. Defined by Kumar and Vassilvitskii (2010) on the basis of a click-through rate, these weights have been chosen to focus on the head of the rankings.

3.6. Sensitivity analysis

Ranking results in MCDA depends on the weights distribution among criteria and indicators. A sensitivity analysis with respect to the weights is performed to provide the decision maker with a better comprehension of the robustness of the methods under weight uncertainty.

3.7. Summary of the suggested methodology

Fig. 1 presents the methodological framework of the MCDA approaches under consideration in the decision-making problem. It is worth noticing that this scheme of operation is in line with the procedure developed by the OECD (2008). This approach identified a ten-step process, with the aim to establish a common guideline as a basis for the development of composite indices (i.e., aggregations of a set of indicators), generally applied to multidimensional concepts like welfare, well-being, human development, environmental sustainability, and industrial competitiveness. Greco et al. (2019) recently proposed a more recent outlook on the advances made in this field over the past years, comprising details on the issues of weighting, aggregation, and robustness.

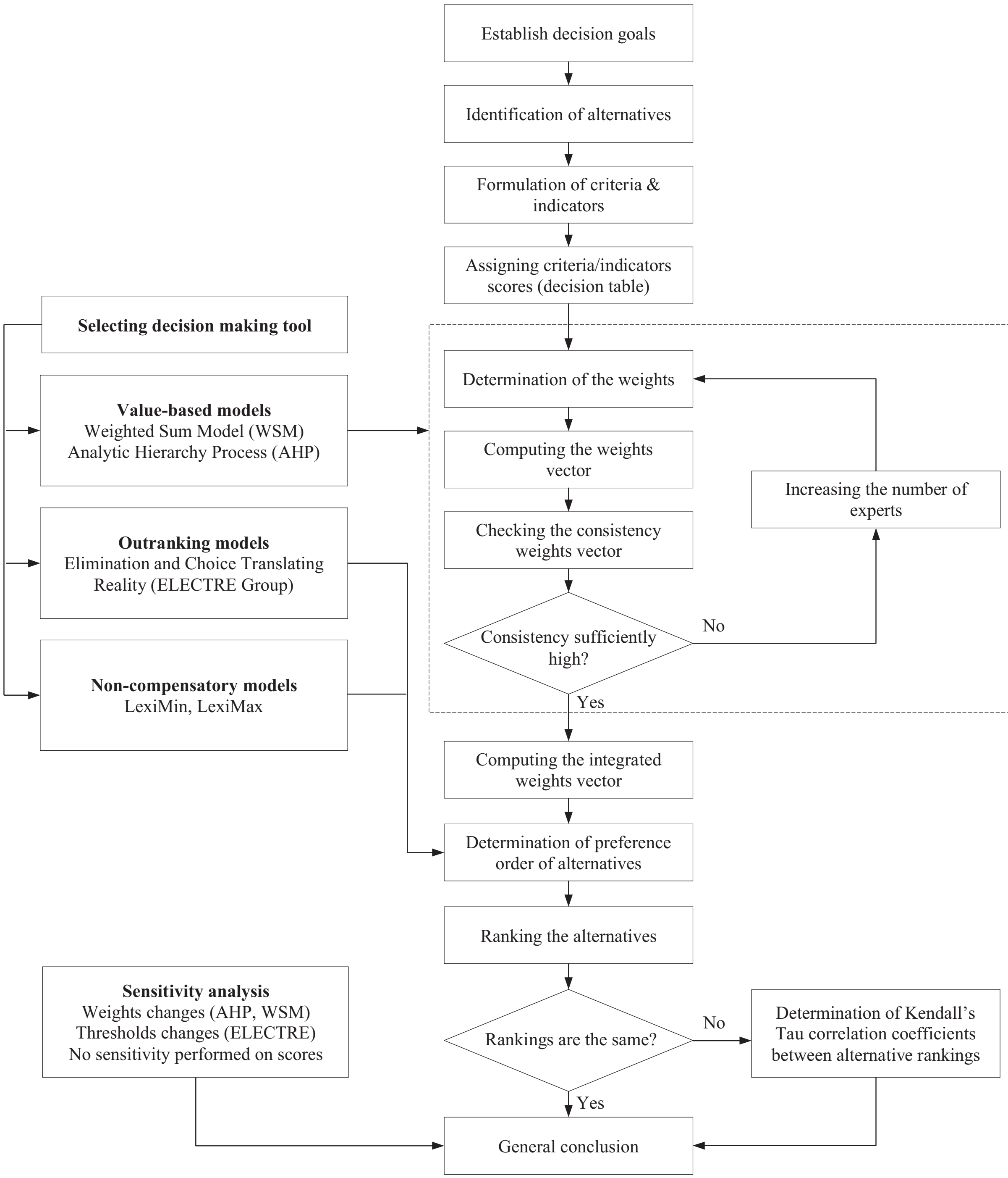

Fig. 1. Methodological framework of the MCDA.

4. Results and discussion

This paper aims to assess CO_2 conversion pathways for short-to mid-term deployment in industry offering the best trade-offs between economic and environmental outcomes. The MCDA methods (LexiMin/LexiMax approaches, AHP, WSM and ELECTRE) were applied to the case study data, where the alternatives were evaluated against criteria and indicators, to designate a preferred alternative and/or rank alternative in a preference order.

4.1. Identification of the finite set of alternatives

Potential CO_2-based products were identified from previous work (Chauvy et al., 2019). The products were selected together with the routes used to synthetize them from carbon dioxide. To reduce the panel of alternatives and define the finite set, it was decided that (i) the processes must have a Technology Readiness level (TRL) higher than TRL 6, to ensure that the technology will be brought to commercialization in the next fifteen years; (ii) the CO_2-based products that involve CO_2-based intermediates should

Table 6
Shortlist of CO_2 conversion options for short- to mid-term deployment.

CO_2-based products		CO_2-conversion process
$\boldsymbol{a}_1$	Calcium carbonate	Mineral carbonation
$\boldsymbol{a}_2$	Dimethyl carbonate	Organic synthesis
$\boldsymbol{a}_3$	Ethanol	Microbial process
$\boldsymbol{a}_4$	Formic acid	Electrochemical reduction
$\boldsymbol{a}_5$	Methane	Hydrogenation
$\boldsymbol{a}_6$	Methanol	Hydrogenation
$\boldsymbol{a}_7$	Microalgae	Biological process
$\boldsymbol{a}_8$	Polycarbonates	Organic synthesis
$\boldsymbol{a}_9$	Sodium carbonates	Mineral carbonation
$\boldsymbol{a}_{10}$	Syngas	Dry reforming

not be shortlisted, such as polyurethanes (polyols and isocyanates involved); and (iii) the CO_2-based products should not be currently produced using CO_2 as raw material, such as salicylic acid and urea.

Ten products were therefore selected for further assessment, presented in Table 6.

4.2. Building a coherent set of criteria and indicators

4.2.1. Definition of the criteria and indicators

Based primarily on an extensive literature review, Chauvy et al. (2019) defined nine key performance indicators (KPIs) to evaluate the shortlisted CO_2 technologies, that were grouped into the 3E performance criteria (see Table 7), involving Engineering, Economic and the Environmental performances. These indicators consider the characteristic of the CCU processes and are consistent with the decision maker's objective. They reflect the performances of alternatives from different aspects. For more details about these indicators, additional information is provided in the Supporting Information file (SI. 1).

4.2.2. Definitions of the weights

To determine the weighting factors at both levels, the AHP method was performed using the steps and equations described in the previous section, reflecting the initial decision maker's preferences established in Chauvy et al. (2019). Table 8 provides the pairwise comparison matrix for the main criteria. Pairwise comparison matrices of indicators with respect to the 3E criteria are given in Tables 9 (a), (b) and (c).

Table 8
Pairwise comparison matrix for the 3E criteria.

Criteria no	C_1	C_2	C_3	Local weights Level one
$\boldsymbol{C}_1$	1.00	0.50	0.50	0.20
$\boldsymbol{C}_2$	2.00	1.00	0.50	0.31
$\boldsymbol{C}_3$	2.00	2.00	1.00	0.49
			CR	5%

Table 9a
Pairwise comparison matrices of indicators with respect to the 3E criteria.
The comparison matrix of indicators with respect to criterion $\boldsymbol{C}_1$.

Criterion C_1	g_1	g_2	g_3	Local weights Level two
$\boldsymbol{g}_1$	1.00	0.33	0.14	0.08
$\boldsymbol{g}_2$	3.00	1.00	0.20	0.19
$\boldsymbol{g}_3$	7.00	5.00	1.00	0.73
			CR	6%

Table 9b
Pairwise comparison matrices of indicators with respect to the 3E criteria.
The comparison matrix of indicators with respect to criterion $\boldsymbol{C}_2$.

Criterion C_2	g_4	g_5	g_6	Local weights Level two
$\boldsymbol{g}_4$	1.00	2.00	0.14	0.15
$\boldsymbol{g}_5$	0.50	1.00	0.20	0.11
$\boldsymbol{g}_6$	7.00	5.00	1.00	0.74
			CR	10%

Table 9c
Pairwise comparison matrices of indicators with respect to the 3E criteria.
The comparison matrix of indicators with respect to criterion $\boldsymbol{C}_3$.

Criterion C_3	g_7	g_8	g_9	Local weights Level two
$\boldsymbol{g}_7$	1.00	0.25	3.00	0.22
$\boldsymbol{g}_8$	4.00	1.00	6.00	0.69
$\boldsymbol{g}_9$	0.33	0.17	1.00	0.09
			CR	5%

The overall consistency was calculated by summing for all levels, with weighted consistency index (*CI*) in the numerator and weighted random consistency index (*RI*) in the denominator, and it equals to 5.6%. It follows from the calculations that the pairwise

Table 7
Criteria and key performance indicators to evaluate the CO_2 utilization technologies.

Criteria		Key Performances Indicators (KPIs)		Definition
$\boldsymbol{C}_1$	Engineering Performance	$\boldsymbol{g}_1$	Technological maturity	Indicates the level of maturity of the different pathways and the estimated time needed to reach commercial technological maturity.
		$\boldsymbol{g}_2$	Geographical constraints	Takes into consideration geographical constraints that may prevent the technology from reaching its full-scale potential, or limit its application to a few advantageous locations across the globe.
		$\boldsymbol{g}_3$	Fossil-free operations	References the co-reactants and determines whether it is possible to be independent from fossil sources.
$\boldsymbol{C}_2$	Economic Performance	$\boldsymbol{g}_4$	Size of the market	Identifies how big the overall market is today in Mton per year.
		$\boldsymbol{g}_5$	Competitiveness with other technologies	Evaluates if the CO_2 use is price-competitive with alternative technology, products or processes, achieving the same outcome, including low-carbon alternatives e.g., hybrid and electric vehicles; other green building products.
		$\boldsymbol{g}_6$	Relative added value	Indicates the economic viability of the process, i.e. a CO_2 conversion process is economically feasible if the production unit cost is less than or equal to a reference case, usually the conventional way of production, or if the process is forecast as being close to profitability.
$\boldsymbol{C}_3$	Environmental, health and safety performance	$\boldsymbol{g}_7$	CO_2 uptake potential	Defines the maximum quantitative CO_2 uptake potential on a stoichiometric basis, corresponding to the amount of CO_2 that can be fixed by the reaction.
		$\boldsymbol{g}_8$	Environmental potential	Evaluates two environmental impacts: the global warming potential and the fossil depletion potential.
		$\boldsymbol{g}_9$	Health and safety considerations	Lists of health and safety considerations (in terms of the use of hazardous substances, etc.) for each alternative.

Table 10
Weighting factors determined using the AHP method.

Criteria	Local weights Level one	KPIs	Local weights Level two	Global weights
C_1	0.20	g_1	0.08	0.0158
		g_2	0.19	0.0369
		g_3	0.73	0.1431
C_2	0.31	g_4	0.15	0.0466
		g_5	0.11	0.0328
		g_6	0.74	0.2314
C_3	0.49	g_7	0.22	0.1074
		g_8	0.69	0.3409
		g_9	0.09	0.0451

comparisons for the evaluation of the weights are consistent, because the overall consistency is less than 10%.

Table 10 presents the aggregated weighting factors for the nine indicators, the local weights being rounded to two decimal places.

Based on the AHP results, the environmental potential was deemed the most important indicator (g_8 = 34%) for the evaluation of the alternatives, followed by the relative added value (g_6 = 23%) and fossil-free operation (g_3 = 14%). The least important indicator is the technological maturity, which was assigned a relative importance of 2%. This is mainly due to the fact that the technological maturity was already considered as a threshold (TRL 6) to elicit the final set of alternatives.

Thus, it appears in particular that g_8 is necessary, and $\{g_3, g_6, g_8\}$ and $\{g_6, (g_7, g_8, g_9)\}$ are both sufficient conditions to determine if an alternative outranks another one.

4.3. Building the decision table

The decision table was built and presented in Table 11. A five-level score scale was considered, following the scoring guide established in previous work (Please refer to the Supporting Information file (SI. 1) and Chauvy et al. (2019) for more details). First dominance relations between alternatives can be highlighted directly from the decision table.

$$\begin{array}{l} \boldsymbol{a}_1 \succ \boldsymbol{a}_{10} \\ \boldsymbol{a}_5 \succ \boldsymbol{a}_1 \\ \boldsymbol{a}_5 \succ \boldsymbol{a}_3 \\ \boldsymbol{a}_5 \succ \boldsymbol{a}_{10} \\ \boldsymbol{a}_6 \succ \boldsymbol{a}_9 \end{array} \xrightarrow[\text{transitivity}]{\text{by}} \begin{array}{l} \boldsymbol{a}_5 \succ \boldsymbol{a}_1 \succ \boldsymbol{a}_{10} \\ \boldsymbol{a}_5 \succ \boldsymbol{a}_3 \\ \boldsymbol{a}_6 \succ \boldsymbol{a}_9 \end{array}$$

In all the MCDA approaches applied hereafter, these aforementioned dominance relations have to be validated.

4.4. Ranking alternatives and comparison of alternative rankings using different MCDA methods

4.4.1. LexiMin/LexiMax approaches

The LexiMin and LexiMax approaches were applied directly on the decision table. LexiMin ranked methanol (a_6), dimethyl carbonate (a_2), sodium carbonate (a_9) and microalgae (a_7) as best alternatives, where their scores on their weakest performances were the highest. Ethanol (a_3), formic acid (a_4) and syngas (a_{10}) were identified as the worst alternatives. Selecting the alternative with the minimum lowest performance as the optimal solution, LexiMax approach ranked microalgae (a_7), methanol (a_6), methane (a_5) and dimethyl carbonate (a_2) as best alternatives, and sodium carbonate (a_9), syngas (a_{10}) and formic acid (a_4) as worst (see Table 14 where the results of all approaches are compared). In particular, the discrepancy in the sodium carbonate rank may be explained by uncertainties linked to input data due to lack of information regarding the process.

4.4.2. AHP method

The score matrix was built following the procedure introduced in the Methodology section (See Table 12). The predefined translation table T as well as the pairwise comparison matrix $R^{(i)}$ related to each indicator are presented in the Supporting Information File, Table SI. 6. and SI. 7, respectively.

Total AHP scores in Table 12 indicate that methanol (a_6), dimethyl carbonate (a_2), microalgae (a_7), and polycarbonates (a_8) exhibit higher scores, while syngas (a_{10}), ethanol (a_3), and formic

Table 11
Decision table (Chauvy et al., 2019).
Color code: from dark red for the lowest score to dark green the highest score.

		Alternatives									
Criteria	Indicators	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
Engineering Performance	g_1	2	4	2	1	3	4	3	4	1	1
	g_2	2	3	3	0	4	2	3	3	2	2
	g_3	2	2	0	4	2	2	4	0	2	2
Economic Performance	g_4	4	1	4	1	4	3	3	1	3	4
	g_5	0	1	0	3	0	2	2	2	1	0
	g_6	2	4	0	0	2	2	0	4	2	0
Environmental, health & safety Performance	g_7	4	2	4	1	4	4	4	1	3	0
	g_8	2	2	2	0	2	4	2	2	2	2
	g_9	2	2	0	2	2	2	4	2	2	2

Table 12
Score matrix.
Color code: from dark red for the lowest score to dark green the highest score.

Criteria	Indicators	Alternatives									
		a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
Engineering Performance	g_1	0.05	0.21	0.05	0.02	0.10	0.21	0.10	0.21	0.02	0.02
	g_2	0.05	0.13	0.13	0.01	0.28	0.05	0.13	0.13	0.05	0.05
	g_3	0.07	0.07	0.02	0.28	0.07	0.07	0.28	0.02	0.07	0.07
Economic Performance	g_4	0.18	0.02	0.18	0.02	0.18	0.07	0.07	0.02	0.07	0.18
	g_5	0.03	0.07	0.03	0.30	0.03	0.15	0.15	0.15	0.07	0.03
	g_6	0.09	0.29	0.02	0.02	0.09	0.09	0.02	0.29	0.09	0.02
Environmental, health & safety Performance	g_7	0.17	0.04	0.17	0.02	0.17	0.17	0.17	0.02	0.07	0.01
	g_8	0.08	0.08	0.08	0.02	0.08	0.35	0.08	0.08	0.08	0.08
	g_9	0.08	0.08	0.02	0.08	0.08	0.08	0.35	0.08	0.08	0.08
Total AHP scores		0.089	0.122	0.067	0.068	0.099	0.185	0.120	0.115	0.076	0.058

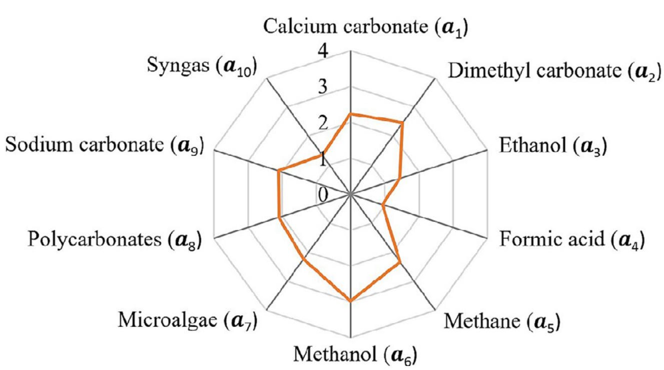

Fig. 2. Total weighted scores of the selected CO_2-based compounds.

acid (a_4) are the worst performing alternatives. The full order is displayed in Table 14.

4.4.3. AHP-WSM integrated method

Fig. 2 displays the total weighted scores of the selected alternatives. Methanol (a_6), dimethyl carbonate (a_2) and methane (a_5) have higher scores and are the CO_2-based compounds to further investigate. Formic acid (a_4), syngas (a_{10}), and ethanol (a_3) are the worst performing alternatives. The full order is displayed in Table 14. The contributions of individual indicators to the final scores of alternatives are presented in the Supporting Information File, Table SI. 9.

4.4.4. ELECTRE method

Concordance and discordance matrices with respect to the ten alternatives are given in the Supporting Information File, Table SI. 10 (a) and (b), respectively. The concordance level c^* equals to 0.710. The veto threshold (δ_i) was set at 3 for indicators g_2, g_3, g_6, g_7, and g_8. By setting a high threshold value, a veto is effective only when an alternative is by far worse than another one. This way, veto thresholds have a reinforcement effect and express the power attributed to the given indicators to be against the assertion "a_1 outranks a_2". No veto was set for g_1, g_4, g_5, and g_9.

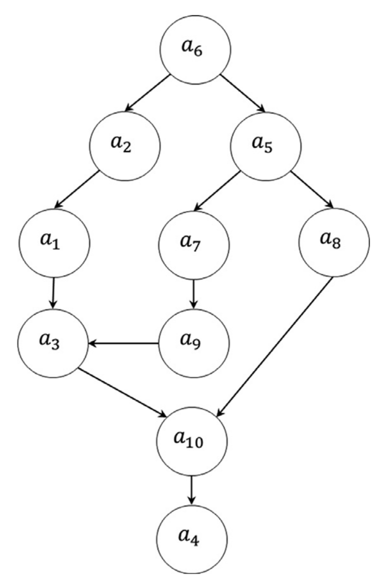

Fig. 3. Hasse Graph identifying the best CO_2-based alternatives using the ELECTRE approach.

In addition, the global weights w_i are kept as previously, which was validated by the decision maker.

Table 13 presents the final results exploiting concordance and discordance matrices with respect to the ten alternatives.

Fig. 3 displays the Hasse Graph to identify the CO_2-based alternatives outranking using the ELECTRE approach.

In Fig. 3, methanol (a_6) outranks the other alternatives. Dimethyl carbonate (a_2) and methane (a_5) are incomparable. Methane may be categorized at higher rank than dimethyl carbonate as two arcs are derived from the node a_5, leading to six submissive alternatives. Formic acid (a_4) is outranked by all the other alternatives. Microalgae (a_7) and polycarbonates (a_8) are also incomparable alternatives (see Table 13).

As there is no cycle, a unique kernel K of the set A forms the dominating subset: {a_6}, i.e. methanol. This kernel might be too

Table 13
ELECTRE final results.

Alternatives		Incomparable alternatives	Outranked alternatives
Calcium carbonate	a_1	–	a_3, a_4, a_{10}
Dimethyl carbonate	a_2	a_5	a_1, a_3, a_4, a_{10}
Ethanol	a_3	–	a_4, a_{10}
Formic acid	a_4	–	–
Methane	a_5	a_2	a_3, a_4, a_7, a_8, a_9, a_{10}
Methanol	a_6	–	a_1, a_2, a_3, a_4, a_5, a_7, a_9, a_{10}
Microalgae	a_7	a_8	a_3, a_4, a_9, a_{10}
Polycarbonates	a_8	a_7	a_4, a_{10}
Sodium carbonate	a_9	–	a_3, a_4, a_{10}
Syngas	a_{10}	–	a_4

Table 14
Ranking results of the alternatives using different MCDA methods.
Color code: from dark red for the lowest rank to dark green the highest rank.

		MCDA methods			
		LexiMin Rank	LexiMax Rank	AHP Rank	WSM Rank
Calcium carbonate	a_1	6	7	6	4
Dimethyl carbonate	a_2	2	4	2	2
Ethanol	a_3	10	6	9	8
Formic acid	a_4	9	8	8	10
Methane	a_5	5	3	5	3
Methanol	a_6	1	2	1	1
Microalgae	a_7	4	1	3	5
Polycarbonates	a_8	7	5	4	7
Sodium carbonate	a_9	3	10	7	6
Syngas	a_{10}	8	9	10	9

restrictive for the decision maker. Additional values for both the concordance level c^* and δ_i are therefore tested in the sensitivity analysis.

Finally, the Net flow score procedure indicates the following relation:

$$a_6 \geq a_5 \geq a_2 \geq a_7 \geq \begin{matrix} a_1 \\ a_9 \end{matrix} \geq a_8 \geq a_3 \geq \begin{matrix} a_4 \\ a_{10} \end{matrix}$$

4.4.5. Comparison of alternative rankings

The obtained ranking results for the methods leading to a linear ranking are displayed in Table 14. It is worth noting the consistency of the results through the methods regarding the top-ranked alternatives. Methanol (a_6) is ranked at the first place in three of the methods (and second in the remaining one). Dimethyl carbonate (a_2) is ranked second in three of the methods (and fourth in the remaining one). On the other hand, the results are also consistent regarding the bottom-ranked methods: ethanol (a_3), formic acid (a_4), and syngas (a_{10}) exhibit low ranking whatever the method. This means that with no further investigation, which is achieved in subsequent sections, than visual inspection, five alternatives out of ten can be clearly classified. Also, the results are in line with generally accepted intuition in the industry.

The rankings' tolerance to change in criterion and indicator weights are compared amongst the selected MCDA methods (i.e., AHP and WSM methods) in the next section (see 4.5.1).

Table 15 presents the Kendall's tau coefficient between alternative rankings computed using the different MCDA methods.

MCDA methods pairs that have equal rankings lead to a Kendall's tau coefficient value equal to 1. All tested methods conclude that methanol (a_6), dimethyl carbonate (a_2), and methane (a_5) are CO_2-based products to investigate. They also highlight that formic acid (a_4), syngas (a_{10}), and ethanol (a_3) were the worst performing alternatives. LexiMin and WSM act most correspondingly; with the two methods prioritizing 30% of the alternatives in identical position, followed by WSM and AHP where 20% of the alternatives have identical position (see Table 15).

In addition, Table 16 presents the weighted distance K_Ω.

Table 15
Kendall's tau coefficient (τ) between alternative rankings using different MCDA methods.
Color code: from dark red for the lowest score to dark green the highest score.

MCDA methods	LexiMin	LexiMax	AHP	WSM
LexiMin	1.000	0.333	0.644	0.689
LexiMax	0.333	1.000	0.600	0.467
AHP	0.644	0.600	1.000	0.689
WSM	0.689	0.467	0.689	1.000

Table 16
Weighted distance K_Ω between alternative rankings using different MCDA methods.
Color code: from dark red for the lowest score to dark green the highest score.

MCDA methods	LexiMin	LexiMax	AHP	WSM
LexiMin		0.136	0.014	0.018
LexiMax	0.136		0.072	0.063
AHP	0.014	0.072		0.016
WSM	0.018	0.063	0.016	

A low K_Ω indicates a high similarity at the top of the rankings, as illustrated by the low K_Ω between the LexiMin and AHP approaches (see Table 14).

All methods produced different ranking results. The LexiMax approach is the most inconsistent method, in this specific application case, compared to the other tested methods in terms of alternatives rankings.

4.5. Sensitivity analysis

4.5.1. Impact of weights' changes on the ranking for AHP and WSM methods

For analyzing the impact of the weights on the ranking, a sensitivity analysis was conducted. It was completed by changing one weight such that the highest-ranked alternatives in the preference ranking remain on top of the ranking, while all the other weights were adjusted to keep the weighting constraint $\sum_{i=1}^{n} w_i = 1$ (Mareschal, 1988). Subsequently, the rankings were repeated, and the results were compared with the initial state. The stability intervals of the 3E criteria (Local weights - Level one) for both AHP and WSM methods are displayed in Fig. 4. The initial value of the weights is marked with a dot. The intervals show the range in which the weight can be varied without changing the highest-ranked alternatives.

Similarly, Fig. 5 presents the stability intervals of the nine indicators' weighting factors (i.e., Global weights) for both AHP and WSM methods, showing the range in which the global weights can be varied without changing the highest-ranked alternatives. It can be observed that some indicators are more sensitive than others, i.e. a small change in the weight would result in a new ranking. For instance, the indicators g_3, g_6, g_7, and g_8 are more sensitive, while the remaining are more stable for both methods. This can be explained by the compensatory nature of AHP and WSM methods, which have high dependency to the weights of some dominant indicators. Concretely, this means for example that methanol (a_6) will remain the best performing alternative when the weight allocated to the indicator g_8 (environmental potential) changes between 23.86% and 40.91% for the AHP methodology. If the weight should become either lower than 23.86% or higher than 40.91% for the AHP methodology, another CO_2-based alternative will come on top of the ranking. Also, the top of the ranking will be insensitive to changes in the weight of indicators that present large weight stability intervals. For instance, methanol (a_6) will remain the best performing alternative when the weight allocated to the first indicator (g_1) changes between 0% and 93.15% for the AHP methodology. If the weight should become higher than 93.15%, another CO_2-based alternative will come on top of the ranking.

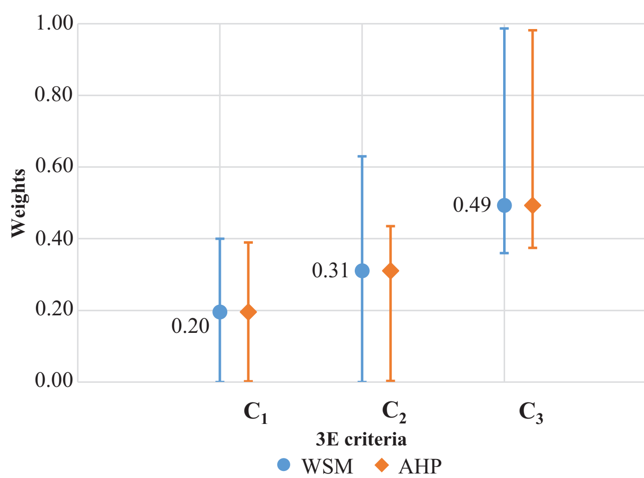

Fig. 4. Sensitivity analysis on the 3E criteria weights.

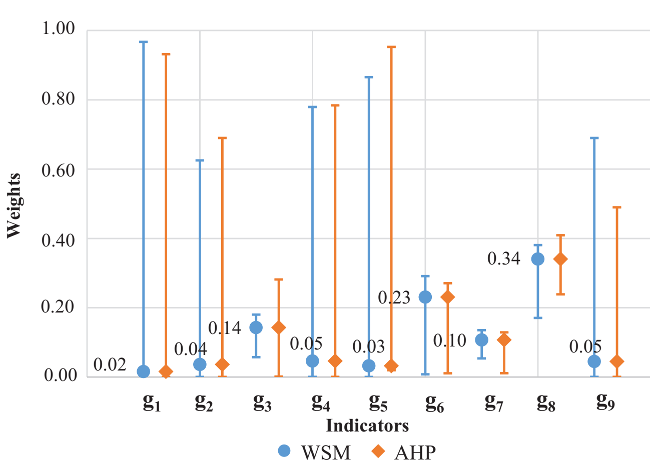

Fig. 5. Sensitivity analysis on the indicators' weights.

4.5.2. Impact of thresholds changes on outranking relations for the ELECTRE method

To test the robustness of the results obtained by the ELECTRE method, the values of the concordance and veto thresholds ($c^*$and δ_i) were varied and the effects on the final outcome were observed using the NFS (see Table 17).

If there is no veto, or if the veto thresholds δ_i are too high, the outranking relation bails down to the concordance. Thus, a decrease in the veto threshold allows to prevent more comparisons in the outranking relations. On the other hand, a value of 1 on the concordance threshold keeps only the obvious comparisons, where an alternative dominates another. Then, the NFS is used to summarize the outranking relation in a ranking. A decrease in the concordance threshold c^* includes more comparisons in the outranking relations.

The NFS rankings presented in Table 17 demonstrate that dimethyl carbonate (a_2), methanol (a_6), and methane (a_5) are in general at the highest position, regardless of the threshold values considered. The change of the thresholds permits to elicit the order when the concordance index varied between 0.7 and 0.9 and when the discordance set of thresholds is sufficiently restrictive.

4.6. Study limitations and recommendations

Some limitations and recommendations can be derived based on the previous analysis and discussion, which can be summarized as follows.

4.6.1. Criteria and indicators formulation

The indicators chosen to perform the analysis were grouped into the 3E performance criteria, as explained by Chauvy et al. (2019). While this approach has been utilized for assessments of new energy technologies or sustainability trends (Pan et al. (2016) and references herein), it excluded from a sustainability perspective the societal pillar, even though the social acceptance is a key aspect for technology deployment. However, as discussed by Jones et al. (2017), to date very few researches into the social acceptance of CO_2 utilization have been carried out. These studies mainly highlight the lack of awareness and technical knowledge, but with a positive general perception of CCU (Arning et al., 2018). To this extent, discretizing the societal pillar to one or several indicators and performing a complete evaluation was considered, at this stage of CCU deployment, beyond the scope of this present work. It is worth noting that a social

Table 17
Sensitivity analysis for the ELECTRE method.

		$\boldsymbol{\delta_i}$			
		No veto.	4 for all the indicators (more restrictive than Base case).	**Base case** – 3 for indicators g_2, g_3, g_6, g_7, and g_8. No veto for g_1, g_4, g_5, and g_9.	2 for all the indicators (less restrictive than Base case).
c*	0.60	$a_6 \geq \begin{matrix}a_1\\a_2\\a_5\end{matrix} \geq \begin{matrix}a_8\\a_9\end{matrix} \geq a_7 \geq a_{10} \geq a_3 \geq a_4$	$a_6 \geq \begin{matrix}a_1\\a_2\\a_5\end{matrix} \geq \begin{matrix}a_7\\a_8\\a_9\end{matrix} \geq \begin{matrix}a_3\\a_{10}\end{matrix} \geq a_4$	$a_6 \geq \begin{matrix}a_1\\a_5\end{matrix} \geq a_2 \geq a_9 \geq a_7 \geq a_8 \geq a_3 \geq \begin{matrix}a_4\\a_{10}\end{matrix}$	$\begin{matrix}a_5\\a_6\end{matrix} \geq a_7 \geq a_2 \geq \begin{matrix}a_1\\a_9\end{matrix} \geq \begin{matrix}a_4\\a_8\end{matrix} \geq \begin{matrix}a_3\\a_{10}\end{matrix}$
	0.71 **Base case**	$a_6 \geq a_5 \geq a_7 \geq \begin{matrix}a_2\\a_8\end{matrix} \geq \begin{matrix}a_1\\a_9\end{matrix} \geq a_3 \geq a_{10} \geq a_4$	$a_6 \geq a_5 \geq a_2 \geq \begin{matrix}a_7\\a_8\end{matrix} \geq \begin{matrix}a_1\\a_9\end{matrix} \geq a_3 \geq \begin{matrix}a_4\\a_{10}\end{matrix}$	$a_6 \geq a_5 \geq a_2 \geq a_7 \geq \begin{matrix}a_1\\a_9\end{matrix} \geq a_8 \geq a_3 \geq \begin{matrix}a_4\\a_{10}\end{matrix}$	$\begin{matrix}a_5\\a_6\end{matrix} \geq a_7 \geq a_2 \geq \begin{matrix}a_1\\a_9\end{matrix} \geq \begin{matrix}a_4\\a_8\end{matrix} \geq \begin{matrix}a_3\\a_{10}\end{matrix}$
	0.80	$a_6 \geq a_7 \geq \begin{matrix}a_1\\a_2\\a_5\end{matrix} \geq \begin{matrix}a_4\\a_8\end{matrix} \geq a_9 \geq a_3 \geq a_{10}$	$a_2 \geq a_6 \geq a_7 \geq a_5 \geq \begin{matrix}a_1\\a_8\end{matrix} \geq a_9 \geq a_3 \geq a_4 \geq a_{10}$	$a_2 \geq a_6 \geq a_7 \geq a_5 \geq a_1 \geq a_8 \geq a_9 \geq a_3 \geq a_4 \geq a_{10}$	$\begin{matrix}a_5\\a_6\end{matrix} \geq a_7 \geq a_2 \geq a_1 \geq \begin{matrix}a_4\\a_8\\a_9\end{matrix} \geq a_3 \geq a_{10}$
	1.00 More restrictive	$a_5 \geq a_6 \geq \begin{matrix}a_1\\a_2\\a_4\\a_7\\a_8\end{matrix} \geq \begin{matrix}a_3\\a_9\end{matrix} \geq a_{10}$	$a_5 \geq a_6 \geq \begin{matrix}a_1\\a_2\\a_4\\a_7\\a_8\end{matrix} \geq \begin{matrix}a_3\\a_9\end{matrix} \geq a_{10}$	$a_5 \geq a_6 \geq \begin{matrix}a_1\\a_2\\a_4\\a_7\\a_8\end{matrix} \geq \begin{matrix}a_3\\a_9\end{matrix} \geq a_{10}$	$a_5 \geq a_6 \geq \begin{matrix}a_1\\a_2\\a_4\\a_7\\a_8\end{matrix} \geq \begin{matrix}a_3\\a_9\end{matrix} \geq a_{10}$

indicator was somehow integrated into the environmental criteria (indicator g_9, Health and safety considerations). Overall, it is acknowledged that social aspects should be included in future work as the deployment of CCU technologies grows, to take into account how key stakeholders involved in CCU affect the development and innovation, the deployment, and the investment of CCU facilities and CO_2-based products.

Regarding the environmental performance, it is worth noting that the indicator g_8 (environmental potential) – which has been identified as the most important indicator – only focuses on climate change (CO_2-eq) and fossil depletion (oil-eq) as proxy in the suggested method. Nevertheless, within a broader sustainability perspective, the environmental impacts of each alternative should also be evaluated in a full life cycle assessment (LCA) in order to cover a broad set of environmental areas of concern. Furthermore, depending on the scenario, optimizing one indicator may lead to negative effects in other environmental aspects (or economic and/or social aspects) and thus trade-offs between multiple objectives may be desirable, as recently illustrated by Vandepaer et al. (2020).

4.6.2. MCDA approaches selection

Various representative MCDA strategies that are believed to be well suited for the purpose of this study were selected together with the decision maker. This choice was mainly motivated by the decision maker's and authors' knowledge of the given methods and availability of software supporting the methods. However, as seen in this work, applying various methods can lead to different results for the same problem, so the selection of a proper MCDA approach for a given situation is important. The authors recommend thus to properly chose a suitable method for solving a specific decision problem, as also recently discussed by Wątróbski et al. (2019). Additionally, in the specific context of CCU, the authors recommend selecting methods that have a low degree of compensation, such as outranking approaches, leading to strong sustainability (i.e., the economic, social, and environmental aspects are complementary but not interchangeable, by contrast to weak sustainability), similarly to what it is recommended in the wider issue of environmental policy and sustainability assessment (Cinelli et al., 2014).

4.6.3. Scores and weights determination

The relevance, quality and robustness of MCDA results strongly depend on the quantification of the indicators, which may be questionable. The set of scoring guides proposed by Chauvy et al. (2019) to evaluate the performance of each alternative against the criteria and indicators, including the evaluation method and the detailed five-level scoring factors assigned for each indicator, was peer-reviewed by experts, increasing the credibility of the value indicators. However, sensitivity analysis on the quantification of the indicators, i.e. by varying performance measurement, should be performed to assure to what extent it is affected by subjectivity.

Additionally, the choices of the weighting factors may be also disputed, as it strongly depends on cultural factors, as well as the occupation, location and background of the decision maker. For instance, the environmental concerns were given much more importance than the economic indicators, which might be related to the academic background of the authors and decision maker. Thus, a representative group of stakeholders across the field of CCU, including industry, policy, general public, etc. allows avoiding biased weights and accounting for all needs of the sector. The authors suggest performing a deep sensitivity analysis to determine the impacts of the weight choices on the results, such as the one proposed in this work. Also, the application of outranking MCDA approaches allows establishing preference relations, where references are used to assign higher preference to specific criteria than others.

Finally, it is worth mentioning that there are discussions relating to the interpretation of weights (Munier et al., 2019), especially in the AHP, where the weights derived from preferences (pairwise comparison) are trade-off values, indicating how the weight of an indicator changes when another indicator weight varies. Munier et al. (2019) thus advocate to use objective weights (e.g., elicited by entropy method). In the present work, although the authors use the weights derived from AHP in other MCDA methods, they ensure that these weights represent well the decision maker's preferences, given that there is no bias from the decision maker. Indeed, while weights in compensatory models represent trade-off factors between criteria evaluation scales, weights in non-compensatory models (as ELECTRE) are associated to the power of each criterion to impact the decision, in favor of one or the other alternative, with respect to a coalition threshold. Therefore, the meaning of the elicited weights should be explained to the decision maker in the spirit of the chosen MCDA approach and validated by him. Also, to find out whether the assigned weights to criteria and indicators really reflect the decision maker's true opinions, behavioral and procedural biases related to the size and structure of the criteria and indicators' hierarchy and to weight elicitation should be further examined, as argued by Marttunen et al. (2018) and references herein.

4.6.4. Robustness analysis

Traditional MCDA preference models have been considered. In particular, the exact values for the weights were elicited by applying dedicated weight elicitation technique, such as the AHP model. It was then followed by a sensitivity analysis to explore the robustness of the model, especially related to small changes in the weight values. However, as discussed by Tervonen et al. (2013), many decision makers may have doubts about the exact values provided for the weights and/or criteria. To this extent, the Stochastic Multicriteria Acceptability Analysis (SMAA) (Lahdelma et al., 1998) and/or the Robust Ordinal Regression (ROR) (Greco et al., 2008) could be considered.

4.6.5. Interpretation of results

The present study does not include any deliberative component allowing to make flexible interpretations of the results. Even if decision maker and end users agree with the results, it might neglect additional considerations that are specific to the CCU technology under scrutiny. The authors thus recommend organizing deliberative components in MCDA prior to make the conclusion, as also advocated by Workman et al. (2020). Overall, the rankings provided in this work should be seen as indicative. Additionally, the combination of several MCDA models of different spirits (compensatory and non-compensatory ones) can enhance the decision maker's trust in the results. Finally, visual presentation of sensitivities and their impacts on choices, such as the visual feature GAIA (geometrical analysis for interactive aid) initially developed for the PROMETHEE method, could be an option to further explore in order to provide the decision maker with a synthetic visual representation of the main characteristics of the decision problem, including synergies and conflicts between the preference measures or alternatives, as discussed by Arcidiacono et al. (2018) and references herein.

5. Conclusion

This paper aimed to identify the most promising CO_2-based conversion processes by application of several MCDA methods, i.e. the LexiMin/LexiMax approaches, AHP, weighted sum, and ELECTRE methods. Applying these MCDA approaches allowed to explore and illustrate their associated outcomes and how these both differ and complement each other, with regard to the process and the nature of the outcome, i.e. evaluation, ranking, outranking, etc., and the final conclusions per se. Also, comparing resulting rankings using a different MCDA method is also a way to assure the robustness of the results.

The proposed MCDA approaches aid the decision maker for solving different reference problematics; either by building a complete order of alternatives according to preferences (LexiMin/LexiMax approaches, AHP, weighted sum methods), or by providing aid in choosing a small subset of alternatives (ELECTRE method). Also, an important characteristic of the investigated MCDA methods is the degree of compensation of the criteria. While the AHP and WSM methods lead to full compensation, i.e. the gain on one indicator can compensate the loss on another, the LexiMin/LexiMax methods lead to no compensation, in a way that the low values of some indicators could not be compensated for by other indicators. In the outranking ELECTRE method, compensation is only allowed at the level of criteria coalitions and may be excluded by using veto thresholds.

Thus, the LexiMin/LexiMax approaches proposed a weak order by the direct exploitation of the decision table. The AHP method, used to first elicit the criteria and indicators' weights and then to rank the alternatives, as well as the WSM approach, proposed full comparability of all alternatives in the ranking (i.e., total order). The decision-making results were directly influenced by criteria and indicators' weights. Hence, the ELECTRE method was relevant as there was a strong heterogeneity with the nature of evaluations among criteria (e.g., CO_2 uptake potential, technological maturity, size of the market, etc.). In addition, the compensation of the loss on a given criterion by a gain on another one was not acceptable by the decision maker. Overall, using methods that have a low degree of compensation is recommended in the wider issue of environmental policy and sustainability assessment.

Additionally, the different methods were compared using both Kendall tau coefficient and weighted distance of Kendall's tau. The score scales and distributions within criteria and indicators did not have the same impact on all the MCDA approaches investigated in this paper. Moreover, the defined weights had effects on the result, that were observed when the sensitivity analysis was carried out. The sensitivity analysis took into consideration that the weights were established on the basis of authors perception, which may be subjective. It led to weight stability intervals in which the highest-ranked alternatives were not permuted. Some indicators were therefore more sensitive than the others, in particular the indicators Fossil free operations, Relative added value, CO_2 uptake potential, and Environmental potential. Therefore, it is recommended to have an intensive investigation on these indicators and the chosen weights. Additionally, the sensitivity analysis helps the decision maker to address uncertainty in the decision problem and find out the least sensitive approach.

In environmental decision-making, it appears to be necessary that several MCDA methods are applied to get the ranking orders of alternatives. Even though the results obtained by the aggregation methods (i.e., AHP, WSM) are more rational, the outranking methods propose outranking relations that provide more qualified conclusions in expressing their preferences. The former methods lead to weak sustainability (high level of compensation), while the latter to strong sustainability, meaning that the techno-economic and environmental aspects are complementary but not interchangeable. Also, outranking methods also deepen the understanding of the decision-making problem and focus on the quality of the decision process itself, instead of on determining an optimal solution. Thus, combining and/or performing aggregation methods together with outranking methods can mitigate disadvantages of MCDA methods when used alone, and direct the analysis to a more robust conclusion.

In the framework of CCUS, making decision using MCDA methods will play an important role, improving the quality of decisions. Considering the relatively small differences in the results, they showed that methanol (a_6), dimethyl carbonate (a_2), and methane (a_5) are CO_2-based products considered the best courses of action to be implemented in near future with respects to engineering, economic, and environmental performances.

Areas for future work includes considering fuzzy set methodology to take care of the qualitative criteria, the imprecision inherent in the information, and uncertainties in authors and experts judgment especially for weights elicitation. Also, the discussions of the limitations of this study lead to several recommendations that can guide further assessments in this field.

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.

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Supplementary materials

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