Multi-Attributional Decision Making in LCA & TEA for CCU:

An Introduction to Approaches and a Worked Example

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Foreword

Climate change is one of the largest challenges of our time. It is proven that excess amounts of carbon dioxide that humanity has added to the atmosphere plays a key role, and left unaddressed, this will alter ecosystems and fundamentally change life as we know it. Under the auspices of the UN Framework Convention on Climate Change and through the Paris Agreement, there is a commitment to keep global temperature increase to well below two degrees Celsius. Meeting this goal will require a variety of strategies including increased renewable power generation and broad scale electrification, increased energy efficiency, and carbon-negative technologies. Carbon-negative technologies serve two purposes, as a climate mitigation tool near term, and to create a new carbon economy that recycles carbon over the long term- balancing emissions of still essential industrial sectors such as cement and steel. Overall, carbon-negative technologies are a valuable strategy in an overall portfolio of approaches to stabilize the atmospheric carbon dioxide concentration at a level that supports human life on Earth.

Increased attention is being paid to the notion that carbon dioxide can become a valuable resource instead of being a waste product with severe negative consequences to the earth's climate. New technologies, new use cases, interest from the investment community, and growing legislative support poise the use of a carbon dioxide feedstock as a viable economic and societal opportunity.

But not all that glitters is gold! Thorough assessment of the environmental and economic benefits of new technologies is paramount prior to deployment. Transparent and consistent life cycle assessments and techno-economic assessments must provide unbiased information to decision makers to enable sound decisions on investments, deployments, and public support for such.

International demand from government bodies, industry, investors, non-profits, and researchers for harmonized approaches to conduct life cycle assessments and techno-economic assessments for carbon dioxide utilization led us to coordinate and fund an international effort to develop and disseminate Guidelines for TEA & LCA for CO2 Utilization. First published in 2018, these Guidelines have found widespread attention and use and have recently been updated (http://hdl.handle.net/2027.42/162573). A growing list of case studies, and worked examples, is made available to illustrate how to use these Guidelines.

We hope that this case study will be useful to you and we will be grateful for any feedback!

April 2021, Volker Sick, Global CO_2 Initiative

List of Abbreviations

Abbreviation	Definition
ADP	Abiotic Depletion Potential (Elements) Indicator
ADPf	Abiotic Depletion Potential (Fossil) Indicator
AHP	Analytical Hierarchy Process
AP	Acidification Indicator
CapEx	Capital Expenditure
CBA	Cost-Benefit Analysis
CCS	Carbon Dioxide Capture and Storage
CCU	Carbon Dioxide Capture and Utilization
CCUS	Carbon Dioxide Capture and Utilization and Storage
CEA	Cost-Effectiveness Analysis
CI	Consistency Index
CR	Consistency Ratio
ELECTRE	Elimination Et Choix Traduisant la Realité / Elimination and Choice Translating Reality
EP	Eutrophication Indicator
FAET	Freshwater Aquatic Ecotoxicity Indicator
GWP	Global Warming Indicator
HT	Human Toxicity Indicator
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LP	Linear Programming
MACBETH	Measuring attractiveness by a categorical-based evaluation technique
MADM	Multi-Attribute Decision Making
MAET	Marine Aquatic Ecotoxicity Indicator
MAUT	Multi-Attribute Utility Theory
MCA	Multi-Criteria Analysis
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MODM	Multi-Objective Decision Making
MOLP	Multi-Objective Linear Programming
MOO	Multi-Objective Optimization
ODP	Ozone Depletion Indicator
OpEx	Operational Expenditure
PEM	Polymer Electrolyte Membrane
POCP	Photochemical Oxidation Indicator
PROMETHEE	Preference Ranking Organization Method for Enrichment of Evaluations
REMBRANDT	Ratio Estimation in Magnitudes or deci-Bells to Rate Alternativews which are Non-Dominated
RI	Random Consistency Index
SIA	Social Impact Assessment
SMART	Simple Multi Attribute Rating Technique
SMARTER	Simple Multi Attribute Rating Technique Exploiting Ranks
TEA	Techno-Economic Assessment
TET	Terrestrial Ecotoxicity Indicator
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

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Part 1: Introduction to Multi-Attribute Decision Making

1.1 Preface for this Worked Example

This worked example has been released at an intermediate timeframe within the CO_2nsistent project, fitting in between the release of version 1.1 and 2.0 of the '*Techno-economic Assessment & Life Cycle Assessment Guidelines for CO_2 Utilization*' [1]. This means the subject matter of this worked example (combined assessment, in particular multi-criteria approaches to decision analysis/making) remains to a degree uncovered by the overarching guidelines associated with this project until the release of version 2.0. As such this worked example will include more contextual sections than has been typical in previous examples, in part bridging the gap until a more detailed guidance section on combined assessment can be included in version 2.0.

This does not mean that no guidance can be drawn from version 1.1 of the guidelines document in the intermediate timeframe. Version 1.1 contains some guidance on both combined LCA & TEA studies (see section A) and the individual TEA section itself also contains a brief section and guideline rules on multi-criteria decision analysis (MCDA) for use within the field. Ultimately this guidance is useful even for application in a combined study, as ultimately the same concept applies with the complication of needing to ensure that both the LCA & TEA study are aligned with suitable precision.

1.2 Scope of this Worked Example

This worked example considers only the elements of the whole process relevant for the integrated assessment in greater detail. This worked example builds on a prior study, covering CO_2 to methanol conversion [2], and as such a more detailed overview of the technology can be found there. A brief overview of the methanol technology is included for familiarization, along with details on the alignment approach taken to ensure that a 'preference-based' integration can be completed. The focus of this worked example is the application of multi-attribute decision making (MADM) approaches and their potential use within combined LCA & TEA studies. The practical part of this examples sees the application of one MADM method to a multi-criteria problem with relevancy in CCU that utilizes the outputs of both an LCA & TEA study.

1.3 Combining LCA & TEA Studies: A Brief Introduction

Before considering anything else, the primary question to answer is why should one consider combining LCA & TEA studies? The obvious answer, particularly for CCU and other emerging technology fields, is that combining the two allows for the development of a better understanding of performance in both particularly in the understanding of the potential tradeoffs in performance between the two. Tangible examples can be given of situations where:

- When designing a product, process or service the designer may be interested in balancing economic and environmental performance through process optimization, here combined enviro-economic indicators may be of use as may approaches such as multi-objective optimization

- When selecting from a range of alternatives each with their own economic and environmental profiles, in particular where there is no 'dominant' best choice. Multi-attributional decision making approaches can be of use here which aid the decision maker in developing their preferences to ensure the 'correct' decision is made
- Reporting on both the environmental and economic performance of a product, process or service. Well aligned studies in this sense allow for more detailed and reliable qualitative and quantitative analysis to be produced, strengthening the quality of any conclusions drawn

The examples above require differing degrees of integration (aligning and combining) between the LCA & TEA elements.

Version 1.1 offers guidance on the types of potential integration identified for combining LCA & TEA studies. As stated in the guidelines, both *ex-ante* (conducting a singular study covering both LCA & TEA criteria) and *ex-post* (combining LCA & TEA studies have been conducted) approaches can be taken to integration; with the likely approach taken dependent more on circumstance than any other reasoning (i.e. whether an LCA and/or TEA already has been conducted suitable for the combined study goal). Both approaches do bring their own advantages, *ex-ante* studies offer a reduced risk of misalignment as all methodological choices are made with both the LCA & TEA aspects in mind but do require additional resource to complete. Meanwhile, *ex-post* approaches allow practitioners to utilize existing studies streamlining the assessment approach but with the added risk of misalignment or inconsistent methodological choices being made.

Secondly, an integration type should be identified with three given in the guidelines:

- Qualitative, discussion-based integration
- Combined indicator-based integration
- Preference-based integration

It should also be noted that more than one type of integration may be used in a study should this be deemed beneficial

Each of these types is summarized in more detail in the guidelines document, however it should be noted that little methodology guidance is provided in version 1.1. As a brief introduction a summary of each of the three is included here. Qualitative integration aims to compare the economic and environmental results through discussion, integration can focus on the whole process/service or specific elements/sub-processes (e.g. known 'hotspots' that are highly impactful of overall economic or environmental performance). The discussion is likely to consider such concepts as trade-offs, where a choice can be made to improve performance in one area at the expense of another. Qualitative integration is arguably the easiest to implement but the lack of additional quantitative analysis may limit the scope and preciseness of any additional conclusions that can be drawn. Another advantage for qualitative approaches is that they can be undertaken with a lower level of precision in the alignment between the TEA & LCA studies than those that require quantitative calculations (although care should be taken to make sure the alignment should be sufficient enough to ensure that any conclusions made are valid).

Combined indicator-based integration sees the calculation of additional *enviro-economic* indicators to aid in process analysis, quantitatively combining both economic and environmental dimensions to give further insight into a particular facet of the product. Unlike qualitative approaches there is less flexibility in the precision required for alignment to limit errors resulting from combination. A commonly used combined indicator in CCU is the GHG abatement cost – often used to identify the cost efficiency of abating CO_2 through re-utilization. Combined indicators can be utilized on their own or combined with other indicators (either combined or LCA/TEA only) in further analysis to give a more balanced picture. For example, a fixation on GHG abatement cost alone may result in 'burden shifting' where other environmental impacts are increased in the pursuit of ever-greater performance in the one category.

Preference-based integration 'aims to include the decision makers preferences by following a multi-criteria approach' [1]. MCDA concerns the development & application of a structure to solve issues with multiple criteria; with these criteria typically being decided upon by the practitioner or other interested party. The strength of this approach is that these criteria can be diverse and independent, yet still be compatible for analysis – making the approach beneficial for use in combining LCA & TEA in instances where the goal requires the practitioner (or a third party) to make a decision. What exactly amounts to a solution depends on the goal and the type of problem to be assessed, with this is covered in more detail later in this worked example. As would be expected, the confidence one can have in a decision made using a MCDA approach is dependent on the relative success in aligning the LCA & TEA used.

Guidance is also provided on how to determine the type of integration required both in the guidelines and in a stand-alone paper [3], however briefly the following three steps are outlined:

1. Define the purpose of integration
2. Identify restrictions imposed by technology maturity
3. Identify resource limitations for the assessment

1.3 Multi-Criteria Decision Analysis Overview

Before considering any particular type of decision making in detail it is worthwhile considering how approaches are generally classified.

Three 'principal streams' of research into decision making are highlighted in source [4]:

- The *descriptive* stream which examines how actors actually undertake decision making in practice
- The *normative* stream which tries to establish how rational actors should choose between competing options
- The *prescriptive* stream which tries to utilize the findings of the descriptive stream to develop approaches that bring 'intuitive unaided human decision making' closer to the 'normative ideals' highlighted in the prior category

The latter two streams in particular are of interest here, as they are the basis for many of the models used in CCU decision analysis. The identified streams are each associated with their own decision analysis techniques, with this reflected later on within this section when reviewing multi-attribute decision making approaches in detail.

1.3.1 Other Analytical Approaches Frequently used in Decision Making

Before considering MCDA in detail, an overview is included on other types analysis or evaluation that could potentially be applied in decision making using LCA & TEA outputs. This is not intended to be an exhaustive overview, nor one of great critical depth, and is included merely to provide a broader view of analysis techniques. In general, this section focuses on quantitative approaches, although qualitative options are also viable (some of these such as decision trees are discussed below).

A more structured overview can be found in source [5], where three broad classifications are outlined: multi-criteria decision making, artificial intelligence and 'other methods' (an umbrella term for methods not captured by the prior two).

Systems such as *decision trees* are used elsewhere within the guidelines (given direction to practitioners regarding various methodological choices such as determining a function unit or a comparison case) and could have potential for deployment in other decision making processes, given that it allows a formulaic approach to be outlined to allow for a consistent application of a set of attributional preferences. *Pairwise comparison* [6] can be used also as a standalone technique, although it is often used in part of a larger framework such as the *analytical hierarchy process* (a form of MCDA) and is such not discussed independently here. Similar approaches such as *conjoint analysis* can also be used to determine preferences on specific attributes compared by a specified audience/stakeholders.

Techniques such as *cost-effectiveness analysis* and *cost-benefit analysis* are tools used frequently in program evaluation [7], with the former being of most interest to the concept of integrating LCA & TEA in decision making. Cost-effectiveness analysis (CEA) is frequently used in healthcare and health economics, the aim of the study is to 'identify and place dollars on the cost of a program' whilst relating these to specific measures of program effectiveness [7]. CEA results in the production of a ratio:

$$\text{Cost-effectiveness ratio} = \text{Total Cost} / \text{Units of Effectiveness}$$

The 'unit of effectiveness' is any quantifiable outcome, setting this to the number of tonnes of CO_2 abated for example would result in deriving a carbon abatement cost for example. The calculated ratio can then be compared across the range of options available to determine the optimal solution. The advantage to utilizing a CEA framework is that much of the steps required for the end result are already covered by the conducting of the LCA & TEA studies, however there are practical limits to the complexity of the 'units of effectiveness' which may be problematic when determining across a broad set of criteria.

Cost-benefit analysis (CBA) is defined as the process 'used to measure the benefits of a decision or taking action minus the costs associated with taking that action' [8]. CBA involves using measurable financial metrics (e.g. revenue earned, costs saved) as a result of the decision made – although 'intangible benefits' (e.g. customer or employee satisfaction) can be included in the calculation. Given the focus on financial elements CBA is arguably better suited to TEA solely (as with net present value calculations).

Linear programming (LP) is a tool used in many fields, including LCA [9][10], with the intention of determining a 'best outcome' in a mathematical model in which requirements are represented by linear equations. A short introduction to LP can be found in [4], with the prior mentioned sources also providing details on its application in LCA. LP is particularly useful for identifying optimal designs as it is a form of continuous multi-criteria analysis, allowing for the consideration of an infinite number of possible combinations – rather than a finite set of options with specified attributes. LP utilizes a set of decision variables, x_j, and it is these that are combined in all possible combinations with the aim of maximizing a given 'linear objective function' whilst also obeying a set of constraints which restrict the combinations of x_j that are allowable. Like the objective function, these constraints are also represented by linear functions and the final constraint is that the values of x_j are non-negative allowing for a (graphical) 'feasible region' to be determined with the size of this feasible region determined by the constraints placed on the objective function. The conventional form of the LP model is as follows [4]:

Maximize (or minimize): $\sum_{j=1}^{n} a_j x_j$

Subject to: $$\sum_{j=1}^{n} a_{ij} x_j \leq b_i (i = 1, \dots, m)$$

$$x_j \geq 0 \ (j = 1, \dots, n)$$

As stated x_j represents the decision variables, these are the variables that the decision maker has control of, a_j are numerical parameters that represent the relative contributions in each of the decision variables in achieving the overall aims. $\Sigma a_j x_j$ is therefore the objective function, expressing the overall goal as a function of the decision variables and their contributions. The $\Sigma a_{ij} x_j$ terms are the functional constraints and they express how x_j is limited in the decision context. The final term $x_j \geq 0$ are the non-negativity constraints limiting the contribution from any particular x_j to zero, in instances where the value of x_j can be negative (such as negative CO_2 emissions due carbon sequestration in an x_j that considers carbon emitted) this needs to be accommodated for 'indirectly'.

The aim of the LP analysis is to find the point within the feasible region in which the objective function achieves its maximum value. A visualization of a LP system is given in figure 1.

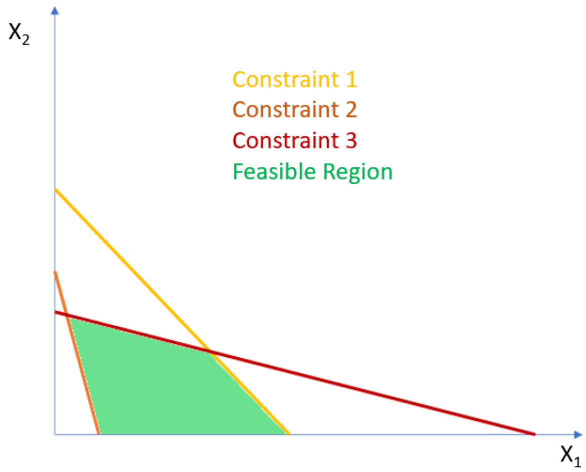

Figure 1 – Graphical representation of a linear programming approach

One potential drawback for LP approaches in integrating LCA & TEA is the need to determine the objective function [4]. Applying LP to LCA leads to an obvious objective function – minimize the environmental impact of the process/product/service (although alternatives may be of interest in some specific cases). For TEA this approach may be more difficult, the most obvious objective function would be to maximize profit or return on investment but feasible alternatives may also have appeal especially in a broader business sense: maximizing market share, brand identity or minimizing capital costs may be of more value dependent on company structure or business plan. When considering integrating LCA & TEA together in a combined enviro-economic assessment this situation becomes more complex once again – several objectives can be identified (maximize profit, minimize environmental impact) but deciding upon which should be the objective function requires a choice to be made. The addition of further dimensions can further complicate this, adding social impact assessment (SIA) to the combined LCA & TEA study would allow for a more complete sustainability assessment but with the added complexity of introducing further potential objective function options. *Multi-objective Linear Programming* (MOLP) is capable of dealing with the limitations of LP, enabling the practitioner to optimize with more than one objective function identified. Source [11] provides one such example of MOLP application within LCA, to combine this with life cycle costing (LCC) in an approach that has a similar objective to the combined LCA & TEA assessments considered as part of the CO_2nsistent project. MOLP is a form of *Multi-objective optimization* (MOO) which is discussed in the next section.

Authors note: We have chosen here to not classify simple linear programming as a form of MOO (or multi-objective decision making) for the reasons explained above, however other publications may do so.

These types of problems can be addressed by *multi-criteria analysis* (MCA) or *multi-criteria decision analysis* (MCDA). It should be noted that the terms MCDA and MCA are often used interchangeably, although in some sources MCA and MCDA are reported as similar but slightly different where the addition of the word 'decision' is a differentiator (i.e. MCA doesn't necessarily involve decision making). Here, the term MCDA is used throughout as the aim of this worked example is to demonstrate the application of MCDA approaches for decision support reasons. MCDA is said to have evolved as 'a response to the observed inability of people to effectively analyze multiple streams of dissimilar information' [12]. As such the intention of MCDA is to provide a framework in which these decisions can be structured as to best aid a decision maker to make a 'correct' decision determined by their preferences.

1.3.2 Multi-Criteria Decision Analysis: MCDA, MODM, MADM and MOO

As mentioned above the naming conventions for various aspects of MCDA (alternatively MCDM for *Multi-Criteria Decision Making*) can be confusing, particularly for those not familiar with the concepts. As part of this an attempt to clarify this to a degree is included here, or at least provide a consistent basis for the use of these terms within the context of this worked example and the TEA & LCA Guidelines for CO_2 Utilization in general.

In the TEA section of the guidelines document MCDA (sourced originally from [13]) is defined as follows:

'*MCDA is a method for supporting decisions that involve multiple dimensions or criteria and thus allows evaluation of trade-offs. It allows economic, social, and environmental criteria, including competing priorities, to be systematically evaluated*'

MCDA can be seen as a way of discovering and quantifying decision-maker and stakeholder 'considerations' about various factors in order to compare alternative 'courses of action' [14]. A broad range of MCDA techniques are available, each with its own framework and methodology offering a range of advantages and disadvantages.

MCDA approaches have been applied across a range of fields, including environmental science [14], 'sustainable' energy provision [13][15], healthcare [16] and has been used in aiding results interpretation in LCA studies [17] for a significant period of time.

Here, and in the guidelines, two broad types of MCDA study are identified: *Multi-Attribute Decision Making* (MADM, sometimes referred to as *Multi-Attribute Decision Analysis* or MADA) and *Multi-Objective Decision Making* (MODM, sometimes referred to as *Multi-Objective Decision Analysis* or MODA). Whilst both MADM and MODM can be used to identify a preferred solution it should be noted that the methods used in doing this differ somewhat.

Multi-attribute approaches consider a finite set of options, where specific *attributes* of these options are assessed to determine a best set of alternatives amongst them. This assessment typically involves normalizing and weighting the criteria, with these weightings determined through consideration by one or more stakeholder groups. The outcome of the study depends on the type of problem to be assessed (this is covered in a later section) but ultimately leads to a preferential selection or ordering from the options given.

Multi-objective approaches consider an infinite set of options bound by physical limitations with specific *objectives* used as the criteria for optimization, analysis or assessment. This approach in a sense is somewhat similar to that of the LP approach discussed in the previous section in that objective functions form a basis for the process rather than discrete attribute values. As with MADM approaches, MODM approaches utilize weighting in the technique to determine preference of specific criteria by the assessing party or other stakeholder.

Source [18] defines three 'motivating scenarios' for use of MODM:

- Scenario 1 (unknown weights scenario) sees the identification of a multi-objective decision problem; the problem is then processed through a chosen algorithmic approach to produce a *coverage set*. This coverage set is then weighted based on the best available data and is put through a 'scalarization' process as part of the selection phase, with this leading to a single solution in the execution phase. Scalarization can only be applied in this scenario as each of the objective functions can be determined in a quantified manner. If this is not possible, either because an impact is hard to quantify or because its value is unknown/uncertain than an alternative approach must be taken.
- Scenario 2 (decision support scenario) sees the identification of a multi-objective decision problem; the problem is then processed through a chosen algorithmic approach to produce a coverage set. Unlike scenario 1, the selection phase here utilizes a 'user selection' approach, with this leading to a single solution in the execution phase. In this scenario scalarization isn't possible due to the difficulty in specifying a value for weighting or a formulaic way of expressing the objective function as a quantity. This scenario is useful for instances where scenario 1 cannot be applied, such as instances where stakeholders have 'fuzzy' preferences that cannot be quantified meaningfully.
- Scenario 3 (known weights scenario) is similar to scenario 1, with one meaningful difference in that both the multi-objective decision problem and the weights are known from the outset. Here only a planning (choosing of and application of an algorithm) and an execution phase (application of the chosen alternative) are required, as the pre-determination of weighting values eliminates the need for a selection phase.

In the above scenarios a coverage set is defined as a subset of the non-dominated set – with the non-dominated set being the set of options present at the Pareto front, with these terms being Pareto optimal (i.e. changes made to improve one function will result in poorer performance in another). These contrast with dominated solutions which can undergo what is deemed as a Pareto improvement – where improvements can be made to one function without loss of performance in another.

Source [18] explains that whilst the non-dominated set does not contain dominated solutions it does contain redundant ones – the coverage set removes this redundancy whilst 'covering' all optimal solutions for the objective functions and weightings. Without further intervention all solutions in the coverage set, and the broader non-dominated set, should be assumed to be equally as good as each other. It is for this reason that intervention is required to determine a singular (or set of) solution(s) through determining the preferences of the decision maker or other stakeholder and it is this aspect that varies in the scenarios above.

The determining of the Pareto optimal/non-dominated set is a computational task and several approaches/algorithms are available. This general field is often referred to as Multi-objective optimization (MOO), with this umbrella covering a range of techniques for determining the non-dominated set, for quantifying trade-offs in the competing objectives and for finding solutions that suit the preferences of a given stakeholder. As stated whilst some groups utilize the term MOO to incorporate the making of decisions here MODM is used to give distinction between the act of optimizing and decision making.

Ultimately, the differences between MADM and MODM approaches can be seen in the method followed:

- For MADM the criteria of assessment are a collection of predefined attributes of which a finite set of predetermined alternative options exist. The goal is to determine the most preferred solution from this list of alternatives
- For MODM the criteria of assessment are a collection of predefined objectives which act as constraints on a function to be optimized. There are infinite solutions to this optimization problem, the goal is to determine the most preferred optimal solution

The attributional approach is the equivalent of going to a car sale showroom, recording key attributes (e.g. safety rating, fuel efficiency, acceleration rate, price) of each car type and using this information and a set of determined weighting factors to identify your preferred option from the finite options. The objective approach is the equivalent of going to a car manufacturer with a set of objectives ('it must have a high safety rating', 'it must be fuel efficient', 'it must accelerate quickly' and 'it must be affordable') and optimizing the design to produce a car that best fits your preferences regarding the competing objectives.

Regarding combined assessment of LCA & TEA in CCU both MADM and MODM approaches have uses in differing applications – depending on whether attributes or objectives can be determined. For example, process design & optimization naturally lends itself to MOO and MODM type approaches as one would expect. Attributional approaches on the other hand may be of more use when a defined set of alternatives is available, such as selecting one from a range of technologies for deployment in a given location/scenario.

Throughout this section discussion has focused on both multi-attribute and multi-objective approaches to decision making, however the practical element of this worked example focusses on multi-attribute approaches and as such these methods will be considered in greater detail than MODM methods from this point forward.

1.4 Multi-Criteria Decision Analysis: An Overview of Attributional Approaches

1.4.1 Categorizing MADM Approaches

This section aims to provide a basic and relatively short general, non-CCU overview of the various categories of MADM typically used. Key features, strengths and weaknesses are discussed for the broad categorizations established by other reviewers. Little detail is given for specific methods within classes for brevity, details of these can be founded in several of the sources given. The intention is to provide an introduction to MADM methods for those not familiar with topic and as such this section can be skipped by those with experience or knowledge. Categorization of MCDA approaches varies across publications, although similar groups are consistent.

Both sources [14][19] assess the use of MCDA in environmental science, and identify three main approaches: multi-attribute utility theory (MAUT), outranking and the *analytical hierarchy process* (AHP) and its associate variations. Source [14] does mention linear additive approaches as a 'basic approach.

Source [4] utilizes the same list, but expands upon this to include *linear additive approaches* and *non-compensatory methods* as distinct categories. The latter category should be used sparingly due to its inability to establish overall preferences, working predominantly on a 'process of elimination' considering each attribute from most important to least to determine a solution. Source [20] considers two 'schools of MCDA' – the American school, covering *normative* approaches, in which 'the view of the decision-maker is disaggregate in the sense that the decision-maker is assumed to have a complete preference system' and the French school where 'the existence of a well-ordered preference system is questioned and the view is more that of the decision-maker as a rational economic man'. The MAUT-type approaches, the AHP-type approaches and simple linear approaches are classified as being part of the American school, with the outranking approaches classified as part of the French school. Source [21] identifies 11 different MCDM methods, many of which are attributional approaches and provides a brief literature overview for each.

A more comprehensive categorization is provided by B. Roy (a key figure in the development of the ELECTRE outranking method) in source [22]:

1. *Approaches based on synthesizing criterion*: the most traditional approach, formal rules are used to aggregate the performance of alternatives across *n* criteria into a single score, leading to a 'complete preorder' of preference. These formal rules typically consist of a mathematical formula to determine a, and 'imperfect knowledge' (i.e. incomplete data sets or known uncertainties) can only be included in probabilistic or fuzzy models. This classification covers MAUT, SMART, TOPSIS, MACBETH and AHP.
2. *Approaches based on synthesizing preference relations*: these are the outranking methods (such as ELECTRE and PROMETHEE). As with the prior category a mathematically explicit multi-criteria aggregation procedure is used to determine a preference order, but unlike above the aim is not to establish a complete preorder but to assess using pairwise comparisons to create a preference relational system. Data used can be crisp or fuzzy, and the methods allow for the inclusion of concepts such as indifference and incompatibility of comparisons.

3. *Other operational approaches*: included in this category are approaches that are mathematical in nature but do not fit the proceeding categories and those that are not mathematically explicit such as interactive approaches.

In the classifications of B. Roy the concept of fuzziness is introduced, and as stated various models within the classifications are capable (or incapable) of dealing with this. The need to utilize a model capable of dealing with fuzzy data is problem specific, and as such this isn't considered in detail here as the focus is not to discuss specific models in great detail.

1.4.2 Linear Approaches

Linear additive approaches are generally considered to be the simplest to use, with approaches such as the aptly named *Simple Multi Attribute Rating Technique* (SMART) based on this. An introduction to SMART can be found in sources [4] and [20], with the latter giving a stage by stage breakdown of completing the process. The key calculation steps in the SMART process are to assign values to each criteria, to determine the weight of each criteria and then to normalize the final score to make a decision. Finally, a sensitivity analysis is then performed to validate this decision or express its limitations. Should the assessment of value functions and weights prove to be difficult (or should the practitioner have little confidence in accurately assessing this) the approach can be modified as the *SMART Exploiting Ranks* (SMARTER) where the individual criterion are ordered from most to least important and a rank order distribution method is selected for use [20]. Criticisms of SMART (and linear additive approaches in general) are also reported. Source [20] states that the SMART approach tends to oversimplify the problem if used as a screening method, whilst also stating that there is also a high demand on the level of detail required on the input data. However, it should be noted that such restrictions on input data are not unique to linear models. Others have pointed to SMART containing an error in its logic, which was corrected by the development of SMARTS [23]. More damning is the criticism that the same simplicity that makes the models attractive may also lead to the creation of 'pitfalls' that can be avoided using more complex multiplicative relationships [24], in some areas where decision making outcomes may involve assessing critical outcomes (such as life-critical situation in healthcare for example) reviewers have labelled additive MCDA approaches as 'inadequate' for use [25] when compared to alternatives. Others label SMART as 'one of the simplest forms of MAUT' [21] in place of creating a distinct category for linear approaches.

1.4.3 Multi-Attribute Utility Theory

Multi-attribute utility models are, as stated above, normative approaches with these being defined as the type of approach that 'establish how rational individuals, groups and organizations should choose between competing options' [4]. Generally the work of von Neumann & Morgenstern [26] is seen as the starting point for the development of normative approaches in multi-criteria applications, with the work of Savage [27] expanding upon this. MAUT was developed by Keeney & Raiffa [28], following the axioms outlined by von Neumann & Morgenstern [14], with MAUT described as 'adding a layer of complexity' to linear additive models by transforming the scores into utility functions.

The four axioms are known as the basis of the 'von Neumann & Morgenstern utility theorem' [VNM] [29]. When these axioms (completeness, transitivity, continuity and independence) are satisfied by a decision maker & their preferences the decision maker is said to have a utility function and as such the decision maker will always prefer options that maximize expected utility. This utility function is required to have a real value and a decision maker is said to be VNM rational if every preference is tailored to maximizing this value. It should be noted that in the VNM model the decision maker is not claimed to be actively (consciously) trying to maximize utility, merely that the concept of a maximum utility exists for the decision maker.

There exist a range of MAUT approaches, with varying levels of complexity derived from the work of Keeney & Raiffa, which itself contained three key stages[4]: the determination of a performance matrix, the determination of whether attributes are independent of each other or not and the estimation of parameters in a mathematical function designed to estimate the 'single number index' which expresses the overall valuation of an alternative in relation to its performance in each of the criteria. The final stage, the estimation of a single number index, can be seen to draw directly from the utility function derived in the VNM. The simplest MAUT models are those that have wholly independent attributes and no hierarchical structures [14], essentially providing a linear additive approach as discussed above. Weighting to assess importance (or risk) of a category is typical, as is normalizing results between 0 (worst possible value) and 1 (best possible value). Alongside the sources mentioned above, additional reading can also be found in source [30].

1.4.4 Outranking Methods

A commonly used alternative to MAUT approaches are the outranking approaches developed initially in France during the 1960s [31], with the basis of this developed by Bernard Roy & colleagues a summary of which can be found in source [32]. One of the drawbacks of utility approaches is the need to make all alternatives comparable in a transitive way (remembering that one of the axioms is transitivity) requires a large amount of information and a large amount of analysis to detail all trade-offs between attributes [31] and the preferences of the stakeholder need to be precise [21]. Obviously this requires a significant amount of resource which may not always be of available. As such prescriptive approaches such as the outranking ones may offer something akin to a middle ground between normative approaches and purely descriptive ones.

A second advantage that outranking methods provide is that they seek to make fewer assumptions about how preferences are arrived at [4]. Practically this means that there is more flexibility for the decision maker to finalize their choice through 'fine-tuning' in elements such as the pairwise comparison thresholds rather than being dictated to through axiomatic logic. Thus the outranking methods are sometimes referred to as being a 'more interactive process between decision maker and model' [4].

As with the prior approaches a preference relation is required – with this usually referred to as the 'outranking relation' [31]. This outranking relation is arrived at through evaluating alternatives on several attributes selected by the decision-maker. For most outranking methods this relation is constructed through a series of pairwise comparisons, with many methods using the '*concordance-discordance principle'* for this, including the ELECTRE family of models developed by Roy et al. The concordance-discordance principle states an alternative x is at least as preferable to alternative y if a 'majority' of the attributes support this assertion (concordance condition) provided the opposition of the other attributes isn't too 'strong' (non-discordance condition) [33]. Thus the outranking methods can be seen as approaches that involve holding a number of 'votes' across a range of dimensions [14], with this being a noticeably different approach to the function driven ones discussed above.

Outranking approaches are generally conducted in two phases: a precise method for determining whether one alternative outranks another and a method for determining how all the pairwise ranking assignments can be combined to suggest an overall preference ranking for the set of alternatives [4].

Many outranking models are available with the ELECTRE & PROMETHEE model families being popular examples used in a broad range of applications. Source [21] states the advantages and disadvantages of both approaches:

- ELECTRE models take into account uncertainty and vagueness, but have the disadvantage of the outcomes being hard to explain in 'layman's terms' (note: this criticism may be of particular importance should the decision need to be relayed to other parties as is often the case in CCU technology development)
- PROMETHEE models are easy to use and do not require the user to assume that criteria are proportionate, but have the disadvantage that they do not provide a clear method by which weights can be assigned to criteria

A more general criticism of outranking methods is there lack of axiomatic foundations, although this criticism has lessened over time as the field has developed, and as more elaborate models have been developed with some aspects of the process becoming more 'axiomatized' [31]. Given a criticism of MAUT approaches is their axiomatic nature it is clear to see that there exists an argument for the utilization of both types of approach with the final choice likely determined on the preferences & resource availability of the practitioner or decision maker.

Qualitative outranking methods also exist, whilst such methods may be of limited interest for combining LCA & TEA, the introduction of social indicators (that are often more difficult to quantify) may warrant future revision.

1.4.5 Analytical Hierarchy Process

The next MCDA approach to be discussed is the *analytical hierarchy process* (AHP), a method originally devised by Saaty in the 1980s [34] and remains frequently used (either in its original form or through one of the derived similar methods) across a broad range of applications to this day. The central premise of the AHP is the deployment of a method for converting subjective assessments of relative importance into overall (weighted) scores [4]. Similar to outranking methods discussed above pairwise comparisons are made, however here criteria are compared, with the intention of establishing which is more important to the preferences of the decision maker. These preferences are scored using the preference index, a scale scoring from 1 to 9, so when comparing criterion *A* to criterion *B*:

- A score of 1 would mean that both A and B are equally important
- A score of 3 would mean that A is moderately more important than B
- A score of 5 would mean that A is strongly more important than B
- A score of 7 would mean that A is very strongly more important than B
- A score of 9 would mean that A is overwhelmingly more important than B

The even numbers act as intermediate values between the above categories which can be used if required. If B is adjudged to be more than A, the reciprocal score is given i.e. the relative importance of

A to B will be scored as 1/*x* where *x* can be any of the scores in the range of 1 to 9. Table 1 below gives a general example considering three criteria: *A, B* and *C*, where each is scored in the pairwise manner described above. For criterion A it can be seen that it is of equal importance to itself, strongly more important than B and moderately less important than C.

Table 1 – Example matrix of an AHP pairwise comparison of criteria

		In relation to…		
	Criterion	A	B	C
Importance of…	A	1	5	1/3
	B	1/5	1	1/7
	C	3	7	1

After establishing the comparison matrix the next step is to estimate weights that are 'most consistent with the relativities expressed in the matrix' [4], this becomes a challenge of finding a 'best fit' because there are no transitive guarantees in the table beyond the reciprocating pairs. The basic method of Saaty estimates weights using matrix algebra, calculating each weight as part of the eigenvector associated with the max eigenvalue for the matrix [34]. As this is a complex task it is advisable to use specialist AHP software to do this. A simpler alternative is detailed in [4], given as follows:

1. Calculate the geometric mean of each row in the matrix
2. Total the geometric means
3. Normalize each of the geometric means by dividing by the total computed in the prior step

This provides a result that is generally 'very close' to the calculated weights from the eigenvalues (often to 2 or 3 decimal places) without the need for the use of specialist software. A significant advantage to the AHP is the ability to group criteria and organize these in a hierarchical structure allowing for the reduction in the number of pairwise comparisons that need to be held. Each level of each branch can then be treated independently with a pairwise matrix developed for this. In the example structure shown in figure 2, 3 pairwise comparison matrices would be required with the diagram color-coded to demonstrate each (the criteria, the sub-criteria for criteria A and the sub-criteria for criteria C), in each case the total weight would be normalized to one.

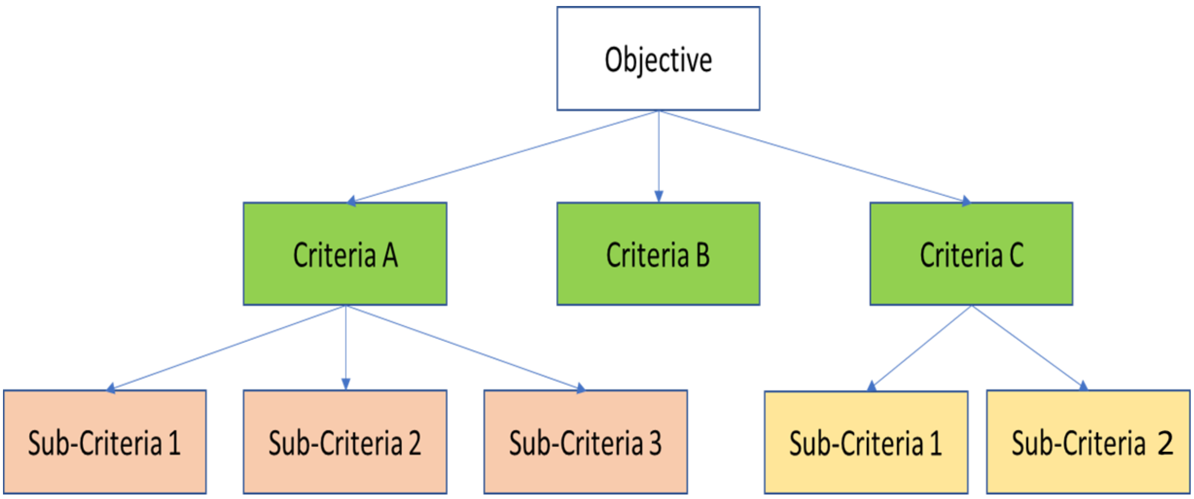

Figure 2 – Example of an AHP structure with numerous criteria and sub-criteria

Alongside calculating the weights, the pairwise comparison method is also used to assess the performance of each alternative against each criterion 'tree' as shown below in figure 3. As can be seen assessment takes place for each alternative at the lowest level of the tree, whether this be at the sub-criteria (or below, if sub-criteria further division is required) or criteria level. Pairwise comparisons are calculated for each configuration of alternatives using the same scale as before.

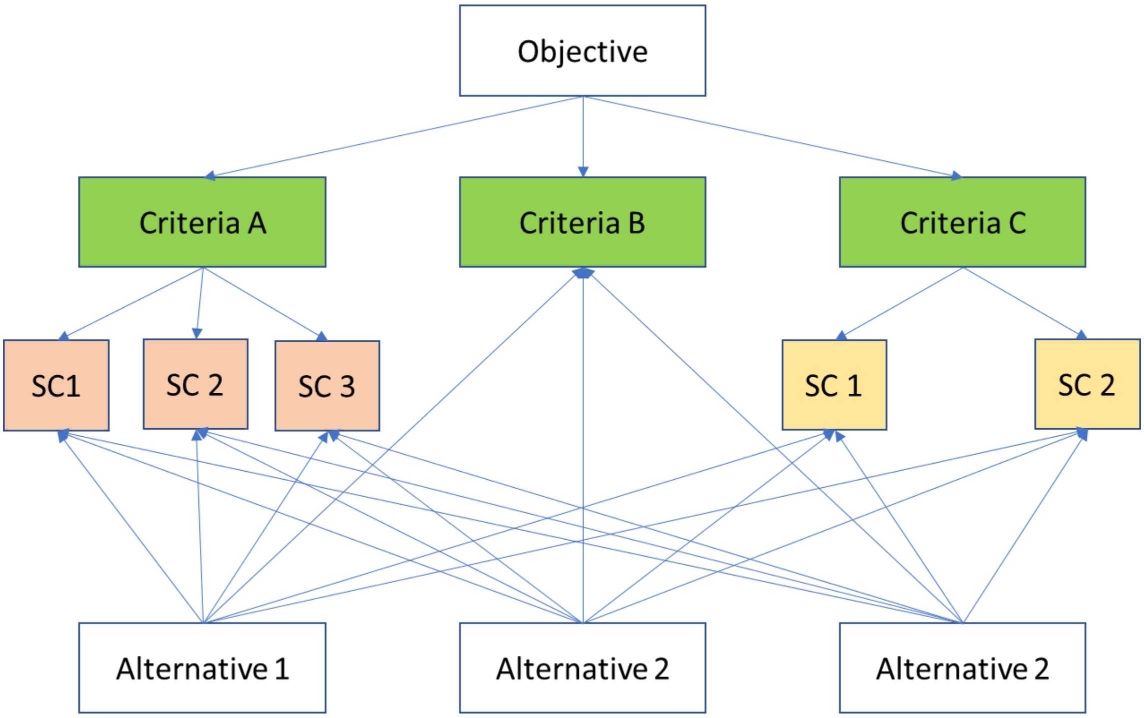

Figure 3 – Example of an AHP structure including alternatives options to be assessed

Upon calculating weights and scores all that remains is a simple linear addition of these to determine a final weighted score. The option with the highest score is the preferred one, subject to sensitivity and/or uncertainty analysis of the result.

The AHP method, and other methods derived from it, are popular due to their relative ease of use, even with little experience of previous MADM application, a second benefit is that not only is the hierarchy system useful for limiting the number of pairwise comparisons that need to be held it offers the advantage of being relatively easy to scale to larger problems and the method itself is not as data intensive as many of the other models discussed [21]. Alongside this lower data intensity, the AHP method can also be used in situations where judgements rather than measurements of performance are required for assessment [4].

Whilst popular, it should be noted that there exists a range of criticism of the AHP method, with sources [4][21][30] providing more details if required. Five criticisms are common:

1. The 1 to 9 scale can be internally inconsistent – if not well controlled. Consider two pairwise comparisons, of *A, B* and *C* where A is scored at 5 against B and where B is scored at 5 against C. Logically, A is considered more important than C, to the order of 5 x 5 = 25, however the scale is capped at 9 thus the importance of A over C is under-represented. In this example the fix is relatively simple given there are only three criteria (score A to B as 3, B to C as 3 and then A to C can be scored as 9) but in a more complex problem this may be difficult to do. To counter this problem an AHP alternative has been developed in REMBRANDT, here the 1 to 9

scale is replaced by a direct rating system on a log scale [35][36]. The eigenvector approach for establishing weights is also replaced in REMBRANDT, with an approach based on the use of the geometric mean used (the use of pairwise comparisons remains consistent). Another solution to this problem is to change from a linear scale as developed by Saaty to a number of alternatives (e.g. geometric, power, logarithmic) as suggested in source [37]. All alternatives maintain the 1 to 9 ranking but give additional flexibility not offered by the linear option

2. The 1 to 9 scale and associated descriptions are in essence arbitrary – there is no theoretical foundation for the scale
3. The AHP process involves the establishing of weights for criteria before measurement scales have been set. This means that the decision maker is asked to make statements about the relative importance of criteria without knowing what is being compared. See section 6.2.10 source [4] for a more detailed example of this issue and 'swing weighting and the nominal-group technique' in general. It may be that some categories are important on an absolute scale, yet the differences in the 'shortlisted' alternatives may mean that the relative importance is somewhat lower. For example, when buying a new computer price may be of high importance in an absolute sense, but if all the selected alternatives vary by an amount that is relatively inconsequential (i.e. 'whether I buy the computer that costs $*x* or $*x* + 50 is not important to me') it would be unwise to weight this heavily
4. Introducing new options (either criteria or alternatives) can change the relative ranking of some of the original options. This is referred to as 'rank reversal' and was first discussed in source [38] and is deemed to be a product of 'failing to consistently relate scales of performance measurement to their associated weights' [4]
5. There is a frequently held opinion that the axioms on which AHP is based lack sufficient clarity to allow for empirical testing

As consistency is reportedly the most common criticism, an inconsistency ratio was proposed by Saaty in a later paper [34], a score of 0.1 or less on a scale with a maximum of 5.84 represents a tolerable error in measurement and provides a result that is not biased by this.

As stated above alternatives to the AHP method that utilize a similar basic concept have been developed, such as REMBRANDT mentioned above. A second alternative that has been developed is MACBETH (*Measuring Attractiveness by a Categorical-Based Evaluation Technique*) [39][40], developed originally in 1994 by Bana e Costa, Vansnick and De Corte. The associated sources can provide further information on both of these models should it be required.

1.4.6 TOPSIS Method

The final model to be discussed in this section is the *Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS). First outlined by Hwang and Yoon in 1981 [41] and later developed further by a range of contributors. The fundamental concept of TOPSIS is that the best solution is the one that has the shortest geometric distance to the ideal solution, and the worst has the furthest distance [42]. These distances are calculated as part of completion of the basic five-step method for TOPSIS, summarized below and discussed in more detail in source [42]:

1. The performances of the different criteria are normalized to allow for comparison across non-comparable units (such as dollars and tonnes of CO_2e emitted). A selection of normalization

approaches are available, common choices are distributive normalization and ideal normalization

2. Weights (determined beforehand) are taken into account; a weighted normalized decision matrix is constructed through multiplying the normalized scores to the corresponding weight
3. The weighted scores are compared to an ideal (known as the 'zenith') and an anti-ideal (the 'nadir'), these points can be determined using one of 3 approaches:
    a. Collecting the best and worst performance on each criterion of the normalized decision matrix
    b. Assuming an absolute ideal and anti-ideal point which are defined without considering the alternatives
    c. The ideal and anti-ideal points are defined by a third party, such as the decision maker or the study commissioner. It should be noted that this approach is not often used due to needing to elicit input from the user or another party
4. Calculate the distance for each alternative from the ideal and the anti-ideal, using an approach such as the Euclidean distance (most popular) but other options are available (e.g. the Manhattan distance where the distance between two points is the sum of the absolute differences of their Cartesian coordinates)
5. Calculate the closeness coefficient of each alternative, this is a relative figure scored between 0 and 1, with values that approach 1 being closer to the ideal and vice versa

Figure 4 below shows the TOPSIS method represented graphically, covering 2 criteria (1 and 2), and 2 alternatives (A and B) showing their distance to the ideal and anti-ideal. It's also clear to see why step 1 is required, as without normalization such geometric approaches would not be applicable.

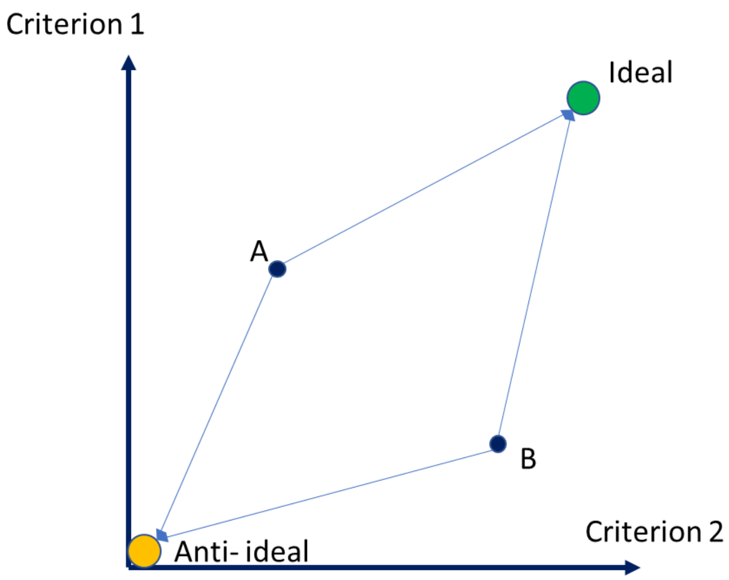

Figure 4 – Simple graphical representation of a TOPSIS approach for a multi-criteria approach

In terms of advantages, TOPSIS is a simple to implement process and the number of steps remain the same regardless of the number of attributes considered in the assessment [21]. As TOPSIS is a compensatory MADM approach (like MAUT and AHP) it does allow for poor results in some criteria to be compensated by better performance in others which may have useful applications in some situations. A major disadvantage however is the that the central premise (measuring the Euclidean distance) does not consider correlation of attributes [21], a second problem can be the difficulty in assigning weights and keeping judgement constant.

This brief introductory section demonstrates that a range of multi-attribute approaches are available to those wishing to apply them for CCU problems. The preferred option for use is likely to vary dependent on a number of factors including: resource availability, data availability, whether the decision maker is a group or a singular agent and personal preference. In the following section how MADM can be tied to LCA & TEA for CCU is considered, with the intention of identifying the types of problem that may be best suited to each MADM approach.

1.5 MADM problems in LCA & TEA Studies for CCU

After discussing the various types of MADM, attention can be turned to identifying the type of problems that can be solved using these approaches. Given the scope of this document is combined assessment for TEA & LCA this will form the basis for contextualizing this.

Source [43] provides some insight on common types of problems that can be addressed using MADM approaches:

- Choice problem: This selects one single alternative as the best or can reduce a group of options to “all good options”.
- Ranking problem: The alternatives are ordered from best to worst, these can be scores, comparisons, etc.
- Sorting problem: The alternatives are sorted into categories and decisions can be made on these classifications (e.g. preferred alternatives in scenario X, preferred alternatives in scenario Y and rejected alternatives)
- Description problem: The goal of the study is to help describe the alternatives and the consequences of these
- Elimination problem: Similar to the sorting problem, but with only two classes defined, accepted and rejected
- Design problem: The goal of the study is to create a new alternative to meet the needs of the decision maker (essentially a link to MODM approaches)

The research/decision question, goal and desired outcomes are likely to be driving factors in the type of problem identified. For example, there is significant overlap in choice and ranking problems, both in the type of question typically asked and in the type of approaches used to answer these. The likelihood is that most of the problems encountered within the application of MADM on combined LCA & TEA studies will fall into the first three categories and as such these will be considered in a little more detail below.

In this respect the application of MADM is similar to that of LCA & TEA – in that determining a clear goal is a key pre-requisite to a successful study. A clear goal statement is not only beneficial for the decision maker, but also for any intended audience who may wish to read the report and follow the decision logic. This point can actually be expanded more broadly, in that clear communication is vital throughout the recording of the MADM given the subjective nature of determining preferences. The type of MADM problem to be assessed should also be easy to determine from the goal statement, if this is not the case it is advisable to specify the type of problem within this.

Considering MADM for specific use in combined LCA & TEA for CCU, the range of research/decision goals available remains endless, but in each case it is expected that the goal carries an obvious requirement for considering both environmental and techno-economic performance to ensure that the alternatives are assessed on these. Beyond this no specific requirement is envisioned, with the degree of specificity dependent on the desires of the decision-maker or other stakeholder, e.g. a goal could ask for consideration of ‘economic and environmental performance’ (vague, open to interpretation) or it could specify the inclusion of specific indicators for consideration (such as CapEx or global warming potential).

After considering the types of goal attention can now be turned to determining the approaches that best suit meeting that goal, a summary of this is provided in table 2 below, with many of the options have been described in detail in an earlier part of this review. The decision on which method to apply is ultimately one for the practitioner or decision-maker to make.

Table 2– Types of MADM identified for use in each problem type and selected software options for these, adapted from [43]

Problem	MCDA method	MCDA software/tool	Output
Choice	AHP, ANP, MAUT/UTA, MACBETH,PROMETHEE,ELECTRE (I, II, II), TOPSIS, hybrid methods	Smart Picker Pro, Electre III-IV, Right choice, MakeItRational, M-MACBETH, Win4DEAP	Single score
Ranking	AHP, ANP, MAUT/UTA, MACBETH,PROMETHEE,ELECTRE (I, II, II), TOPSIS, DEA, Hybrid methods	Smart Picker Pro, Electre III-IV, Right choice, MakeItRational, M-MACBETH, Win4DEAP	Rank
Sorting	AHPSort, UTADIS, FlowSort, Electre-Tri	Smart Picker Pro, Pro Electre Tri	Classification

Attention can now be turned briefly to considering the types of CCU decision problem in which the application of MADM may be of interest. This is quite a broad scope, as in reality any type of problem in which a finite number of alternatives can be identified for assessment on a chosen set of criteria is feasible for use with MADM. Here, the scope is narrowed to a degree in that only those concerning combined LCA & TEA outputs are of interest and as such the potential set of criteria is reduced to environmental, economic and technological indicators only. The indicators used are likely to be determined or influenced by the problem to addressed, i.e. some problems may require specific criteria whilst others may require a more generic (e.g. ‘include all typical LCA indicators’) approach.

The scope for the alternatives is also likely to vary dependent on the problem, with MADM methods scalable to both the scope of application and the number of alternatives considered. In terms of application, MADM can be applied to problems concerning the selection of a singular element within a plant such as the selection of a catalyst for chemical synthesis or to larger problems such as the selection of a specific CCU technology for application with relative ease. MADM approaches can also be applied at a range of technology readiness levels, even the lower levels associated primarily with research and development more so than deployment. Whilst most R&D scenarios may be best served by MOO there are times when choosing between distinct alternatives is required and in these cases attributional approaches can be deployed (see the last problem listed below for ne such example).

Common problems that may be of interest include:

- ‘I have a limited source of highly pure CO_2 (e.g. from a brewery off-gas stream, or from a SMR plant) which of the following CCU technologies best suits my resource?’

- 'I have a CCU technology for deployment, which location from my chosen list of alternatives is best suited for deployment?'
- 'Which is the best CO_2 capture technology for my needs?'
- 'I wish to develop a catalyst for methanation – should I use nickel, rhodium or ruthenium as my starting point?'

1.6 Implementing MADM with Combined LCA & TEA Studies for CCU: Basic Approach Applied

As discussed earlier in this worked example, the application of a 'preference-based' type of integration requires a high degree of alignment between the LCA & TEA elements of the combined study. As stated previously, this worked example utilizes inputs from a prior one: the conversion of CO_2 to methanol [2]. Given that much of the data required for this study was extracted from the prior one, the following steps were taken to ensure sufficient alignment of the constituent studies for a 'preference-based integration':

- The goal statement of both studies is checked in order to identify any potential misalignment in terms of basic information such as location or time period
- The boundaries of the original study were revisited to ensure they are consistent, for this example only a 'cradle to gate' study is required and as such only aspects of the prior studies within this boundary were included
- The functional unit considered in the constituent studies should be consistent, a functional unit of '1 tonne of methanol' is used in this study and in the contributing LCA & TEA studies. The selection of this functional unit and the setting of a cradle to gate boundary above is due to the goal of the combined study (which is discussed in a later section) fitting such decisions
- As the LCA & TEA study were conducted in parallel initially the inventory was drawn from a common dataset produced for the studies. As such a consistent approach to data is held throughout both studies – there is no misalignment of values and technology choices are consistent across costings and environmental impact e.g. if 'grid electricity' is utilized the price data entry and the environmental impact factor data entries reflect reported values for one specific energy profile, or checking to ensure that the cost of catalyst & the environmental impact assigned to the catalyst reflect a singular catalyst choice
- The constituent LCA & TEA studies were checked for inconsistencies in their methodologies that may make results incompatible – this was done by reviewing the studies against the guidelines rules and checking for any deviation in approaches to achieve the 'shall' guidelines. None were found and thus the methodological choices made were assumed to be compatible for integration

Whilst this does not amount to a full methodology for aligning the constituent studies it does provide some details on basic steps to ensure that alignment is feasible.

Part 2: MADM Example Application: Using AHP to Solve a Multi-Criteria Decision Problem

DISCLAIMER: As always the worked example published here should only be considered as an illustrative example of how to apply the methodologies discussed. The data used is not to be utilized by third parties beyond this explicit basis, although the referenced data sources may be of interest to said third parties. The results of the studies should not be quoted, and in this case the weightings applied in the MADM approach should not be used nor do they represent the beliefs/views of the authors or the wider CO_2nsistent project – these are pure illustrational and are not drawn from any audited process

2.1 Justification for the use of the AHP Method

After discussing MCDA and particularly MADM in previous part of this worked example this part investigates the application of MADM to solve a specific problem.

Here, AHP has been used for three reasons:

1. As discussed above the AHP approach (and its associated derivatives) remains popular, despite its potential shortcomings. Studies for CCU [44], CCUS [45] and CCS [46] can also be found readily
2. A driving force behind the popularity of the AHP approach is how accessible and easy to use it is: with manual implementation of the approach being feasible using programs such as Excel (as is done here, with eigenvalues calculating manually as described in the MADM review above) it is clear to see why it remains popular with actors not familiar with MCDA, something that is likely the case for many LCA & TEA practitioners
3. The identified shortcomings make for an interesting discussion case to highlight how there may be issues with application on a complex problem such as a combined LCA & TEA study where a large number of indicators may be of interest

The following six steps are considered as the basis of most MADM methodologies including AHP:

1. Define problem (identifying objectives, identifying options for achieving these objectives)
2. Define criteria
3. Assign weights to each criterion
4. Assess the performance of each alternative and assign scores
5. Make the final decision
6. Investigate the relevant sensitivities to check the strength of the decision made

2.2 Defining the Problem and Writing the Goal Statement

As covered previously the goal statement is a key aspect to consider when defining the LCA or TEA study, and this is no different for a combined study that incorporates an MADM approach. In lieu of guideline provisions for combined studies, provisions B.1 and C.1 (Goal definition in TEA & LCA) are used here.

The goal statement for the worked example is given below, and addresses each of the 'shall' provisions:

This study intends to rank four distinct renewable energy sources available for use in the production of methanol from CO_2 in the USA in the present day (2020) in a 'first of a kind plant'. The four energy sources investigated are: onshore wind, offshore wind, geothermal power and solar photovoltaic (PV), these will be ranked in order of preference to identify which is deemed most viable for development. Given each resource is deemed to have a differing level of availability the resultant methanol plant is scaled to match this, leaving a decision to made considering environmental impact of production, economic feasibility and production scale. The boundary for assessment is 'cradle to gate' as each of the options produces the same product to be sold to the market. The intended audience of the study are the senior management team of the company who will own and operate the plant, who commissioned the study. The study is conducted by a third party on behalf of the company, with explicit preferences provided by the company.

Authors note: For this example, we have defined a simplified problem to allow for a focus on the application of the AHP approach. Whilst not of great importance here (given the nature of the worked example) an intended audience and commissioner is given for completeness.

Given that it was shown in the prior worked example the methanol plant in question is not economically competitive when compared to existing fossil plants currently the decision was made to create an illustrative scenario independent of this consideration (to demonstrate AHP use in CCU).

As shown in the goal statement the intention of this worked example is to rank four distinct renewable energy sources and their viability for use in methanol production. The central premise to the problem is to assess which of the options best fits the company's preferences: should a focus be made on the 'most profitable'? Least impactful environmentally? Does the production scale matter?

The methanol plant is to be based off the model given in the prior methanol worked example [2], but with this scaled to fit the four energy sources identified. Further details on the model and its initial derivation can be found in that document but briefly:

The plant consists of three main process modules: H_2 production, CO_2 capture and separation and methanol production. H_2 is produced through the use of a polymer electrolyte membrane (PEM) electrolyzer, with CO_2 captured using a combination of membrane and cryogenic separation. Of these technologies, membranes are at the lowest technology readiness level (TRL) deemed to be at TRL 4 and thus the uncertainty around performance is greatest for these. The methanol plant design is based on earlier designs published in academic journals (see section B.6.4 of the methanol worked example for a list) and consists of various process units included a methanol reactor in which CO_2 and H_2 are fed to form a methanol rich product, unreacted gases are recovered and recycled, whilst the product stream is distilled, condensed and flashed to produce a high purity methanol product ready for storage/market.

Having introduced the technology to be considered, a focus can now be made in outlining the particular case to be assessed in this worked example.

As stated above, four different sources of renewable electricity are identified: onshore wind, offshore wind, geothermal and solar PV. Each is taken to have its own environmental impact profile, and each is taken to have its own cost variables (namely capital expenditure (CapEx) and operational expenditure (OpEx)) and to further complicate the picture differing amounts of each energy source are assumed to be available resulting in differing scales for the resultant methanol plant. As such a complex problem can be created in which multi-criteria approaches can be used to determine a preferred ranking for the options available.

For assessment 11 environmental indicators are included (taken from the CML LCA method) and 3 techno-economic indicators are to be assessed (overall plant CapEx, OpEx associated with electricity provision and the scale of production). The four distinct alternatives to be assessed are:

1. A CO_2 to methanol plant powered by geothermal energy capable of producing 100 tonnes per day of methanol
2. A CO_2 to methanol plant powered by solar PV energy capable of producing 250 tonnes per day of methanol
3. A CO_2 to methanol plant powered by onshore wind capable of producing 250 tonnes per day of methanol
4. A CO_2 to methanol plant powered by offshore wind capable of producing 500 tonnes per day of methanol

The 14 indicators are given below in table 3, these are used here as sub-criteria organized under the criteria of 'Environmental' and 'Techno-Economic' with indicators for each measured in tonnes of methanol.

Table 3 – Summary of criteria (bold) and associated sub-criteria

Environmental	Techno-Economic
Global warming (GWP)	Capital expenditure of methanol & electricity plants
Ozone depletion (ODP)	Operational expenditure of electricity plant
Acidification (AP)	Total production volume
Eutrophication (EP)	
Marine aquatic ecotoxicity (MAET)	
Freshwater aquatic ecotoxicity (FAET)	
Terrestrial ecotoxicity (TET)	
Abiotic depletion potential (elements) (ADP)	
Abiotic depletion potential (fossil) (ADPf)	
Human toxicity (HT)	
Photochemical oxidation (POCP)	

The following assumptions are made:

- For the environmental indicators only the impact of electricity generation is considered, all other elements of the process are deemed to be constant and thus can be removed from the analysis. This is assumed to hold true even when changing the scale of production as the 'economies of scale' is adjudged through analysis of the prior worked example to be relatively small in this case (especially when compared to the importance of electricity in the model)
- For CapEx the economies of scale are known to be important for the methanol plant and thus the capital cost for plant construction is factored into the assessment, the capital cost of constructing the dedicated energy source is also included
- For OpEx analysis in the prior worked example shows that OpEx (both variable and overall) is dominated by electricity costs with this representing 86% of the total in the prior worked example, given this domination all other variable and all fixed operational costs are deemed to be constant per tonne of product regardless of scale as electricity costs remain dominant

In making these assumptions the problem is streamlined to only consider aspects of the process that are assumed to be impacted significantly by changes that arise from the four alternatives highlighted above. Such an approach is beneficial

As stated in the goal statement only the boundary of 'cradle to gate' is considered here, given that the product delivered to the market is 'chemically identical' regardless of the alternative chosen and a functional unit of 1 tonne of methanol is used. The functional unit plays a less vital role in the MADM model and is primarily used here to ensure an equal and logical basis of comparison.

2.3 Inventory for the Multi-Criteria Decision Problem

This section focuses on the inventory data used for deriving the 14 sub-criteria for each of the 4 alternatives, in place of considering the broader inventory for the whole plant. The environmental data used here is taken from the following sources:

- Data for the environmental impact of geothermal electricity (location: US) was taken from GaBi ts
- Data for the environmental impact of solar PV electricity (location: US) was taken from GaBi ts
- Data for the environmental impact of onshore wind (location: WECC, US) was taken from Ecoinvent 3.4 database
- Data for the environmental impact of offshore wind (location: rest of world) was taken from Ecoinvent 3.4 database (no specific US offshore wind entry was available)

This data (each given in units of impact per kWh) was combined with the specific electrical consumption of the plant per tonne of methanol produced (10.84 MWh) to give final data figures at the correct scale.

CapEx data for the methanol plant is derived from the prior study. The previous study considered a plant with a capacity of 1000 t/d, with this scaled down to meet the needs of this worked example. Further details on the scaling method can be found in the prior example, here a summary table (Table 4) is included to show the impact changing scale has on both total capital investment (TCI) and the CapEx per tonne of product when considering the same cash flow conditions as previously (50:50 debt to equity split, 9% WACC).

Table 4 – Summary of CapEx per tonne at varying production scales

Production rate (t MeOH/day)	100	250	500	1000
TCI ($USD MM)	226.78	412.64	652.06	1049.29
CAPEX/t MeOH ($USD)	725.90	528.32	417.43	335.86

Data for the determining of CapEx and OpEx for each of the electricity generation sources is taken from source [47], with US specific data used where available. The data in table 5 below was taken from the IRENA source, with all figures bar the OpEx for wind onshore directly transcribed. The value for wind offshore is quoted to be 'around double of that of onshore' in the appendix and this is what is used as the basis for the stated OpEx figure.

Table 5 – Cost data used in determining CapEx and OpEx of electricity plant

Renewable Source	**CapEx**	**Unit**	**OpEx**	**Unit**	**Capacity Factor**
Geothermal	3976	USD/kW	115	USD/kW.year	0.84
Solar (PV)	1210	USD/KW	15	USD/kW.year	0.18
Wind (onshore)	1497	USD/kW	55	USD/kW.year	0.34
Wind (offshore)	4353	USD/kW	100	USD/kW.year	0.43

Final CapEx and OpEx figures were determined by:

- Establishing the daily electrical demand for the entire plant at scale (MWh)
- Calculating a minimum theoretical electrical plant size
- Applying a capacity factor to adjust the size of this to reflect a more 'realistic' estimate. Here we assume that the average output of the renewable electricity plant equates to the power consumed by the methanol plant annually

With all costs determined the CapEx numbers are combined to provide a single sub-criterion, with the OpEx and production volume used to round out the techno-economic set. Whilst it could be argued that the CapEx and OpEx could be combined into a single production cost it was decided that keeping the two figures separate allows for better decision making by allowing an actor the option to weight higher capital risk against greater operational costs with this being the sort of trade-off one may wish to consider as part of a multi-criteria decision.

Table 6 below summarizes all the sub-criteria ('attributes') and the associated values for each of the four different alternatives to be considered. As can be seen, without any weighting each alternative can be seen to outperform another in at least one category, showing that no alternative is clearly dominated by the others and no alternative clearly dominates all others.

Table 6 – Summary of sub-criteria and associated values per tonne of methanol

	Sub-criteria	Values per t/MeOH unless specified			
		Geothermal	Solar PV	Wind onshore	Wind offshore
Environmental	ADP Abiotic Depletion [kg Sb eq.]	5.21E-05	1.37E-02	1.07E-02	4.50E-03
Environmental	ADPf Abiotic Depletion [MJ]	1.88E+02	5.33E+03	2.76E+03	2.10E+03
Environmental	AP Acidification Potential [kg SO2 eq.]	9.50E+01	1.96E+00	2.12E+00	9.47E-01
Environmental	EP Eutrophication Potential [kg Phosphate eq.]	1.06E-02	1.47E-01	1.39E+00	4.62E-01
Environmental	FAET Freshwater Aquatic Ecotoxicity Pot. [kg DCB eq.]	2.73E-01	4.36E+00	2.92E+03	3.28E+02
Environmental	GWP Global Warming Potential [kg CO2 eq.]	6.84E+02	4.67E+02	2.17E+02	1.66E+02
Environmental	HT Human Toxicity Potential [kg DCB eq.]	1.79E+01	3.59E+02	1.19E+03	7.71E+02
Environmental	MAET Marine Aquatic Ecotoxicity Pot. [kg DCB eq.]	5.89E+03	1.75E+05	1.50E+06	4.05E+05
Environmental	ODP Ozone Layer Depletion Potential) [kg R11 eq.]	1.50E-21	2.10E-09	1.36E-05	8.42E-06
Environmental	POCP Photochem. Ozone Creation Potential [kg Ethene eq.]	9.04E-03	1.71E-01	1.79E-01	9.98E-02
Environmental	TET Terrestric Ecotoxicity Potential [kg DCB eq.]	1.34E-02	2.66E+00	9.55E+00	1.96E+01
Techno-Economic	Total CapEx	1038	972	819	1085
Techno-Economic	Electricity plant OpEx	181	110	213	307
Techno-Economic	Production volume daily (t/MeOH)	100	250	250	500

2.4 Weighting the Criteria and Sub-Criteria

When applying the MADM approach to a combined LCA & TEA problem it is here that a significant deviation can be noted from many more 'traditional' applications of MADM in that the likelihood is that the practitioner is likely to already have inventory data collected for the alternatives to be assessed. This is the case for this worked example and it does lead to some advantages and disadvantages:

- In terms of advantages the criteria and sub-criteria for assessment are likely known to the practitioner and as such there is less of a chance that an important (sub-)criteria is missed. A particular benefit for AHP is also that the range of criteria results may also be known allowing to counteract the impact of needing to establish weights prior to measurement scales being set (see point 3 in the criticisms of AHP above for more detail)
- A disadvantage is that this knowledge can lead to the insertion of bias (either deliberately or inadvertently) when considering weighting of both criteria and sub-criteria should a preference for a particular alternative be held. Given the intent of an MADM approach is

identify which option best fits the preferences of the decision maker this may reduce the exercise to something of a triviality

In this example, the weights for criteria and sub-criteria were decided without any acknowledgement of the data given in table 6 above.

Authors note: Before discussing the pairwise comparisons a brief note on scoring is included. The AHP model holds at its center a 1 to 9 scale for pairwise comparisons as detailed above in the review section, scores of 1 between alternatives A and B state no preference between the alternatives and a score of 9 suggests 'extreme importance' of one alternative over the other. Score definitions change with whole odd numbers (e.g. 1, 3, 5, 7 and 9 see differing definitions) and the even values in between represent intermediates within the same classification.

In this worked example we also use decimal numbers as part of the intermediates to allow for better consistency between scores and to score elements (sub-criteria or alternatives) that we deem to be very close in importance. Such an approach also allows for the overcoming of one of the major issues on the AHP scoring scale in that it allows for more scope for 'internal consistency' when considering relative dominance of multiple elements (see the criticisms in the AHP review section for more details). This is of particular use here where a large number of sub-criteria are used under the environment criteria.

The weight of the goal is always given as 1, with every hierarchy below this then equaling a total of 1 also.

The primary set of pairwise comparisons to be made were done between the criteria, of which in this case there are only two identified. Three stages are considered for determining weights: the completion of the pairwise comparison matrix, the completion of the normalized matrix and a test of the consistency of the scoring. Table 7 below shows the pairwise comparison, as stated in this case the matrix is simple given the limited number of alternatives. Comparisons to self (e.g. environmental vs. environmental) will always score 1, and the reciprocating comparison is always the inverse of the opposite comparison – in other words if A vs. B is scored as x, B vs. A will be 1/x.

Table 7 – Pairwise comparison matrix for criteria

Pairwise comparison matrix for criteria		
	Environmental	Techno economical
Environmental	**1.00**	1.50
Techno economical	0.67	**1.00**
Total	**1.67**	**2.50**

Table 8 – Normalized scoring matrix for criteria

Normalized matrix				
Criteria	**Environmental**	**Techno economical**	**Priority Vector**	**%**
Environmental	0.6	0.6	0.6	60.0
Techno economical	0.4	0.4	0.4	40.0
Total	**1**	**1**	**1**	**100**

The total for each element in the normalized matrix (table 8 above) should always equal exactly 1.00, any variation suggests an error somewhere in the calculation.

As stated previously, a set of scores can be seen as consistent providing the consistency ratio (CR) is scored as no greater than 0.10, with the formula for CR being:

$$CR = CI / RI$$

Where:

CI is the consistency index, calculated using the following formula:

$$(Eigen_{max} – n) / (n – 1)$$

Where $Eigen_{max}$ is the maximum Eigenvalue and n is the number of elements for comparison. $Eigen_{max}$ is found by multiplying the priority vector/the eigenvector (from the normalized matrix) by the pairwise comparison total (from the pairwise scoring matrix) and summing the values, so in this case:

$$Eigen_{max} = (1.6667 \times 0.60) + (2.500 \times 0.40) = 2$$

$$CI = (2-2) / (2 – 1) = 0$$

RI is the random consistency index which is a value determined in the work of Saaty [48], with the value dependent on n, with the values below transcribed from [49]:

Table 9 – Values for RI for different values of n

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	058	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

As can be seen for an n of 2 the RI is zero and thus in this case the value of CR is undefined. This makes sense as it is not possible to be inconsistent when making only a single variable comparison. In this case the decision was made to value the environmental criteria slightly more so than the techno-economic.

With the criteria weighted an initial hierarchy can be drawn, as shown in figure 5 below, to map out which sub-criteria fits under each criteria. The sub-criteria weights in this figure are still 'neutral' in that none are weighted preferentially more so than the others.

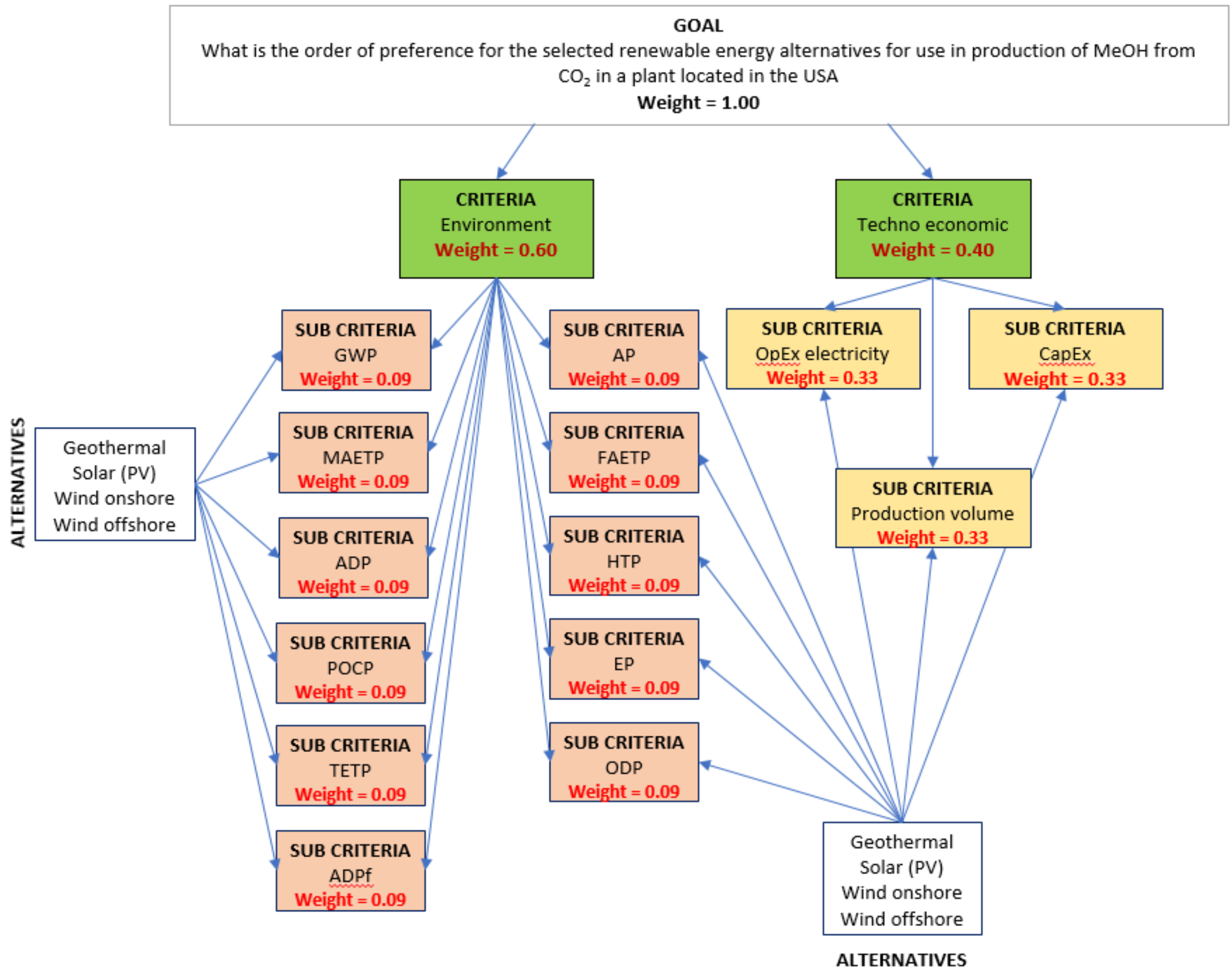

Figure 5 – Overview of the hierarchy process without weighting applied to the sub-criteria

After weighting the criteria, attention can be turned to the sub-criteria. Here, it can be seen that the scale of the problem varies greatly: the techno-economic sub-criteria are relatively few making consistency relatively easy to achieve, whilst the same cannot be said for the environmental ones. Weighting for the individual sub-criteria hierarchies is local, with the global weights for these derived at a later stage.

The pairwise comparisons for the techno-economic sub-criteria are shown in table 10 below, as can be seen three unique comparisons are made (CapEx vs. OpEx, CapEx vs. production volume and OpEx vs. production volume) as such n is significantly great enough to calculate a CR value. The subsequent normalization matrix is also included in table 11 and the CR value is calculated in table 12.

Table 10 – Pairwise comparison matrix for the techno-economic sub criteria

	CapEx	**OpEx**	**Production volume**
CapEx	**1.00**	1.50	3.00
OpEx	0.67	**1.00**	2.00
Production volume	0.33	0.50	**1.00**
Total	**2.00**	**3.00**	**6.00**

Table 11 – Normalization matrix for the techno-economic sub criteria

	CapEx	OpEx	Production volume	Total	Priority vector
CapEx	0.50	0.50	0.50	1.50	**0.50**
OpEx	0.33	0.33	0.33	1.00	**0.33**
Production volume	0.17	0.17	0.17	0.50	**0.17**
Total	**1.00**	**1.00**	**1.00**		**1.00**

Table 12 – CR calculation for the techno-economic sub-criteria

	CapEx	OpEx	Production volume
Eigenvector	0.50	0.33	0.17
Total (Sum)	2.00	3.00	6.00
Maximum eigenvalue	3		
CI	0.00		
RI	0.58		
CR	0.00		

The order of priority determined is: CapEx > OpEx > production volume. This was determined by the decision maker – here all of the categories are relatively close in importance to the decision maker, with the largest score given a 3. The highest priority is handed to CapEx, which is a reasonable position for a decision maker to take when considering the goal statement – it may be that risking a large amount of capital on a first of a kind plant is undesirable, even if this leads to building a smaller plant that operates with a smaller production capacity. There is a clear link between the weightings defined, the goal of the combined LCA & TEA 'preference based' study and the weightings derived from the preferences of the decision maker. A clear goal statement may also help a reader follow the logic in the weighting stage for the sub-criteria, which may be of importance when the intended audience for the report is not the same party as the decision maker.

Authors note: The techno-economic weights are shown to be highly consistent with a CR of 0.00. This is unsurprising given the ease of consistency when considering only 3 categories, this issue becomes more complex as the number of categories is increased – as can be seen in the following environmental section. In response to the inconsistency issue Saaty suggests that the optimal number of maximum categories for comparison should be 5 to 9, although it should be noted that this is obviously only a suggest as RI figures are given for as high as n = 15. This suggested limit can be seen as problematic for those of us wishing to apply AHP to combined LCA & TEA studies, as most LCA methods generate more than 9 environmental impact categories. Here, rather than cutting a category we decide to assess on 11 categories from the CML method – an alternative would be to cut this number down beforehand should it be possible to identify any that are not pertinent to the decision to be made – we would caution against such an approach in most cases.

After establishing the local weights for the more difficult task of establishing the values for the environmental sub-criteria can be done. A total of 55 pairwise comparisons are required to be made to complete the pairwise matrix. With the aim of improving consistency it was decided to use the following questions to help establish a baseline:

1. *Of the 11 sub-criteria, which is the most important?*

   It was determined that the global warming criteria was the most important for assessing the alternatives

2. *Are there any categories that can be assessed to have equal importance?*

   Yes. The abiotic depletion categories (ADP, ADPf) are assessed to be of equal value, as are the eco-toxicity categories (TET, MAET, FAET) and finally the acidification and ozone potential categories (AP, ODP)

3. *Of the 11 sub-criteria, which is the least important?*

   The eco-toxicity categories are deemed to be the least important

By identifying a most important and least important category (or categories in the case of this weighting) points could be fixed for a relative maximum variation of scoring (in this case GW is scored 8 against TET/MAET/FAET). From this point it was determined that everything else would have to fit within to this scale, conceptually the can be mapped out as shown in figure 6 below.

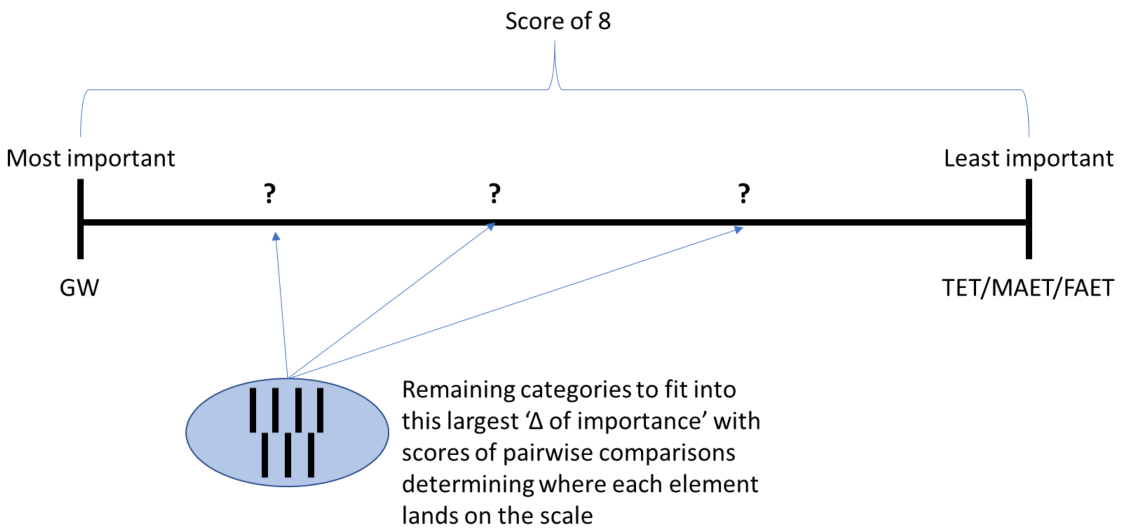

Figure 6 – Conceptual mapping of determining preference for the environmental sub-criteria

Authors note: Alongside determining the most and least important categories the identification of any categories that are assessed to be of equal value is also of value, as this allows for these categories to essentially by counted as 1 grouped category. This can be beneficial in cases such as this where an excessive number of individual categories are used, as it reduces the potential for inconsistency – although equal weight should not be assigned merely as a shortcut. A question can then be raised regarding which value should be used for the RI in calculating the CR – naturally having 11 categories would lead you to using n = 11 and therefore RI = 1.51, however if setting equal values simplifies the problem an argument could be made for using a smaller RI. In our weightings we determine 7 distinct values for 11 elements, using n = 7 gives RI = 1.32.

As can be seen in later tables for this example the change is not of importance, as the CI calculated is 0.035 and an RI of either 1.51 (CR = 0.035/1.51 = 0.0229) or 1.32 (CR = 0.035/1.32 = 0.0262) does not raise the CR even close to 0.100 – but users should be aware of this when considering elements (either criteria or alternatives) as of equal importance.

The remaining sub-criteria were scored as shown in table 13, with decimal scores used where required to ensure all sub-criteria could be weighted adequately on the 1 to 9 scale. Normalization (table 14) and consistency measurements (table 15) are also included to provide the full picture. The order of priority between the environmental sub-criteria is shown to be:

GW > ADP = ADPf > HT > ODP = AP > POCP > EP > TET = AET = FAET

As stated the global warming sub-criteria is determined to be the most important and is given the largest local priority vector, followed by the abiotic depletion categories. As before this is a reasonable position for a decision maker in CCU to take: a preference for the maximum reduction of global warming potential is often desirable and this can be coupled with an intent to reduce raw material demand (both fossil and rare elements) to ensure that the burden is not shifted to another material extraction process. Human toxicity is given the third highest priority vector, scoring slightly below ADP and ADPf, which is another reasonable position – human health is often considered to be of high importance. This list continues down to the lowest priority sub-criteria – the three eco-toxicity indicators.

A major downside to utilizing MADM approaches (not just AHP) is that it does require an order of preference to be taken – essentially forcing a decision maker into determining which of the typical LCA indicators is of least preference/priority. This is a process that many may find challenging – here the determination is not of absolute importance (where all indicators may be considered important) but of relative importance when compared against the other indicators. As such compensatory methods, such as AHP/MAUT/SMART, may be seen as they don't utilize cut-offs and allow for a broader picture to be drawn when compared against non-compensatory alternatives.

The issue of data collection is one typical disadvantage to these approaches, but given that most of this is done here as part of the LCA & TEA studies the approach may be more streamlined (and attractive) when compared to many traditional use cases.

Table 13 – Pairwise comparison matrix for the environmental sub-criteria

	GWP	AP	ADP	ADPf	TETP	MAETP	FAETP	EP	HTP	ODP	POCP
GWP	**1.0**	4.0	2.0	2.0	8.0	8.0	8.0	7.0	3.0	4.0	5.0
AP	0.3	**1.0**	0.5	0.5	4.0	4.0	4.0	3.5	0.7	1.0	2.0
ADP	0.5	2.0	**1.0**	1.0	6.0	6.0	6.0	5.0	1.5	2.0	4.0
ADPf	0.5	2.0	1.0	**1.0**	6.0	6.0	6.0	5.0	1.5	2.0	4.0
TETP	0.1	0.3	0.2	0.2	**1.0**	1.0	1.0	0.5	0.2	0.3	0.3
MAETP	0.1	0.3	0.2	0.2	1.0	**1.0**	1.0	0.5	0.2	0.3	0.3
FAETP	0.1	0.3	0.2	0.2	1.0	1.0	**1.0**	0.5	0.2	0.3	0.3
EP	0.1	0.3	0.2	0.2	2.0	2.0	2.0	**1.0**	0.3	0.3	0.7
HTP	0.3	1.5	0.7	0.7	6.0	6.0	6.0	4.0	**1.0**	1.5	3.0
ODP	0.3	1.0	0.5	0.5	4.0	4.0	4.0	3.5	0.7	**1.0**	2.0
POCP	0.2	0.5	0.3	0.3	4.0	4.0	4.0	1.5	0.3	0.5	**1.0**
Total	**3.6**	**13.0**	**6.6**	**6.6**	**43.0**	**43.0**	**43.0**	**32.0**	**9.4**	**13.0**	**22.4**

Table 14 – Normalization matrix for the environmental sub-criteria

	GWP	AP	ADP	ADPf	TETP	MAETP	FAETP	EP	HTP	ODP	POCP	Total	Priority vector
GWP	0.28	0.31	0.30	0.30	0.19	0.19	0.19	0.22	0.32	0.31	0.22	2.82	**0.26**
AP	0.07	0.08	0.08	0.08	0.09	0.09	0.09	0.11	0.07	0.08	0.09	0.92	**0.08**
ADP	0.14	0.15	0.15	0.15	0.14	0.14	0.14	0.16	0.16	0.15	0.18	1.66	**0.15**
ADPf	0.14	0.15	0.15	0.15	0.14	0.14	0.14	0.16	0.16	0.15	0.18	1.66	**0.15**
TETP	0.04	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.24	**0.02**
MAETP	0.04	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.24	**0.02**
FAETP	0.04	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.24	**0.02**
EP	0.04	0.02	0.03	0.03	0.05	0.05	0.05	0.03	0.03	0.02	0.03	0.37	**0.03**
HTP	0.09	0.12	0.10	0.10	0.14	0.14	0.14	0.13	0.11	0.12	0.13	1.31	**0.12**
ODP	0.07	0.08	0.08	0.08	0.09	0.09	0.09	0.11	0.07	0.08	0.09	0.92	**0.08**
POCP	0.06	0.04	0.04	0.04	0.09	0.09	0.09	0.05	0.04	0.04	0.04	0.61	**0.06**
Total	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**		**1**

Table 15 – Consistency ratio for the environmental sub-criteria

	GWP	AP	ADP	ADPf	TETP	MAETP	FAETP	EP	HTP	ODP	POCP
Eigenvector	0.26	0.08	0.15	0.15	0.02	0.02	0.02	0.03	0.12	0.08	0.06
Total (Sum)	3.55	13.04	6.62	6.62	43.00	43.00	43.00	32.00	9.42	13.04	22.42
Maximum eigenvalue	11.35										
CI	0.03										
RI	1.51										
CR	0.02										

After assigning local priority vectors to the sub-criteria a global priority can also be ascertained. This is determined by multiplying the priority vector of the sub-criteria with the priority vector of the criteria, so in the case of CapEx:

Global priority vector = Techno-economic x CapEx = 0.4 x 0.5 = 0.2

The global priority vectors (or weightings) for all the sub-criteria are given in table 16 below.

Table 16 – Global priority of each sub-criterion for assessment

Sub-Criteria	**Global Priority**
CapEx	0.200
GWP	0.154
OpEx	0.133
ADP	0.091
ADPf	0.091
HT	0.071
Production volume	0.067
AP	0.050
ODP	0.050
POCP	0.034
EP	0.020
TET	0.013
MAET	0.013
FAET	0.013
TOTAL	**1.000**

The full list of priorities show that the highest priority category is CapEx, by a relatively large difference, followed by global warming and the OpEx categories. As before this is a reasonable stance for a CCU decision maker to take: 'I want to deliver my product for the lowest cost with the lowest carbon footprint' is not an uncommon sentiment in the field of CCU.

Authors note: The global priority list does throw up some interesting things to consider. Given that there are far fewer techno-economic categories it can be easy to overvalue their priority globally – we distribute 40% of the global priority to 3 sub-criteria, whilst 60% is shared amongst 11 environmental sub-criteria. Should users find themselves with an equally lop-sided list of sub-criteria it may be worth 'sense checking' the global priority list here to ensure that what is given aligns with the priorities of the decision maker.

Adjusting the criteria weightings may allow for the amendment of the global priority list (a 70:30 split in priority for example would see the techno-economic categories devalued) but this risks a 3rd party reader interpreting your preferences as being highly biased to the environment rather than a compensation tactic for the global priority list. A better practice would be to readdress how the hierarchy is structured to ensure the global priorities and hierarchical priorities remain consistent with the decision maker's beliefs. Whilst here we utilize the AHP model a similar issue could arise with any model that utilizes a hierarchy as part of its weight determining step.

Having established global and local priorities the diagram in figure 6 can be updated to show the (globally) weighted criteria and sub-criteria.

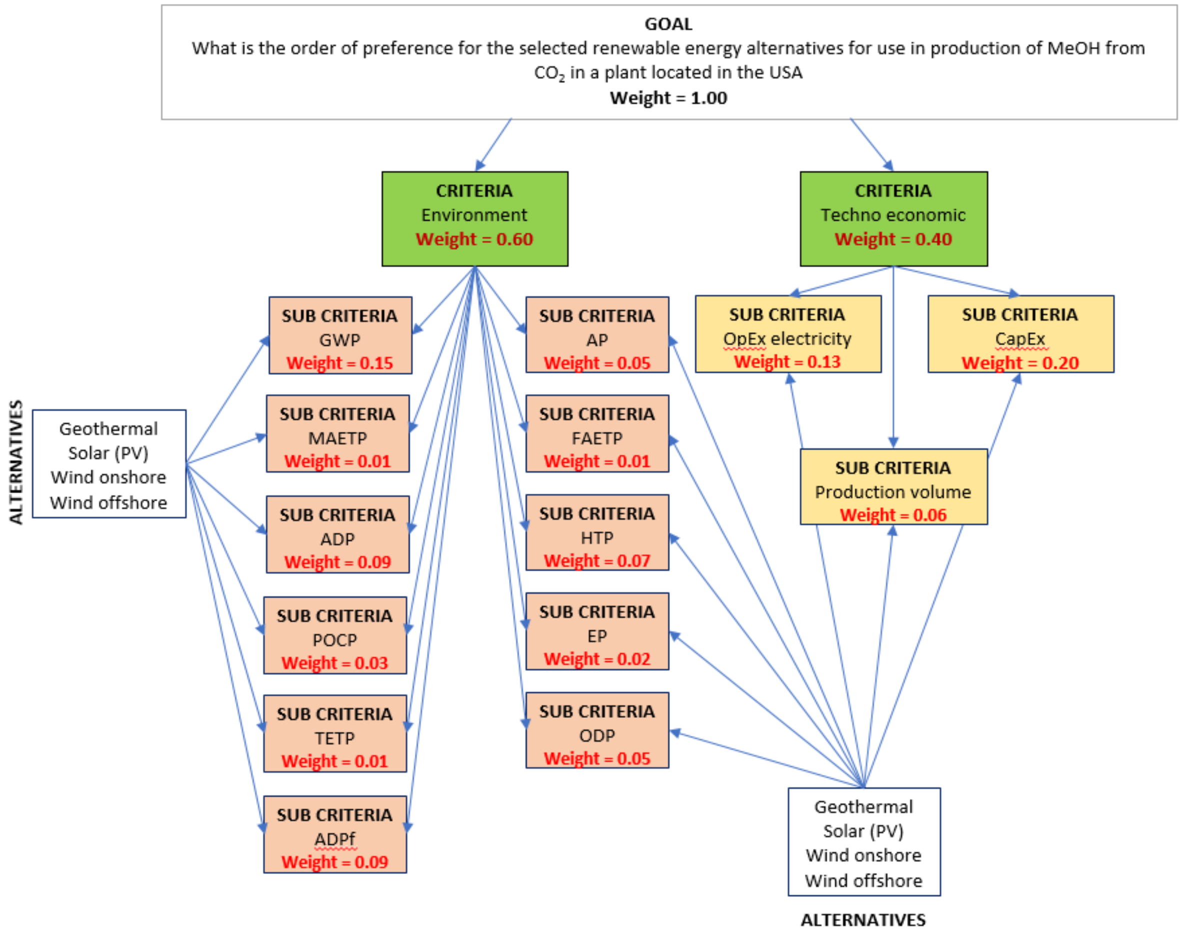

Figure 7 – Globally weighted criteria and sub-criteria

With the criteria and sub-criteria weighted attention can now be turned to making pairwise comparisons between the alternatives for each sub-criteria.

2.5 Assessing the Performance of Each Alternative

The approach taken here is the same as with the sub-criteria: scores are given on a 1 to 9 scale for each pairwise comparison, with these transcribed into the pairwise matrix before being normalized and finally a check on consistency.

With 4 alternatives, 6 unique pairwise comparisons need to be made for each of the 14 sub-criteria – for a total of 84 comparisons. Obviously, increasing the number of sub-criteria or alternatives would make this task even more time – considering even one more alternative in this instance would see the need to make a total of 140 comparisons (a 66% increase), 6 alternatives would see this rise to 210 (a further (a 150% increase on 84). Beyond the increase in the number of comparisons to be made, ensuring consistency between scores becomes increasingly difficult also. As such care should be taken to establish whether all alternatives are worthy of assessment as the resource demand increases greatly. Problems with a large number of alternatives may be best assessed using other MADM methods.

Returning the focus back to the problem at hand, scoring between the alternatives was determined considering the relative performance of each alternative in each sub-criteria. The tables (17 to 42) on the following pages show the pairwise matrices and normalization matrices for each sub-criteria with the consistency ratio for each given in table 43.

Tables 17 - 42 – Summary of pairwise comparison matrices and normalization matrices for assessing the alternatives on each of the sub-criteria

Global warming pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	0.14	0.11	0.33
Wind onshore	7.00	**1.00**	0.50	4.00
Wind offshore	9.00	2.00	**1.00**	7.00
Solar pv	3.00	0.25	0.14	**1.00**
Total	**20.00**	**3.39**	**1.75**	**12.33**

Global warming normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.05	0.04	0.06	0.03	0.18	**0.05**
Wind onshore	0.35	0.29	0.29	0.32	1.25	**0.31**
Wind offshore	0.45	0.59	0.57	0.57	2.18	**0.54**
Solar pv	0.15	0.07	0.08	0.08	0.39	**0.10**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Abiotic depletion (elements) pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	8.00	5.00	9.00
Wind onshore	0.13	**1.00**	0.67	1.28
Wind offshore	0.20	1.50	**1.00**	1.75
Solar pv	0.11	0.78	0.57	**1.00**
Total	**1.44**	**11.28**	**7.24**	**13.03**

Abiotic depletion (elements) normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.70	0.71	0.69	0.69	2.79	**0.70**
Wind onshore	0.09	0.09	0.09	0.10	0.37	**0.09**
Wind offshore	0.14	0.13	0.14	0.13	0.54	**0.14**
Solar pv	0.08	0.07	0.08	0.08	0.30	**0.08**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Abiotic depletion (fossil) pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	7.00	5.00	9.00
Wind onshore	0.14	**1.00**	0.83	1.60
Wind offshore	0.20	1.20	**1.00**	1.90
Solar pv	0.11	0.63	0.53	**1.00**
Total	**1.45**	**9.83**	**7.36**	**13.50**

Abiotic depletion (fossil) normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.69	0.71	0.68	0.67	2.75	**0.69**
Wind onshore	0.10	0.10	0.11	0.12	0.43	**0.11**
Wind offshore	0.14	0.12	0.14	0.14	0.54	**0.13**
Solar pv	0.08	0.06	0.07	0.07	0.29	**0.07**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Terrestrial eco-toxicity pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	6.00	9.00	3.50
Wind onshore	0.17	**1.00**	1.10	1.00
Wind offshore	0.11	0.91	**1.00**	0.83
Solar pv	0.29	1.00	1.20	**1.00**
Total	**1.56**	**8.91**	**12.30**	**6.33**

Terrestrial eco-toxicity normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.64	0.67	0.73	0.55	2.60	**0.65**
Wind onshore	0.11	0.11	0.09	0.16	0.47	**0.12**
Wind offshore	0.07	0.10	0.08	0.13	0.39	**0.10**
Solar pv	0.18	0.11	0.10	0.16	0.55	**0.14**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Marine aquatic eco-toxicity pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	9.00	4.00	2.20
Wind onshore	0.11	**1.00**	0.77	0.67
Wind offshore	0.25	1.30	**1.00**	1.10
Solar pv	0.45	1.50	0.91	**1.00**
Total	**1.82**	**12.80**	**6.68**	**4.97**

Marine aquatic eco-toxicity normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.55	0.70	0.60	0.44	2.30	**0.57**
Wind onshore	0.06	0.08	0.12	0.13	0.39	**0.10**
Wind offshore	0.14	0.10	0.15	0.22	0.61	**0.15**
Solar pv	0.25	0.12	0.14	0.20	0.71	**0.18**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Freshwater aquatic eco-toxicity pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	9.00	7.00	2.00
Wind onshore	0.11	**1.00**	0.91	0.29
Wind offshore	0.14	1.10	**1.00**	0.33
Solar pv	0.50	3.50	3.00	**1.00**
Total	**1.75**	**14.60**	**11.91**	**3.62**

Freshwater aquatic eco-toxicity normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.57	0.62	0.59	0.55	2.33	**0.58**
Wind onshore	0.06	0.07	0.08	0.08	0.29	**0.07**
Wind offshore	0.08	0.08	0.08	0.09	0.33	**0.08**
Solar pv	0.29	0.24	0.25	0.28	1.05	**0.26**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Eutrophication pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	9.00	4.00	2.30
Wind onshore	0.11	**1.00**	0.83	0.45
Wind offshore	0.25	1.20	**1.00**	0.77
Solar pv	0.43	2.20	1.30	**1.00**
Total	**1.80**	**13.40**	**7.13**	**4.52**

Eutrophication normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.56	0.67	0.56	0.51	2.30	**0.57**
Wind onshore	0.06	0.07	0.12	0.10	0.35	**0.09**
Wind offshore	0.14	0.09	0.14	0.17	0.54	**0.13**
Solar pv	0.24	0.16	0.18	0.22	0.81	**0.20**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Human toxicity pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	9.00	8.00	7.00
Wind onshore	0.11	**1.00**	1.00	0.50
Wind offshore	0.13	1.00	**1.00**	0.67
Solar pv	0.14	2.00	1.50	**1.00**
Total	**1.38**	**13.00**	**11.50**	**9.17**

Human toxicity normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.73	0.69	0.70	0.76	2.88	**0.72**
Wind onshore	0.08	0.08	0.09	0.05	0.30	**0.07**
Wind offshore	0.09	0.08	0.09	0.07	0.33	**0.08**
Solar pv	0.10	0.15	0.13	0.11	0.50	**0.12**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Ozone depletion pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	9.00	9.00	9.00
Wind onshore	0.11	**1.00**	1.00	0.50
Wind offshore	0.11	1.00	**1.00**	0.50
Solar pv	0.11	2.00	2.00	**1.00**
Total	**1.33**	**13.00**	**13.00**	**11.00**

Ozone depletion normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.75	0.69	0.69	0.82	2.95	**0.74**
Wind onshore	0.08	0.08	0.08	0.05	0.28	**0.07**
Wind offshore	0.08	0.08	0.08	0.05	0.28	**0.07**
Solar pv	0.08	0.15	0.15	0.09	0.48	**0.12**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Photochemical oxidation pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	9.00	6.50	7.00
Wind onshore	0.11	**1.00**	0.48	1.04
Wind offshore	0.15	2.10	**1.00**	0.50
Solar pv	0.14	0.96	2.00	**1.00**
Total	**1.41**	**13.06**	**9.98**	**9.54**

Photochemical oxidation normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.08	0.08	0.05	0.11	0.31	**0.08**
Wind onshore	0.11	0.16	0.10	0.05	0.42	**0.11**
Wind offshore	0.10	0.07	0.20	0.10	0.48	**0.12**
Solar pv	1.00	1.00	1.00	1.00		**1.00**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Capital expenditure pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	0.12	1.50	0.50
Wind onshore	8.50	**1.00**	9.00	7.50
Wind offshore	0.67	0.11	**1.00**	0.36
Solar pv	2.00	0.13	2.75	**1.00**
Total	**12.17**	**1.36**	**14.25**	**9.36**

Capital expenditure normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.08	0.09	0.11	0.05	0.33	**0.08**
Wind onshore	0.70	0.73	0.63	0.80	2.87	**0.72**
Wind offshore	0.05	0.08	0.07	0.04	0.25	**0.06**
Solar pv	0.16	0.10	0.19	0.11	0.56	**0.14**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Operational expenditure pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	1.50	3.00	0.20
Wind onshore	0.67	**1.00**	4.00	0.17
Wind offshore	0.33	0.25	**1.00**	0.11
Solar pv	5.00	6.00	9.00	**1.00**
Total	**7.00**	**8.75**	**17.00**	**1.48**

Operational expenditure normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.14	0.17	0.18	0.14	0.63	**0.16**
Wind onshore	0.10	0.11	0.24	0.11	0.56	**0.14**
Wind offshore	0.05	0.03	0.06	0.08	0.21	**0.05**
Solar pv	0.71	0.69	0.53	0.68	2.61	**0.65**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Production volume pairwise comparison matrix

	Geothermal	Wind onshore	Wind offshore	Solar pv
Geothermal	**1.00**	0.33	0.11	0.33
Wind onshore	3.00	**1.00**	0.17	1.00
Wind offshore	9.00	6.00	**1.00**	6.00
Solar pv	3.00	1.00	0.17	**1.00**
Total	**16.00**	**8.33**	**1.44**	**8.33**

Production volume normalization

	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Priority vector
Geothermal	0.06	0.04	0.08	0.04	0.22	**0.05**
Wind onshore	0.19	0.12	0.12	0.12	0.54	**0.14**
Wind offshore	0.56	0.72	0.69	0.72	2.69	**0.67**
Solar pv	0.19	0.12	0.12	0.12	0.54	**0.14**
Total	**1.00**	**1.00**	**1.00**	**1.00**		**1.00**

Table 43 – Calculated consistency ratio values for the performances in the 14 sub-criteria

Sub-criteria	**Maximum eigenvalue**	**CI**	**RI**	**CR**
GWP	4.122	0.041	0.900	**0.045**
AP	4.120	0.040	0.900	**0.045**
ADP	4.003	0.001	0.900	**0.001**
ADPf	4.010	0.003	0.900	**0.004**
TETP	4.112	0.037	0.900	**0.041**
MAETP	4.181	0.060	0.900	**0.067**
FAETP	4.012	0.004	0.900	**0.004**
EP	4.094	0.031	0.900	**0.035**
HTP	4.043	0.014	0.900	**0.016**
ODP	4.147	0.049	0.900	**0.054**
POCP	4.200	0.067	0.900	**0.074**
CapEx	4.161	0.054	0.900	**0.060**
OpEx	4.172	0.057	0.900	**0.064**
Production volume	4.113	0.038	0.900	**0.042**

As can be seen the determined scores are deemed to be sufficiently consistent throughout the categories. However, it should be noted that given that performance in all (and presumably at least ‘most of’ in the majority of combined LCA & TEA cases) sub-criteria in this case are quantifiable care should be taken to not only ensure that scores are consistent but also reflect performance. Tunnel vision regarding the former may lead to practitioners to not account for dominance (or lack of) in performance by 1 or more alternative in a given sub-criterion.

For example, consider the CapEx category in this study. From the global priorities assigned above it can be seen that performance in this category is likely to be important in determining the final ranking preference. In terms of raw performance by the alternatives ‘wind onshore’ outperforms all alternatives at $819 USD per tonne of methanol. The difference between wind onshore and the second best performing, ‘solar PV’, is $153 USD per tonne a value larger than the difference between solar PV and the worst performing alternative ‘wind offshore’ (a difference of $114 USD per tonne). Given this dominance the scores aggregated for each alternative in the total row in the pairwise column should also show a similar relative dominance – and not just a collection of values that achieve the required attribute of CR < 0.100. The scores given in this example are arguably a little too favorable to wind onshore – the other scores are grouped together suitably but the relative distance between the 2nd best (2nd lowest) score and the best score may be too large.

As such another pitfall for users to be wary of is identified: the need to ensure that weightings and scores reflect accurately the perception of the decision maker when considering the relative (or absolute) performance of the alternatives. It should be noted that as this is preference based the relationship between ‘real performance’ and preference of performance (determined through the pairwise scoring) does not have to be directly proportional or linear. For example, in this case the scores were not adjusted above as the dominance of wind onshore was judged to be much more preferential over the performance of the other 3 alternatives. This is obviously an opinion, and as such it segues into a key take away for readers:

It should be clear by now that any MCDA approach cannot fix bad decision logic, it can only highlight this to a third party who may wish to change, challenge or discard the decision made. MCDA is a tool for mapping the decision process and aids decisions through the provision of a framework. This may

help a decision maker address faults in their logic that had been previously unnoticed but it will not fundamentally change preferences of a decision maker.

2.6 Making the Final Decision

When scoring is both reflective of the decision maker's preferences and sufficiently consistent the priority vectors from the alternatives normalization matrices can then be multiplied by the relevant sub-criteria global priority to give a global priority score for each alternative in each category. To give an example:

Global priority score for 'wind onshore' in global warming =

local priority of wind onshore x global priority of global warming sub-criterion =

0.314 x 0.154 = 0.048

For this example, table 44 shows the global priority scores for each alternative in each category (also shown are the local priority vectors for completeness).

Table 44 – Global priority scores for the alternatives in each sub-criteria

Sub-criteria	Local priority					Global priority				
	Geothermal	Wind onshore	Wind offshore	Solar pv	Total	Geothermal	Wind onshore	Wind offshore	Solar pv	Total
GWP	0.046	0.314	0.544	0.097	**1.000**	0.007	0.048	0.084	0.015	**0.154**
AP	0.055	0.263	0.358	0.324	**1.000**	0.003	0.013	0.018	0.016	**0.050**
ADP	0.697	0.092	0.136	0.076	**1.000**	0.063	0.008	0.012	0.007	**0.091**
ADPf	0.687	0.108	0.134	0.071	**1.000**	0.062	0.010	0.012	0.006	**0.091**
TETP	0.649	0.117	0.096	0.138	**1.000**	0.008	0.002	0.001	0.002	**0.013**
MAETP	0.574	0.097	0.153	0.176	**1.000**	0.007	0.001	0.002	0.002	**0.013**
FAETP	0.582	0.072	0.083	0.263	**1.000**	0.008	0.001	0.001	0.003	**0.013**
EP	0.574	0.088	0.135	0.202	**1.000**	0.012	0.002	0.003	0.004	**0.020**
HTP	0.719	0.075	0.082	0.124	**1.000**	0.051	0.005	0.006	0.009	**0.071**
ODP	0.738	0.071	0.071	0.120	**1.000**	0.037	0.004	0.004	0.006	**0.050**
POCP	0.696	0.078	0.106	0.120	**1.000**	0.023	0.003	0.004	0.004	**0.034**
CapEx	0.082	0.716	0.061	0.141	**1.000**	0.016	0.143	0.012	0.028	**0.200**
OpEx	0.157	0.139	0.053	0.652	**1.000**	0.021	0.019	0.007	0.087	**0.133**
Production volume	0.055	0.136	0.674	0.136	**1.000**	0.004	0.009	0.045	0.009	**0.067**

The final step is to add together the global priority scores to give a total score for each alternative, with this captured in table 45 below. The alternative with the highest score is the most preferred. To ensure consistency, checks are made to ensure that all the weighted scores across the alternatives add up to the correct value (0.600 for all environmental sub-criteria, 0.400 for all techno-economic criteria).

It can be seen that the total score of the goal (1.000) is divided into the criteria (0.600 for environmental and 0.400 for techno-economic) before being divided further into the sub-criteria (as shown in figure 7). The score available in each sub-criteria is then split and awarded to each of the alternatives based on the assessment of their performance in that category.

Table 45 – Final preference scores and ranking of the alternatives

		Alternatives				
		Geothermal	**Wind onshore**	**Wind offshore**	**Solar PV**	**Total**
Environmental	**GW**	0.007	0.048	0.084	0.015	**0.600**
	AP	0.003	0.013	0.018	0.016	
	ADP	0.063	0.008	0.012	0.007	
	ADPf	0.062	0.010	0.012	0.006	
	TET	0.008	0.002	0.001	0.002	
	MAET	0.007	0.001	0.002	0.002	
	FAET	0.008	0.001	0.001	0.003	
	EP	0.012	0.002	0.003	0.004	
	HT	0.051	0.005	0.006	0.009	
	ODP	0.037	0.004	0.004	0.006	
	POCP	0.023	0.003	0.004	0.004	
Techno-economic	**CapEx**	0.016	0.143	0.012	0.028	**0.400**
	OpEx	0.021	0.019	0.007	0.087	
	Production Vol.	0.004	0.009	0.045	0.009	
	TOTAL	**0.32**	**0.27**	**0.21**	**0.20**	**1.000**
	FINAL RANK	**1**	**2**	**3**	**4**	

The final order of preference is:

1. A CO_2 to methanol plant powered by geothermal energy capable of producing 100 tonnes per day of methanol
2. A CO_2 to methanol plant powered by onshore wind capable of producing 250 tonnes per day of methanol
3. A CO_2 to methanol plant powered by solar PV energy capable of producing 250 tonnes per day of methanol
4. A CO_2 to methanol plant powered by offshore wind capable of producing 500 tonnes per day of methanol

So in this example the smaller geothermal plant is preferred over the larger solar PV and wind plants. This is a rather surprising result in some regards – when considering the 3 sub-criteria with the largest global priority geothermal generally ranks rather poorly: CapEx (3rd best, scoring only 8% of the total score available in the category), global warming (4th best, scoring only 5% of the total) and OpEx (2nd best, but still only 16% of the total). However, as the table shows geothermal outperforms the other alternatives in most other categories allowing it to accumulate the highest total score. A closer look at the scores show that in the categories where geothermal scores well it tends to dominate, picking up more than 50% of the total score available.

As suggested at other stages of the AHP process this would be an opportune moment to 'sense check' the results given. In this example it would be worthwhile for the decision maker to review whether geothermal is the best alternative: is its relatively poor performance in the 'most important' categories offset by its dominance in those of lower priority? A more formulaic approach to this would be to conduct a sensitivity analysis as is done in the following section

2.7 Checking the Decision Sensitivity

A final step, and one which may help address the question posed above, can be to consider sensitivities within the system, with three areas identified for consideration: weights, local priorities and comparisons [37]. Sensitivity analysis is useful for checking what happens if the priorities change – for example – what happens if it is decided that the global warming is the most important and the global priority list alters to reflect this? Does the result stay the same? In this sense a sensitivity test, much like in LCA or TEA, helps to determine how 'robust' an outcome is. An outcome can be seen to be robust if the required change in sensitivity is greater than the uncertainty in the associated weight/priority/comparison.

Several approaches are available for undertaking sensitivity analysis, with popular choices being to use specialist software such as Expert Choice. However as identified above, AHP can be implemented using readily accessible spreadsheet software (with this being a major reason for why it was selected here) and as such sensitivities can be applied manually too, as is done here.

Source [50] provides an often cited method for conducting a sensitivity analysis on both criterion and on 'performance' (the scoring of the alternatives). The basic method for both is similar, when exploring the sensitivities of the criteria the performance scores are kept fixed and the weights varied, when the sensitivities of the performance scores are of interest the reverse is true –performance scores are varied and the weights are kept constant.

When considering criteria, the first step is to determine what is referred to as the *most critical criterion* with two definitions available for this, one which considers only the 'smallest change' required to change the top preference and one which considers the 'smallest change' to change any position in the order of preference. Here the smallest change can refer to either absolute or relative change e.g. if criterion C_1 is weighted at 0.05 and C_2 at 0.10, and taking a change of weight of + 0.04 for C_1 and of + 0.05 for C_2 would result in changing the order of preference the absolute change for C_1 is smaller than C_2 but the reverse is true when relative terms are considered). In this sense the approach is akin to a local sensitivity check which should be familiar to many LCA & TEA practitioners.

In most cases it is advised to consider the relative 'smallest change' given that this is more contextually correct, and this is used as the focus here. Aside from this decision, the most critical criterion can also be defined as:

1. The *absolute-top critical criterion* in which the most critical criterion is the one with the required smallest change to change the order at the top of the preference ranking
2. The *absolute-any critical criterion* in which the most critical criterion is the one with the required smallest change to change the order of preference in any location

Given the goal of this study is to determine an order of preference both of these definitions will be considered in this sensitivity analysis.

Readers are encouraged to read source [50], as this example primarily applies the analysis in place of deriving and defining it. The naming convention outlined is also partially used here:

- A is used here to define an alternative, with a subscript used to define its pre-sensitivity test preference rank – geothermal is therefore A_1, wind onshore A_2 and so on

- P refers to the overall priority calculated above, with the same subscript notion as before, ergo P_1 is the priority vector for geothermal and is equal to 0.32
- C refers to a criterion, here instead of numbering the criterion the name is used, for example C_{GWP} would be the global warming criterion
- *'a'* is used to refer to a local priority vector for a given alternative and criterion these values can be found in table 44 above, for example $a_{1,GWP}$ would be the local priority for geothermal, global warming with the value 0.046
- δ refers to the minimum quantity needed to reverse the current ranking, with δ' used for the relative (percentage change) value
- W refers to the current weighting of the criterion (the priority vector of the sub-criteria in this case), and W* refers to the new weight

In this method it is assumed that the user wishes to alter the ranking of A_1 and A_2 (or any other pair of alternatives but here the subscripts 1 and 2 are used) by ONLY changing the weight W_i of criterion C_i, where currently $P_1 \geq P_2$. For this to be true one of the following two relationships needs to be satisfied:

$$\delta_{i,1,2} < \frac{(P_2 - P_1)}{(a_{2,i} - a_{1,i})}, \qquad \text{if } (a_{2,i} > a_{1,i})$$

$$\delta_{i,1,2} > \frac{(P_2 - P_1)}{(a_{2,i} - a_{1,i})}, \qquad \text{if } (a_{2,i} < a_{1,i})$$

A second condition is also required to be satisfied for the new weight ($W_i^* = W_i - \delta_{i,1,2}$) to be feasible:

$$0 \leq W_i^*$$

Implying:

$$0 \leq W_i - \delta_{i,1,2}$$

Implying:

$$\delta_{i,1,2} \leq W_i$$

In other words, the value of the new weight must (logically) be larger than zero and the value of the $\delta_{i,1,2}$ term must be equal to or less than the original weighting of C_i. The value of W_i^* does not have the same limit of 1, as the weights need to be 'renormalized' before adding up to 1. From the rules above it should be clear that in some cases it may not be possible to flip the rankings of A_1 and A_2 solely through changing the weight of C_i, explicitly this is not possible when the $\Delta P/\Delta a$ term is greater than W_i. General forms of all of these conditions are available in the source material [50]:

$$\delta'_{k,i,j} < \frac{(P_j - P_i)}{(a_{j,k} - a_{i,k})} \text{ x } \frac{100}{W_k}, \qquad \text{if } (a_{j,k} > a_{i,k})$$

$$\delta'_{k,i,j} > \frac{(P_j - P_i)}{(a_{j,k} - a_{i,k})} \text{ x } \frac{100}{W_k}, \qquad \text{if } (a_{j,k} < a_{i,k})$$

With the following condition needing to be satisfied:

$$\frac{(P_j - P_i)}{(a_{j,k} - a_{i,k})} \leq W_k$$

Thus the first step in investigating sensitivity is calculating all possible δ terms for the matrix. Below is the calculated δ term for A_1 (geothermal) and A_2 (wind onshore) for the global warming criterion:

$$\delta_{GWP,1,2} < \frac{(0.267 - 0.323)}{(0.314 - 0.046)}$$

$$\delta_{GWP,1,2} < -0.208$$

As -0.208 is less than the value of W_{GW} (0.154) the value is feasible, a value for W_i* (prior to normalization) can also be calculated:

W_i* = 0.154 – (-0.208) = 0.361

The value -0.208 can also be expressed in relative terms (as a percentage of change):

(-0.208/0.154) x 100 = -135%

A key aspect to note here from the source material is that a negative value (either in absolute or relative terms) means that an increase is required, so in this example the value of W needs to increase by 0.208 or by 135%. This process is repeated for all elements in the matrix, with all feasible values of δ included in table 46 and all relative (percentage change) values in table 47.

Table 46 – All feasible (minimum) values of δ (absolute change in criteria weights) calculated as shown in [50]

	Comparison (absolute change, value of δ)					
Sub-criteria	**A1 - A2**	**A1 - A3**	**A1 - A4**	**A2 - A3**	**A2 - A4**	**A3 - A4**
GWP	-0.208	-0.226	-2.435	-0.247	N/F	0.025
AP	-0.269	-0.372	-0.461	-0.597	-1.109	N/F
ADP	N/F	N/F	N/F	-1.278	N/F	N/F
ADPf	N/F	N/F	N/F	-2.183	N/F	N/F
TET	N/F	N/F	N/F	N/F	-3.244	-0.275
MAET	N/F	N/F	N/F	-1.029	-0.864	-0.479
FAET	N/F	N/F	N/F	-4.988	-0.357	-0.063
EP	N/F	N/F	N/F	-1.232	-0.600	-0.167
HT	N/F	N/F	N/F	-8.075	-1.381	-0.267
ODP	N/F	N/F	N/F	N/A	-1.372	-0.227
POCP	N/F	N/F	N/F	-2.073	-1.633	-0.790
CAPEX	-0.088	N/F	-2.112	0.087	0.119	-0.143
OPEX	N/F	N/F	-0.251	N/F	-0.133	-0.019
Production Vol.	-0.688	-0.182	-1.534	-0.106	N/A	0.021

Table 47 – All feasible (minimum) values of δ' (percentage change in criteria weights)

Sub-criteria	Comparison (% change needed to change rankings between alternatives)					
	A1 - A2	**A1 - A3**	**A1 - A4**	**A2 - A3**	**A2 - A4**	**A3 - A4**
GWP	-135	-147	-1584	-161	N/F	16
AP	-533	-739	-916	-1185	-2202	N/F
ADP	N/F	N/F	N/F	-1409	N/F	N/F
ADPf	N/F	N/F	N/F	-2407	N/F	N/F
TET	N/F	N/F	N/F	N/F	-24973	-2119
MAET	N/F	N/F	N/F	-7920	-6654	-3686
FAET	N/F	N/F	N/F	-38392	-2748	-484
EP	N/F	N/F	N/F	-6078	-2960	-825
HT	N/F	N/F	N/F	-11308	-1934	-374
ODP	N/F	N/F	N/F	N/A	-2724	-451
POCP	N/F	N/F	N/F	-6183	-4872	-2356
CAPEX	-43.9	N/F	-1056	44	59	-71
OPEX	N/F	N/F	-188	N/F	-100	-14
Production Vol.	-1032	-273	-2300	-159	N/A	32

The term of N/F is used in the table in places where a value for δ is 'not feasible' and the term N/A is used where the term is undefined (due to the need to divide by zero). Highlighted cells are used to identify the most critical criterion with the 'absolute top' and 'absolute any' criterion in the absolute change table shown and the 'percentage top' and 'percentage any' shown in the percentage table. As stated above, in each case these values represent the smallest changes required to change the ranking for the specified definition.

In this case we find that for both the absolute and the percentage cases the figures are the same, with changes to CapEx weighting given for the percentage/absolute top and changes to OpEx for the absolute/percentage any. To change the top ranking a 44% increase is required for the weighting of CapEx, to change any ranking a 14% increase is required to OpEx (which would result in A_3 wind offshore and A_4 solar PV swapping ranks).

Finally, an ordering of the sensitivity of the sub-criteria can be arrived at by taking the modulus of the smallest necessary change for each category (a term labelled D'_k the criticality degree of criterion C_k) and calculating the value for 1 over this to give the sensitivity coefficient of this:

$$\mathrm{Sens}(C_k) = 1 / D'_k$$

For any criteria in which D'_k cannot be established the sensitivity coefficient is set to 0.00. The sensitivity coefficients for the 14 sub-criteria in this study are given below in table 48.

Table 48 – Sensitivity coefficients for the 14 sub-criteria derived as defined as described in [50]

Sub-criteria	Minimum change (%)	D'	Sens(C)	Rank
GWP	16	16	0.0608	2
AP	-533	533	0.0019	8
ADP	-1409	1409	0.0007	10
ADPf	-2407	2407	0.0004	13
TET	-2119	2119	0.0005	11
MAET	-3686	3686	0.0003	14
FAET	-484	484	0.0021	7
EP	-825	825	0.0012	9
HT	-374	374	0.0027	5
ODP	-451	451	0.0022	6
POCP	-2356	2356	0.0004	12
CAPEX	44	44	0.0230	4
OPEX	-14	14	0.0706	1
Prod Volume	32	32	0.0317	3

The table shows that the most sensitive criteria are OpEx, global warming and the production volume.

Ultimately what is shown here is that the top ranking is unlikely to change unless there is a significantly large amount of uncertainty within the rankings. Here uncertainty is not calculated for this reason, but several approaches are available for calculating this including one developed by Saaty and Vargas [51].

After demonstrating that there is little sensitivity in the criteria attention can now be turned to the performance scores. As before a more detailed description of the method applied (including the establishing of theorems and definitions for terms) can be found in source [50], here a focus is made on applying the method and defining a few key terms.

The intention of this methodology is to determine *the most critical measure of performance* – defined in the source material as a_{xy}, the performance of alternative 'x' in criterion 'y'.

Similar to in the prior test the intention is to quantify the minimum change required in a given value required to change the current ranking between two alternatives, A_x and A_z. This 'threshold value' is quantified as τ here, so τ_{xyz} would represent the threshold value of criterion C_y at which the rankings of A_x and A_z would reverse (mirroring the above τ' is used to denote the relative/percentage change). As a reminder, the terms A_1 to A_4 are used in the same way above as to denote the order of preference established in the AHP.

In this example only the relative change, τ' is of interest and as such the formula for this is given below:

$$\tau'_{x,y,z} = \frac{(P_x - P_z)}{[P_x - P_z + W_y(a_{z,y} - a_{x,y} + 1)]} \text{ x } \frac{100}{a_{x,y}}$$

Where the definitions for P and W remain consistent with those given above, a limiting condition is also required:

$$\tau'_{x,y,z} \leq 100$$

This limitation is in place as it is not possible to reduce the performance by more than 100% of its value. With this established the values for τ' can be established for comparing each alternative against all three others, as is done in the tables (49 – 52) below. As before, a negative number corresponds to an increase in the value of $a_{x,y}$ and a positive a decrease. Where a result is not feasible (as it invalidates the rule given above) the term N/F is given in the table.

Table 49 – Values of τ' for geothermal alternative compare to other alternatives (specified on the final row)

Alternative	**Geothermal (values of τ')**		
GWP	N/F	N/F	N/F
AP	N/F	N/F	N/F
ADP	87.3	N/F	N/F
ADPf	86.4	N/F	N/F
TET	N/F	N/F	N/F
MAET	N/F	N/F	N/F
FAET	N/F	N/F	N/F
EP	N/F	N/F	N/F
HT	95.5	N/F	N/F
ODP	N/F	N/F	N/F
POCP	N/F	N/F	N/F
CAPEX	N/F	N/F	N/F
OPEX	N/F	N/F	N/F
Production Vol.	N/F	N/F	N/F
Compared to	**Wind onshore**	**Wind offshore**	**Solar PV**

The table for the geothermal (A_1) alternative only offers 3 values, all of which can be found when compared to wind onshore (A_2). All three of these values state that a significant decrease in the performance score would be required to switch the rankings.

Table 50 – Values of τ' for wind onshore alternative compare to other alternatives (specified on the final row)

Alternative	**Wind onshore (values of τ')**		
GWP	-312.1	73.9	N/F
AP	N/F	N/F	N/F
ADP	-676.3	N/F	N/F
ADPf	-589.3	N/F	N/F
TET	N/F	N/F	N/F
MAET	N/F	N/F	N/F
FAET	N/F	N/F	N/F
EP	N/F	N/F	N/F
HT	-1205.5	N/F	N/F
ODP	-2780.2	N/F	N/F
POCP	N/F	N/F	N/F
CAPEX	-445.6	63.2	62.3
OPEX	-499.4	N/F	N/F
Production Vol.	-7300.9	N/F	N/F
Compared to	**Geothermal**	**Wind offshore**	**Solar PV**

The table for the wind onshore table contains more values than the prior geothermal one. When compared to geothermal (A_1) significant improvement is required in all categories to reverse the ranking – with global warming requiring a 312% increase being the smallest change required. As such it is fair to assume that at the specified weightings (those determined in the AHP study) the required changes on a single category basis would suggest that the ranking is robust. Comparing wind onshore to wind offshore and solar PV (A_3 and A_4 respectively) there are only 3 valid reductions identified – and all of these are relatively large in scale.

Table 51 – Values of τ' for wind offshore alternative compare to other alternatives (specified on the final row)

Alternative	**Wind offshore (values of τ')**		
GWP	N/F	-171.2	21.6
AP	N/F	N/F	52.7
ADP	-2871.3	-1415.0	86.1
ADPf	-2992.2	-1360.0	87.6
TET	N/F	N/F	N/F
MAET	N/F	N/F	N/F
FAET	N/F	N/F	N/F
EP	N/F	N/F	N/F
HT	-32571.9	-5026.4	N/F
ODP	N/F	N/F	N/F
POCP	N/F	N/F	N/F
CAPEX	-2009.9	-339.4	81.2
OPEX	-6215.2	-1235.0	95.9
Production Vol.	N/F	N/F	39.9
Compared to	**Geothermal**	**Wind onshore**	**Solar PV**

The table shows, that as one would expect, the results required to switch the rankings of A_1 and A_3 are even more extreme than those needed for A_2. The results for comparing A_3 to A_2 also show extreme changes in performance are required to change the rankings here also. The most sensitive categories concern the potential to swap ranks A_3 and A_4. When looking at the global priorities determined for each alternative in the AHP this is hardly surprising, the scores for wind offshore and solar PV are very close to each other and distant to both the score for geothermal and for solar PV.

Table 52 – Values of τ' for solar PV alternative compare to other alternatives specified (specified on the final row)

Alternative	**Solar PV (values of τ')**		
GWP	-5868.0	-596.2	-55.5
AP	N/F	N/F	-85.7
ADP	-7136.0	-3804.5	-176.5
ADPf	-7734.0	-3732.9	-186.4
TET	N/F	N/F	-7217.8
MAET	N/F	N/F	-4698.9
FAET	N/F	N/F	N/F
EP	N/F	N/F	-737.8
HT	N/F	N/F	-159.6
ODP	N/F	N/F	-257.1
POCP	N/F	N/F	-434.1
CAPEX	-1373.7	-197.1	-46.6
OPEX	N/F	N/F	-41.2
Production Vol.	N/F	N/F	-91.4
Compared to	**Geothermal**	**Wind onshore**	**Wind offshore**

Finally, a brief note on the rankings for solar PV (A_4) – following on from the logic outlined above the scores needed to change ranks with A_1 and A_2 are even more extreme than those for A_3. The one exceptional category – CAPEX with this largely being down to the better performance of solar PV in this category when compared to wind offshore. As above the most sensitive performance scores are those that would see a swap of ranks A_3 and A_4.

A final step included in the method of Triantaphyllou and Sánchez is to determine the criticality degree for each performance measure and the sensitivity coefficients for each alternative across each criterion. This is done by selecting the lowest change in required for each criteria across the alternatives (from the tables above) to determine the criticality degree, and then dividing 1 by this number. The most sensitive alternative is the one with the highest sensitivity coefficients, with all figures given in table 53 below.

Table 53 – Sensitivity coefficients for performance scores for all alternatives in all sub-criteria

Indicator	**Geothermal**	**Wind onshore**	**Wind offshore**	**Solar PV**
GWP	0.0000	0.0135	0.0463	0.0180
AP	0.0000	0.0000	0.0190	0.0117
ADP	0.0114	0.0015	0.0116	0.0057
ADPf	0.0116	0.0017	0.0114	0.0054
TET	0.0000	0.0000	0.0000	0.0001
MAET	0.0000	0.0000	0.0000	0.0002
FAET	0.0000	0.0000	0.0000	0.0000
EP	0.0000	0.0000	0.0000	0.0014
HT	0.0105	0.0008	0.0002	0.0063
ODP	0.0000	0.0004	0.0000	0.0039
POCP	0.0000	0.0000	0.0000	0.0023
CAPEX	0.0000	0.0161	0.0123	0.0215
OPEX	0.0000	0.0020	0.0104	0.0243
Production Vol.	0.0000	0.0001	0.0251	0.0109

The table and the prior calculations shows that the highest sensitivity coefficient is for wind offshore in the global warming category. Many of the impact categories are shown to be highly insensitive – likely due to their low weightings. The general findings show that the geothermal alternative is likely robust, as shown in the prior sensitivity test also, with the rankings of wind offshore and solar PV being the most sensitive.

It should be noted here that the sensitivity checks on both performance and sub-criteria weighting are undertaken on a local scale, i.e. only varying one element at a time. Global approaches to sensitivity are not considered here, although a few examples can be found for application with AHP, such as the extended Fourier amplitude sensitivity test [52].

At this point the AHP rankings can be determined to be robust, with the rankings given a fair representation of the preferences decision maker.

2.8 Concluding Remarks

- There are obvious benefits to aligning and combining ('integrating') LCA & TEA as a way of further supporting decisions made utilizing the outputs of these studies: the addition of a combined enviro-economical dimension or the clear identification of trade-offs (either for optimization problems or attributional problems) add an additional layer of depth and context to stand alone LCA & TEA studies – however, integrating studies is something that requires additional resources (e.g. time, and possibly data) and care should be taken to ensure that the benefits of this are relevant to the needs of the practitioner or other stakeholders
- Multi-attributional approaches are useful when a number of discrete alternatives are available for selection, particularly when the performance measures of these alternatives lead themselves to trade-offs and where one option is not dominant other the others – as is the case for many of the scenarios commonly assessed in CCU
- Determining the correct MADM approach to apply when considering combined LCA & TEA studies is a matter of a number of factors including: identifying the type of MADM problem, data and resource availability and personal preference
- The AHP model used shows that even with an extensive number of (sub-)criteria the approach can be applied to assist in decision making utilizing combined LCA & TEA outputs. Concerns over the AHP model are highlighted (in both parts 1 and 2) with a particular concern being that of scoring consistency – however solutions to this issue are available (typically these involve amending the original scoring system of Saaty) and the results here show that a robust and consistent preference can be established. Whilst some concerns are not so easy to address (such as the lack of an entirely axiomatic foundation), the relative ease of application (even without specialist software) ensures that the approach is likely to remain popular with decision makers, including those concerned with CCU

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