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A distance-to-sustainability-target approach for indicator aggregation and its application for the comparison of wind energy alternatives

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Abstract

Sustainability impact assessments studies combine several indicators to cover environmental, economic and social impacts. These indicators describe different impact pathways and are expressed in different units, which makes comparing alternatives challenging. An aggregated metric is required to facilitate the presentation and communication of sustainability. The presented aggregation framework is based on the distance-to-target method NR-TOPSIS and adapted to a distance-to-sustainability-target approach. A procedure is given for aggregating 12 sustainability indicators into a single score sustainability indicator. Reference points for normalization of diverse impact indicators and weighting factors are investigated. The framework was applied to a wind energy case study comparing one offshore and two onshore alternatives. The case study results were compared using both a dashboard of 12 endpoint indicators and an aggregated sustainability indicator. The indicator was presented on a sustainability scale that indicated the distance of the investigated cases to an ideal (sustainable) solution. A sensitivity analysis of the weighting factors showed that the distribution of weights influenced the ranking of alternatives, especially when the alternatives are positioned close to each other on the sustainability scale, as it is the case for the wind energy scenarios. For most of the weighting scenarios, the onshore wind energy project using permanent magnet synchronous generators appeared to be the most sustainable solution.

Keywords

Sustainability assessment, multi-criteria decision analysis, sustainability boundary, indicator aggregation, single score, wind energy

Highlights

- A distance-to-sustainability target approach was used for indicator aggregation.
- NR-TOPSIS was found to be the most suitable method for this approach.
- Sustainability boundaries were defined for 12 impact categories.
- Onshore and offshore wind energy projects are compared.
- Considering several weighting scenarios the most sustainable project was identified.

Word count

8,799

1 Introduction

The energy sector is globally the main contributor to the greenhouse gas emissions balance and thereby main driver of climate change. In the EU, the production of heat and electricity is responsible for 27% of greenhouse gas emissions from member countries [1]. In order to meet agreed emission reduction targets and mitigate the effects of climate change, power generation in the EU needs to be decarbonized. While this energy transition towards low-carbon energy sources is essential, it has several side effects on the environment, economy and society. Land use, local landscapes and global supply chains are just a few examples of aspects that will change with the energy transition. Despite the knowledge of these side effects, the focus of energy transition planning is still on greenhouse gas emissions only. Other sustainability impacts and benefits of the energy transition are given far less consideration.

In service of clear communication of sustainability impacts, a single metric that measures sustainability is preferred to the handling of several individual indicators from different fields. Therefore, there is a need for the aggregation of a comprehensive set of individual impact indicators as part of the assessment [2,3]. In environmental Life Cycle Assessment (LCA) impacts are expressed as midpoint indicators or already aggregated endpoint indicators to ease the comparison of alternatives [4]. This is considered an advantage of the standardized LCA methodology, although the aggregation strategies and impact pathways used to provide endpoint indicators are less mature than the midpoint pathways, and users may risk that the results are being distorted e.g. by unintended weighting [5]. While endpoint indicators mainly exist for environmental LCA, it is still a challenge to combine the results with economic and social indicators to an aggregated metric of sustainability [3,6]. A uniform aggregation methodology is missing for sustainability assessments [7]. For this reason, this study examines the requirements for an aggregation method for a standardized sustainability assessment. In particular, the choice of aggregation method is examined, as there is no consensus in the literature on which method to use. Both the normalization and weighting procedures for calculating a single-score indicator are investigated in detail. Reference values for measuring sustainability on a fixed scale are presented as well as a procedure for testing different weighting factors in the context of a sensitivity analysis.

The aggregation of indicators in sustainability assessment takes place at different levels and can be illustrated in the form of an information pyramid, see Figure 1. This pyramid visualizes the processing of information from the bottom to the top. Inventory data, describing all inputs and outputs connected to the product, constitutes the basis of the pyramid. The inventory data is used to quantify the aggregated impacts of the product, either first to intermediary midpoint or directly to endpoint impact indicators. The next level is the aggregation of these diverse endpoint indicators to a single score sustainability indicator. While part of the original information is lost when moving up the information pyramid, the ease of interpretation is improved. Communication of results and the comparison of several products is the easiest at the top of the pyramid using a single indicator.

Due to the multidimensionality of the sustainability topics relevant for applications within the energy sector, there is not a single sustainability impact pathway but rather a multitude of approaches to aggregate results to a single sustainability indicator. Some energy sector studies use aggregated indicators for the comparison of cases [8–10] but there is no consensus on the method used for aggregation nor is there a clear definition of the sustainability indicator. A commonality, however, is to focus on the greenhouse gas emissions indicator as a proxy for sustainability [11].

In particular, aggregation in sustainability studies of the energy sector differ in three points: (1) the aggregation method, (2) the reference points for the normalization step and (3) the weighting factors. These three points will be addressed with the objective of developing an aggregation strategy resulting in a single score sustainability indicator that can be used to assess and compare energy technologies.

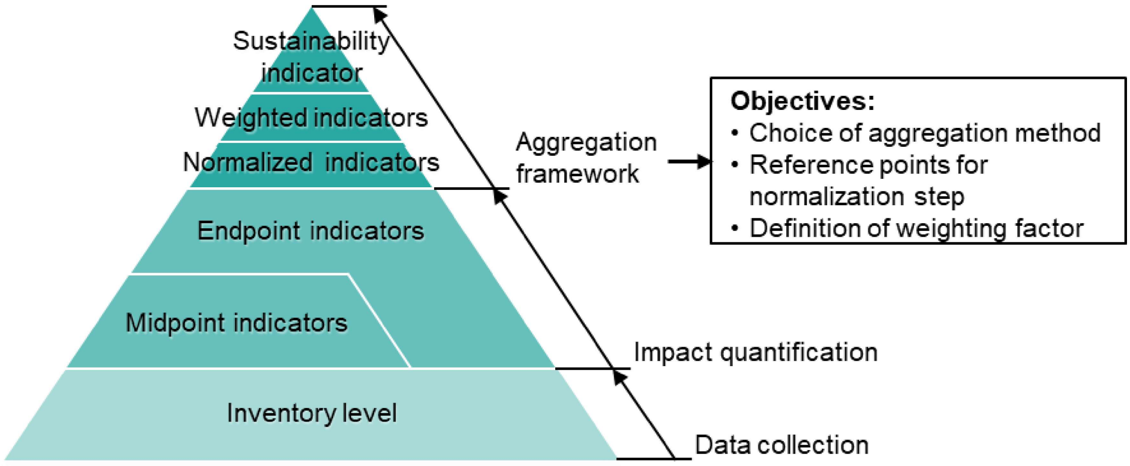

Figure 1: Information pyramid illustrating the procedure of quantifying the sustainability impact, resulting in a single score sustainability indicator

Using multi-criteria decision analysis (MCDA) breaks down complex decision problems to identify the optimal case out of a set of alternatives based on certain decision criteria [12,13]. The reviews of Hottenroth [7] and Antunes and Henriques [14] show that for energy case studies the Analytic Hierarchy Process (AHP) is the most frequently used method, followed by the weighted sum method (WSM) and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluation). Other commonly applied MCDA methods, also for energy case studies, are multi-attribute utility theory (MAUT) and multi-attribute value theory (MAVT), ELECTRE (ELimination Et Choix Traduisant la REalité), TOPSIS (Technique for the Order of Prioritization by Similarity to Ideal Solution), VIKOR (viekriterijumsko kompromisno rangiranje, meaning multi-criteria optimization and compromise solution) and DEA (Data Envelopment Analysis). However, there is no consensus on which MCDA method to use in energy technology studies and sustainability assessments, and to date there is no sustainability indicator that can be used across studies.

Most of these MCDA methods include a normalization and a weighting step [15]. In several studies, the normalization step was identified as more influential than weighting in the aggregation of LCA results [16–18]. A distinction can be made between internal and external normalization. Internal normalization uses the analyzed alternatives as reference points, which has the disadvantage of the results being study-specific and the possibility that normalized results change if alternatives are added or deleted. External normalization uses external reference points, such as the total of global/territorial activities in a specific impact category [19], worst/best/average case scenarios [16], or carrying capacity-based reference points [20]. However, the elicitation of external reference points comes with a bias risk [21].

Weighting is seen with skepticism in LCA studies [19]. On the one hand, weighting is advisable in order to provide a balance between impact categories, e.g. in the case where environmental, economic and social impacts are represented by an unequal number of indicators. On the other hand, weighting factors can introduce bias into the calculation as they represent a value choice made by decision makers or stakeholders, which is dependent on time and context [19]. A common weighting approach in LCA is the use of panel weights, e. g. on the three endpoint dimensions featured in the ReCiPe method [3,22]. Comparably, also the weighting of categories for the calculation of the Environmental Footprint is done based on population and expert panel evaluations [23]. Another approach uses monetarization of environmental impacts as demonstrated by Kosugi et al. [24]. Castellani et al. [25] calculated weights based on the deviation from the EU 2020 emission targets for several environmental impact categories. By focusing on the perspectives of different societies, Hofstetter et al. [26] defined three stakeholder archetypes: Egalitarian, Hierarchist and Individualist. These archetypes are used for instance for environmental LCA to define characterization factors [27] or for weighting between sustainability dimensions in life cycle sustainability assessment (LCSA) [8]. Thus, normalization and weighting can be part of LCA and sustainability assessment practices [28], although they come with the risk of distorting the assessment results [29]. Accordingly, the impact of normalization and weighting procedures on the aggregated indicator should be investigated with care when developing an aggregation strategy.

This literature review showed that there are several aggregation approaches for indicators assessing the sustainability of energy technologies. However, there is no consensus on which of the approaches found in the literature should be systematically used for the sustainability assessment or how sustainability should be presented in the first place. This is a shortcoming for sustainability assessments of energy technologies that is addressed in this paper.

To this end, this paper argues for a standardization of aggregation frameworks. The objective of the study is to propose such a framework for the aggregation of sustainability impact results to a single sustainability indicator for energy technologies. The interdisciplinary assessment of sustainability involves several indicators describing parts of the overall sustainability impacts. A single aggregated indicator for sustainability is missing. Currently, there is no standardized strategy or framework available that guides the selection and application of an aggregation method for sustainability assessment results. For that reason, the aggregated indicators found for energy case studies are not comparable across studies. The applied MCDA methods in energy sector studies differ as well as the related normalization and weighting procedures. The proposed aggregation framework thereby aims at providing a procedure to compare the sustainability of different energy technologies. The framework covers the selection of a MCDA method for aggregation and proposes values for standardized normalization and weighting. This allows the assessment of sustainability across different energy case studies. In this paper the framework will be applied to the case study of wind energy technologies to demonstrate its applicability.

2 Materials and methods

This section describes the essential steps to assess the sustainability of the wind energy case study up to the calculation of the single score sustainability indicator. The sustainability assessment resulting in a single sustainability indicator encompasses two major steps: (1) the impact quantification based on 12 sustainability endpoint impact categories is outlined for the wind energy case study and (2), the aggregation procedure using a MCDA method is described, including method selection, normalization and weighting.

2.1 Impact quantification of wind energy case study

The single sustainability indicator will be calculated for a wind energy case located in Belgium. The case study on wind energy was chosen as this technology has high potential to further expand and therefore will play an important role in the clean energy transition, as stipulated by the European Green Deal. Both onshore and offshore wind farms need to be installed in Europe, and thus also Flanders, to achieve the goal of reducing greenhouse gas emissions [30]. While its contribution to Belgium's climate change mitigation strategy is obviously positive, the overall sustainability of wind energy production, taking into account other environmental and also economic and social impacts, has not yet been investigated thoroughly.

The case study consists of three wind energy project alternatives based on the case study of Buchmayr et al. [31]. An offshore wind energy project was compared with two onshore wind energy projects. The difference in the two onshore cases lies with the type of generator technology used in the wind turbines, i.e. wind turbines using a permanent magnet synchronous generator (PMSG) were compared with ones using a doubly-fed induction generator (DFIG).The sustainability impact analysis of offshore and onshore alternatives as well as of different generator types is particularly relevant for the investigation of social impacts [31]. This dimension is mostly disregarded in energy-transition decision making, leading to a knowledge gap regarding the full sustainability of the different technology options. Table 1 shows a summary of the alternatives included in this wind energy case study.

Table 1: Wind energy case study characteristics

	Offshore wind – PMSG	**Onshore wind – PMSG**	**Onshore wind – DFIG**
Wind park characteristics	50 wind turbines with a capacity of 5 MW (three-bladed with PMSG) mounted on monopile foundations and connected to a central transformer station	7 wind turbines of type Vestas V112-3 MW placed on agricultural land and connected to a central transformer station	7 wind turbines of type Vestas V112-3.45 MW placed on agricultural land and connected to a central transformer station
Location	Belgian Part of the North Sea	Eeklo, Belgium	Eeklo, Belgium
Annual full load hours	4,000	2,808	2,700
Annual electricity output per wind turbine in MWh	20,000	8,424	9,315

Notes: PMSG = Permanent magnet synchronous generator, DFIG = Doubly-fed induction generator

The assessed life cycle was limited to processes until and including the use phase of wind parks. The end-of-life, meaning disassembly and disposal of wind turbines was not included in the assessment due to the uncertainty of end-of-life strategies for the technologies.

The collected inventory data and conversion factors, such as material cost, were collected for the year 2020 as this was the most recent year for which complete data was available. Life cycle impacts were analyzed in reference to the functional unit of 1 MWh of electricity delivered to the electric grid. The sources of the life cycle inventories used in the assessment of the different impact categories can be found in the Appendix, Table A-1.

The sustainability assessment was conducted following the sustainability assessment framework of Buchmayr et al. [11], who propose to quantify sustainability holistically using 12 impact categories. Table 2 provides an overview of the assessed impact categories.

Table 2: Twelve impact categories of sustainability assessment including respective endpoint indicators based on Buchmayr et al. [11]

	Impact category	Description	Unit
1.	Emission damage to ecosystem quality	Air and water pollution along the full life cycle (climate change, photochemical ozone formation, acidification, eutrophication, ecotoxicity)	species · yr/MWh
2.	Land use impact on biodiversity	Direct land use for energy and fuel provision considering impact on biodiversity depending on the type of land use	MJ_{ex}/MWh
3.	Resource use efficiency	Efficiency with which resources are extracted, processed and used along the life cycle in order to provide energy to the grid or user	MJ_{ex}/MWh
4.	Economic feasibility	Levelized cost of electricity	USD/MWh
5.	Resource supply risks	Risk of changing accessibility of energy fuels and required raw materials due to import country concentrations and price volatility	GeoPolRisk g/MWh
6.	Energy supply reliability	Capacity factor in % presenting average power output over a year per nameplate capacity	%
7.	Local job creation	Number of local direct jobs created for installation, maintenance and operation of energy facility	Jobs/MWh
8.	Human health and safety	Air and water pollution along the full life cycle (particulate matter formation, photochemical ozone, human toxicity, ionizing radiation)	DALY/MWh
9.	Responsible supply chains with regard to human rights	Risk of human rights infractions associated with the material or fuel supply chain	Human rights score from -1 to 1
10.	Responsible supply chains with regard to labor conditions	Risk of unfair working conditions associated with the material or fuel supply chain	Labor conditions score from -1 to 1
11.	Quality of residential life	Impact as experienced by the population	Residential quality score from 1 to 4
12.	Landscape quality	Impact as experienced by the population	Landscape score from 1 to 5

The impact quantification steps including the calculation of endpoint indicators for each of the 12 impact categories are explained in Appendix, Section A.1.

2.2 Aggregation using MCDA

2.2.1 Selection of preferred MCDA method

The reviews of Hottenroth [7] and Antunes and Henriques [14] identified the common MCDA methods for decision making and aggregation for energy case studies. A review of these methods, i.e. AHP, WSM, PROMETHEE, ELECTRE MAUT/MAVT, TOPSIS, VIKOR and DEA, was conducted and their characteristics described in the following paragraphs.

AHP is used for complex decision problems when the priorities of decision makers are not known. The method provides a hierarchy for the assessed criteria and based on that, a ranking of alternatives [32,33]. AHP has the advantage of directly translating decision makers' perceptions by breaking down a complex problem into several pair-wise comparisons between alternatives [34]. A disadvantage is that decision problems with a large number of alternatives and criteria require high effort from the decision makers and might ultimately lead to inconsistency in their judgments [35]. Moreover, the results are presented in the form of a ranking of alternatives and not as a (sustainability) score. AHP was used in the energy sector to identify sustainable power plants [33,36] or analyzed countries concerning their fulfillment of environmental and climate goals [37].

The WSM is preferred for many applications due to the easy implementation and transparency of calculation steps. For this reason, the WSM is frequently used for comparing energy systems by means of an aggregated sustainability indicator that is based on several sub-criteria [9,38,39]. However, the range of the WSM indicators varies strongly, depending on the number of aggregated sub-criteria and the normalization methods used.

Outranking methods such as PROMETHEE [40] and ELECTRE [41] use pair-wise comparisons to identify the most beneficial case in a pair of alternatives. Outranking methods use pair-wise comparisons for each criterion which is different from AHP that compares alternatives as a whole. The advantage of outranking methods, e.g. over the WSM and TOPSIS, is that they partially circumvent compensation between criteria [7,42]. Accordingly, the strong performance in one sustainability criterion does not compensate for the weak performance of another criterion, which is the definition of strong sustainability [43]. PROMETHEE is frequently used in sustainability studies, e.g for ranking energy policy alternatives, [44], locations [45] or local energy generation options [46,47]. ELECTRE is used for various sustainability assessments, e.g. for the evaluation of energy efficiency initiatives [48], future local energy sources [49] and waste management systems [50].

In MAVT and MAUT [51], the decision maker defines value functions for each criterion, for example but not necessarily an additive and linear function. The value functions allow the alternatives to be ranked and a total value score to be determined [52]. MAUT is an extended version of MAVT that captures the uncertainty of outcomes and risks [53]. Such aggregated value functions were used by Heinrich et al. [54] to demonstrate the performance of power expansion strategies. MAVT was also used to select electricity supply options based on different sustainability criteria [55,56].

TOPSIS [57] is a distance-to-target method. This means it aims at providing the best compromise within a set of alternatives by minimizing the distance to an ideal solution and maximizing the distance to a non-ideal one [7]. The advantage of TOPSIS over other MCDA methods is the simple and transparent computation of scores. These scores represent the distance to an ideal solution on a normalized scale [58] and thereby provide not only a ranking of alternatives but also indicate a potential for improvement. A disadvantage of TOPSIS is its susceptibility to rank reversal, meaning the possibility that the ranking of alternatives may change when adding or deleting an alternative to the calculation [59]. To avoid rank reversal, Yang [60] proposed the adapted NR-TOPSIS method which delivers a robust ranking and score based on fixed reference points. There are several examples of TOPSIS being used to determine the most sustainable alternative for different energy projects [7,61–64]. The NR-TOPSIS method is not yet applied for the assessment of energy technologies.

VIKOR [65] is also a distance-to-target method similar to TOPSIS but focuses on the distance to an ideal solution, omitting the distance to the non-ideal solution.

DEA is a method that indicates the efficiency of an alternative and the potential for improvement to meet best practice benchmarks that make up an efficiency frontier. The difference to distance-to-target methods such as TOPSIS and VIKOR is that weights are not assigned by the decision maker but are calculated by a linear optimization procedure [66]. DEA have been used for energy case studies in combination with environmental LCA to determine the efficiency of electricity generation technologies [67,68].

Although some methods are already applied for LCSA results, such as WSM [8], PROMETHEE [45] and TOPSIS [69], there is a certain ambiguity in the choice of aggregation procedures for LCSA. To counter this ambiguity, criteria for MCDA methods were defined, with the objective to supply a robust sustainability indicator for energy technologies. The MCDA method used for aggregation needs to have the following characteristics:

- Provide a numerical result: the MCDA method should provide a quantified measure of sustainability for each alternative. The advantage of a numerical result over, for example, a ranking is the fact that the first approach can be used to not only identify the best alternative but also can indicate the distance between the performance of the alternatives, i.e. the numerical indicator shows whether several alternatives are in a close range. Some MCDA methods provide only a ranking of alternatives (e.g. outranking methods). To allow the comparison across studies, as is common practice in LCA, a numerical sustainability indicator is preferred over a simple ranking.
- Distance-to-target method: in order to interpret the numerical result, the indicator should be positioned on a reference scale. Distance-to-target methods provide reference points that define the performance of alternatives. As sustainability is an abstract concept, the definition of a reference point as an ideal, most sustainable solution facilitates assigning a unit to sustainability.
- Resistance to rank reversal: the score should be robust against changes due to the inclusion and removal of alternatives in the evaluation. It should be avoided that ranking and resulting scores are impacted by the number or type of alternatives included in the assessment. A common reference scale again contributes to the comparability of results across studies.
- Incorporation and adjustability of weighting factors: the MCDA method should be able to incorporate external weighting factors, which were for example provided by an expert panel or gathered from literature. External weighting factors allow decision makers to set priorities and compare different scenarios, e.g. environmental vs. social focus.
- Computation of a high number of criteria: the MCDA method should be suitable to process a high number of criteria covering the broad field of sustainability.

These characteristics are summarized in Table 3 for the discussed MCDA methods.

Table 3: Characteristics of MCDA methods commonly applied in the energy sector, based on [7,13,70,71]. Compliance with the sustainability indicator criteria is highlighted in blue.

	MAUT MAVT	AHP	ELECTRE	PROMETHEE	WSM	TOPSIS	NR-TOPSIS	VIKOR	DEA
Result class	Value measure	Value measure	Ranking	Ranking	Value measure	Value measure	Value measure	Value measure	Value measure
Preference elicitation	Utility function	Pair-wise comparison	Pair-wise comparison	Pair-wise comparison	Utility function	Distance-to-target	Distance-to-target	Distance-to-target	Distance-to-target
Robustness to rank reversal	Yes	No	No	No	Yes	No	Yes	No	No
Allows the in-corporation of weighting factors	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of criteria	Low	Low	Low	High	High	High	High	High	High

Notes: MAUT = multi-attribute utility theory, MAVT = multi-attribute value theory, AHP = analytic hierarchy process, ELECTRE = elimination et choice translating reality, PROMETHEE = preference ranking organization method for enrichment evaluation, WSM = weighted sum method, TOPSIS = technique for order preference by similarity to ideal solution, VIKOR = viekriterijumsko kompromisno rangiranje (multi-criteria optimization and compromise solution), DEA = data envelopment analysis

Based on Table 3, the NR-TOPSIS [60] method was selected. NR-TOPSIS meets the five criteria required for an aggregation method to calculate a single sustainability indicator for energy technologies. NR-TOPSIS is a variation of the TOPSIS [57] method. A drawback of TOPSIS is its sensitivity to rank reversal, i.e. the possibility that the ranking of alternatives changes when an alternative is added or removed [59]. To avoid rank reversal, Yang [60] proposed the adapted NR-TOPSIS method which delivers a robust ranking and score based on fixed reference points.

The main difference between TOPSIS and NR-TOPSIS lies in the normalization procedure. While the TOPSIS method uses the best and worst performers among the alternatives as reference points for normalization, NR-TOPSIS uses external normalization. With external normalization, the normalized sub-indicators are independent of the number of investigated alternatives and, provided the same normalization reference points are used, are comparable beyond the current study. Independent reference points for the ideal and non-ideal solutions are important for the assessment of absolute sustainability. For example, using internal normalization, as is done in the original TOPSIS method, a highly polluting energy technology may be rated as the best alternative in a group of equally polluting technologies. This does not mean that the technology is the most sustainable, only that it is the best in the group of poor alternatives. Using external normalization the highly polluting technology would be evaluated against globally best performing technologies or minimum sustainability standards. A step-by-step description of the calculation steps of NR-TOPSIS is included in the Appendix,

Accordingly, the application of NR-TOPSIS requires the definition of ideal and non-ideal solutions for each criterion. After the normalization steps weighting can be applied which is a possibility in both TOPSIS and NR-TOPSIS. The definition of the ideal and non-ideal solutions as well as the weighting factors will be discussed in the following two sections.

2.2.2 Definition of ideal and non-ideal solutions

The NR-TOPSIS method uses external normalization by defining the reference points for the ideal-solution (sustainability target) and an non-ideal solution [60]. As sustainability targets are used as reference points for normalization steps, we refer to this as a distance-to-sustainability-target approach.

The ideal and non-ideal solutions should, according to Yang [60], represent the maximum and minimum values from a global perspective. The ideal and non-ideal solution can thereby be defined by technical limits, represent a market average or reference to a policy target.

Based on literature research in combination with the consultation of experts in the sustainability assessment field, the ideal and non-ideal solutions were identified. Figure 2 shows the decision process for finding these values. The reference points for the ideal solution (sustainability target) in each of the 12 assessed impact categories were indicated by the best performing energy technology in the current market for the respective impact category. The non-ideal solution was first defined as the status quo in the electricity sector. The aim of sustainable solutions should be to improve the status quo and thus contribute to the achievement of European climate and energy policy objectives. For those categories where this approach was not applicable, the minimum standards of the authorities in this field were observed. E.g. it was not possible to define a global or European status quo for human rights infractions along the supply chain of energy technologies. Instead, any infraction of international human rights and working conditions standards should be avoided. Accordingly, standards of the International Labour Organization (ILO), the United Nations (UN), or the Product Social Impact LCA database (PSILCA) were used as reference points. For the remaining categories in which also the minimum standards were not applicable, the non-ideal solution was defined by the worst performing technology. For the recording of perceived impacts on the local quality of life and landscape (categories 11 and 12) a quantitative scale was used.

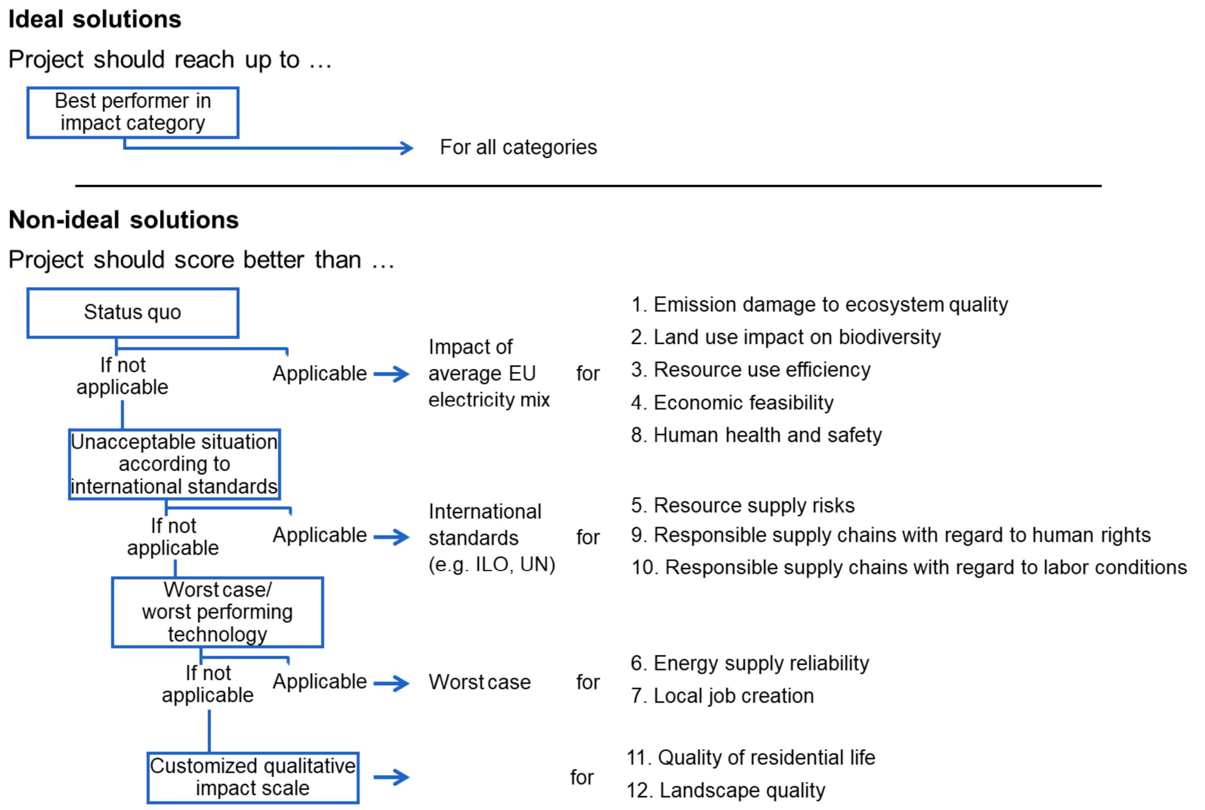

Figure 2: System for the definition of reference points for ideal and non-ideal solutions

For the validation of this decision process, three experts were consulted to solidify this choice of reference points. The experts come from the fields of integrated sustainability assessment, LCA including social LCA, with a focus on energy and environmental technologies.

Table 4 shows the ideal and non-ideal reference points used for the normalization of criteria values as well as an explanation for this choice. The reference points will be used in the following aggregation via NR-TOPSIS.

Table 4: Ideal and non-ideal solutions to define sustainability in 12 impact categories

			Ideal solution		Non-ideal solution	
Impact category	**Unit**	**Sustainability target**	**Value**	**Rationale**	**Value**	**Rationale**
1. Emission damage to ecosystem quality	species · yr/MWh	Minimize	$1.7 \cdot 10^{-8}$	**Best performing technology:** Benchmark for a hydro run-of-river power plant (ecoinvent 3.8)	$1.3 \cdot 10^{-6}$	**Status quo:** Ecosystem damage induced by EU electricity mix of 2020 (inventory data: Eurostat [72], emission data per techno-logy: ecoinvent 3.8, characterization: ReCiPe2016 [27])
2. Land use impact on biodiversity	MJ_{ex}/MWh	Minimize	0.03	**Best performing technology:** Benchmark for an offshore wind energy park (see Appendix, Table A-2)	144	**Status quo:** Average land use by EU electricity mix of 2020 (inventory data: Eurostat [72], direct land use benchmarks see Appendix A, Table A-20)
3. Resource use efficiency	MJ_{ex}/MWh	Minimize	53	**Best performing technology:** Benchmark for a hydro run-of-river power plant (ecoinvent 3.8)	10,111	**Status quo:** Cumulative Exergy Demand for current EU electricity mix (inventory data: Eurostat [72], resource use per technology: ecoinvent 3.8, characterization: CEENE version 2022 [73])
4. Economic feasibility	USD/MWh	Minimize	39	**Best performing technology:** Benchmark for levelized cost of electricity from lifetime extension of a nuclear power plant [74]	60	**Status quo:** Levelized cost of electricity of the EU electricity mix of 2020 (inventory data: Eurostat [72], LCOE factors: [74,75])
5. Resource supply risks	GeoPolRisk g/MWh	Minimize	170	**Best case scenario:** Technology with average material demand that relies on multiple political stable supplier countries	510	**International standards:** Technology with average material demand that is reliant on a single supplier country for the majority of materials; supplier country with medium WGI of 0.5
6. Energy supply reliability	%	Maximize	93	**Best performing technology:** Benchmark for nuclear power plant [76]	12	**Worst case:** Benchmark for commercial roof-mounted PV [76]
7. Local job creation	Jobs/MWh	Maximize	$5.2 \cdot 10^{-4}$	**Best performing technology:** Benchmark for utility scale PV installation [77]	$2.2 \cdot 10^{-5}$	**Worst case**: Benchmark for natural gas power plant [77]
8. Human health and safety	DALY/MWh	Minimize	$1.6 \cdot 10^{-5}$	**Best performing technology:** Benchmark for a hydro run-of-river power plant (ecoinvent 3.8)	$6.3 \cdot 10^{-4}$	**Status quo:** Health damage induced by current EU electricity mix (inventory data: Eurostat [72], emission data per techno-logy: ecoinvent 3.8, characterization: ReCiPe2016 [27]
9. Responsible supply chains with regard to human rights	Human rights score	Maximize	1	**Best performer:** Dimensionless score being equivalent to human rights con-ditions in best performer countries, see Appendix, Table A-4	-1	**International standards:** Dimensionless score being equivalent to unacceptable human rights situations, see Appendix, Table A-4
10. Responsible supply chains with regard to labor conditions	Labor conditions score	Maximize	1	**Best performer:** Dimensionless score being equivalent to labor conditions in best performer countries, see Appendix, Table A-5	-1	**International standards:** Dimensionless score being equivalent to unacceptable labor conditions, see Appendix, Table A-5
11. Quality of residential life	Residential quality score	Minimize	1	**Best performer on qualitative scale** Perceiving no impact	4	**Worst performer on qualitative scale:** Perceiving very negative experiences of impact
12. Landscape quality	Landscape score	Minimize	1	**Best performer on qualitative scale:** Perceiving a strong improvement of landscapes characteristics	5	**Worst performer on qualitative scale:** Perceiving very negative experiences of impact

2.2.3 Definition of weighting factors

The aggregation via NR-TOPSIS was tested under different weighting scenarios with the aim to investigate the sensitivity of results and find the best ranking alternative considering different priorities (weighting factor) of different stakeholder groups. The sustainability assessment consisted, according to the framework of Buchmayr et al. [11], of 12 impact categories which were unevenly distributed over the three sustainability pillars. The use of weighting factors can establish a balance between the sustainability pillars. However, the three-pillar model of sustainability is only one option to provide this balance and other authors introduce additional pillars [78].

Four ways of aggregating the endpoint indicators to a single score were assessed in this study. The four aggregation strategies differed regarding the number of intermediate aggregation dimensions used:

(1) No intermediate aggregation dimensions were used. The 12 endpoint indicators were directly aggregated, using weighting factors distributed between these 12 endpoint categories, into one sustainability indicator.
(2) The endpoint categories can be divided into global and local impacts. The 12 endpoint indicators were allocated to either the global or the local dimension and the weighting factors were distributed between these two aggregation dimensions.
(3) In the definition of Elkington [79], sustainability consists of three pillars, People, Planet and Profit. This is the most common representation of sustainability. The 12 endpoint indicators were allocated to an appropriate sustainability pillar and the weighting factors distributed between the three pillars.
(4) Gaasbeek and Meijer [80] argued that the traditional three-pillar model needs to be expanded for the case of sustainability assessments into precisely defined impact categories and defined the five “Prosuite” impact categories, i.e. natural environment, exhaustible resources, prosperity, human health, and social well-being. Accordingly, weighting factors were distributed between these five dimensions.

In summary, four ways of aggregation are investigated, i.e. using two, three, five or 12 intermediate aggregation dimensions. Figure 3 presents the equal weighting scenarios for these four ways of aggregation where the weights are equally distributed between the aggregation dimensions, which leads to different contributions of the endpoint indicators in the resulting sustainability indicator. The width of boxes in Figure 3 represents this share of weight in the sustainability indicator. With a larger number of indicators in an aggregation dimension, the trade-off for single endpoint indicators is larger. As such trade-offs cannot not be completely avoided, it is important to consider absolute sustainability limits, as is done in the NR-TOPSIS method, together with weighting to provide a balance between the sustainability dimensions.

For this division into aggregation dimensions each endpoint category was explicitly assigned to a single dimension even if there were arguable overlaps for some indicators, e.g. resource use efficiency can be interpreted as both an environmental and an economic issue but was explicitly assigned to the economic dimension. The overlaps of indicators were omitted to maintain an equal weighting within the aggregation dimensions and to avoid overrepresentation of individual indicators due to the inclusion in multiple aggregation dimensions.

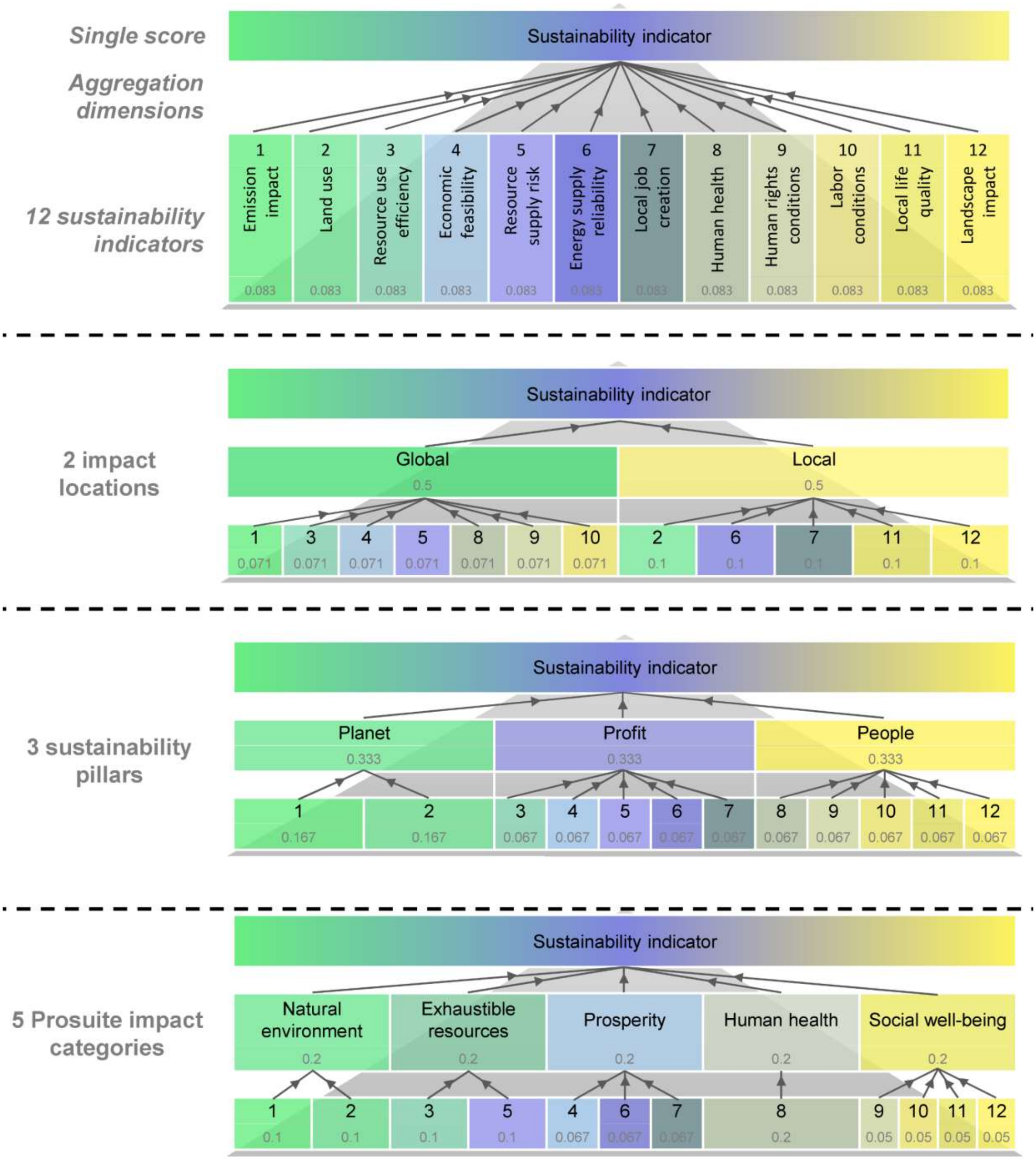

Figure 3: Four ways to divide weighting between endpoint categories using different intermediary aggregated dimensions towards an aggregated sustainability indicator. The grey numbers represent the relative contribution of each impact category and aggregation dimension to the sustainability indicator.

Based on that division into aggregation dimensions, weighting scenarios were generated for the sensitivity analysis. Scenarios were created by varying the weights of each aggregation dimension (i.e. two, three, five and 12 dimensions), as presented in Figure 3. Following the approach of Li et al. [81], the weight of each aggregation dimension was then varied starting from the equal weighting scenario by +/- 10, 20, 30, 40 and 50%, while the weight of the remaining dimensions was adapted so that all weights would sum up to 1. This means that a higher weighting of one dimension was compensated by reducing the weight for all remaining dimensions [81].

Figure 4 shows three exemplary weighting scenarios starting from equal weights between the three sustainability pillars and respective scenarios with +10 and +40 % increased weight on the environmental pillar.

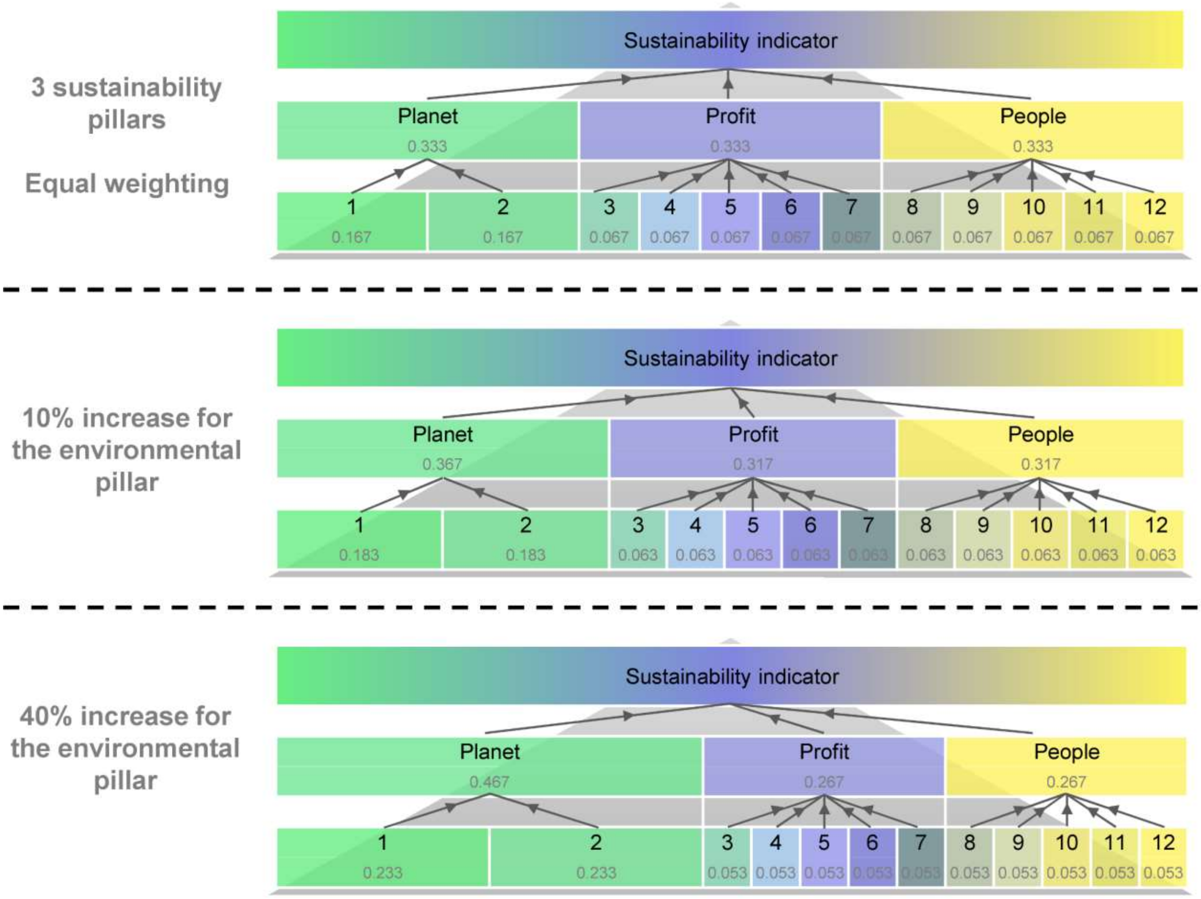

Figure 4: Example of three weighting scenarios with equal weights for all three sustainability pillars, a 10% and a 40% increase of the weight of the environmental pillar

Following this procedure and increasing or decreasing the importance of each aggregation dimension by 10, 20, 30, 40 and 50% resulted in 214 weighting scenarios which were used for the sensitivity analysis.

3 Results and discussion

The sustainability assessment results for the three wind energy cases, i.e. one offshore wind project and two types of onshore wind projects using PMSG or DFIG respectively, are discussed first. 12 endpoint indicators are presented on their specific reference scales in the form of a sustainability dashboard. Secondly, the aggregated results using the distance-to-sustainability approach are discussed for equal weighting scenarios followed by the results of the sensitivity analysis on weighting.

3.1 Sustainability dashboard of wind energy case study

The results of the wind energy case study can be placed on 12 individual sustainability scales according to the reference points for the ideal and non-ideal solution defined in Section 2.2.2. Figure 5 shows the dashboard for the sustainability assessment. The right threshold of the dashboard represents the ideal solution (sustainability target) meaning that a short distance to this point is desirable. For categories that measure negative impacts, the scale was therefore reversed.

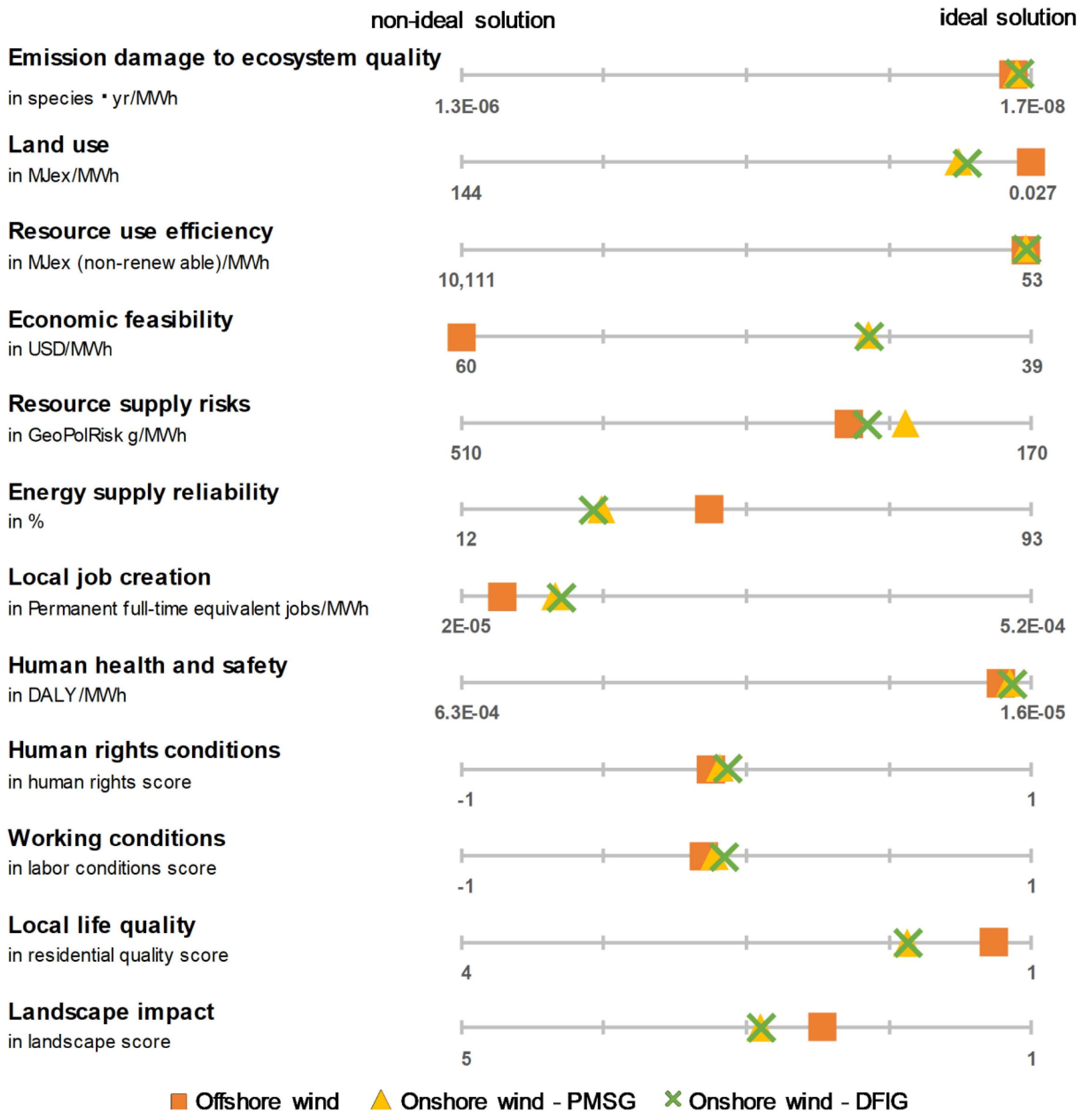

Figure 5: Dashboard of sustainability indicators assessed for three wind energy projects

Using this dashboard of 12 endpoint indicators as the basis for a decision on the sustainability of the three wind energy projects is challenging. The dashboard does not reveal a clear "winner". For six out of the 12 categories, the onshore wind project using a DFIG was closest to the ideal solution. Although, the DFIG wind turbine requires more materials per MWh than the PMSG counterpart, the DFIG material efficiency considering foundations and infrastructure is higher. The high material efficiency of the DFIG case is also reflected in the conventional LCA impact categories, such as emission damage, human health, human rights conditions and working conditions. In the same categories, the offshore wind energy case scored worse due to the comparably high amounts of steel required for the offshore foundations. However, the advantage of the offshore monopile foundations was that they occupy relatively little marine space. Additionally, the area between the wind turbines is classified as non-fishing zone. The assessment of ecosystem and economic impact of the non-fishing zone was considered out of the scope of this study. Only the directly occupied area was considered in order to be comparable with the terrestrial assessment. The onshore turbines occupy land area for placing the foundations and for providing a larger security zone surrounding the tower and access roads, which is usually sealed area that does not contribute to biodiversity.

Overall, the offshore wind case showed an ambiguous performance having the largest negative impact in seven impact categories but also performing best in the other five categories. Considering the performance within each of the three pillars of sustainability, the results are also not clear-cut, with offshore wind ranking last in three out of five economic categories and last in three out of five social categories. The two onshore wind cases scored similarly in almost all categories and showed no difference at all for a few categories. This was the case for impact indicators that have no connection to the electricity output of the projects, e.g. for local job creation, residential quality or landscape impact which were assessed per wind turbine site, irrespective of the provided function (electricity output).

It can be observed that the wind energy cases were close to the ideal solution for both environmental categories, while there is a larger spread for the scales used in the economic and social categories. One reason for this could be the choice of the non-ideal solution, which was determined in the environmental categories as the impact of the average EU electricity mix. Since the EU electricity mix is still dominated by fossil fuels, the performance of a renewable energy technology like a wind park is expected to be better. The definition of reference points therefore should be considered with great care. The aim was to use a realistic interpretation of sustainability rather than choosing the unrealistic aim of reducing impacts to zero, which was supported by the consulted experts.

It is unrealistic to expect one technology to meet the ideal solution in all categories, i.e. maximally reduce life cycle emissions, be the cheapest technology on the market, reduce import dependencies, etc. Therefore, decision makers have to accept compromises for certain impact categories. This highlights the advantage of both displaying results unaggregated in the form of a dashboard and as aggregated sustainability indicator. The unaggregated results show potentials for improvement in each category while an analysis of the sustainability indicator shows the overall distance to the ideal solution and facilitates the identification of the best solution in a multi-criteria setting.

3.2 Sustainability score for four equal weightings scenarios

Using NR-TOPSIS, the 12 endpoint indicators were aggregated into a single score. As explained in Section 2.2.3, four ways of equal weighting were investigated, where the weights were distributed between either two, three, five or 12 intermediate aggregation dimensions. These results are presented in Figure 6. The figure shows that using three or five intermediary aggregation dimensions generated a single score of 0.69 to 0.75 for all wind energy projects, while the scores were lower and ranged from 0.58 to 0.63 when using 12 aggregating dimensions. This difference can be attributed to social indicators such as human rights conditions, local life quality and landscape impact, showing a larger distance to the sustainability goal, see Figure 5. When using two or 12 aggregating dimensions, these social indicators are weighted higher than when using three or five dimensions, resulting in a decreasing sustainability score. Mostly the scores for the three energy alternatives were close together showing only marginal differences on the sustainability scale. Especially, the two onshore wind cases show a similar score, with the alternative using PMSG ranking better in the scenarios using equal weights over two, five and 12 dimensions. For the scenario where global and local impacts where weighted equally, the scores of the alternatives were particularly close to each other. In this case, the offshore wind energy plant slightly performed better than the onshore alternatives in most of the local categories, i.e. land use, energy supply reliability, local life quality and landscape impact. The local categories received a higher individual weight than the global ones, see Figure 3, which contributed to the offshore alternative outperforming the onshore ones.

The results of the ranking of alternatives are remarkable, as a comparison per impact category using the sustainability dashboard, presented in Figure 4, showed that the wind project using DFIG is in half of the impact categories the best-performing alternative out of the three. However, the normalized differences between the two onshore cases are mostly marginal on the sustainability scale with the exception of the resource supply risks (category five) and energy supply reliability (category six), which are also the categories in which the PMSG alternative outperformed the DFIG one. The strong performance in these two categories and only marginal differences in the other categories put the PMSG alternative on top of the DFIG one in the presented equal weights scenarios.

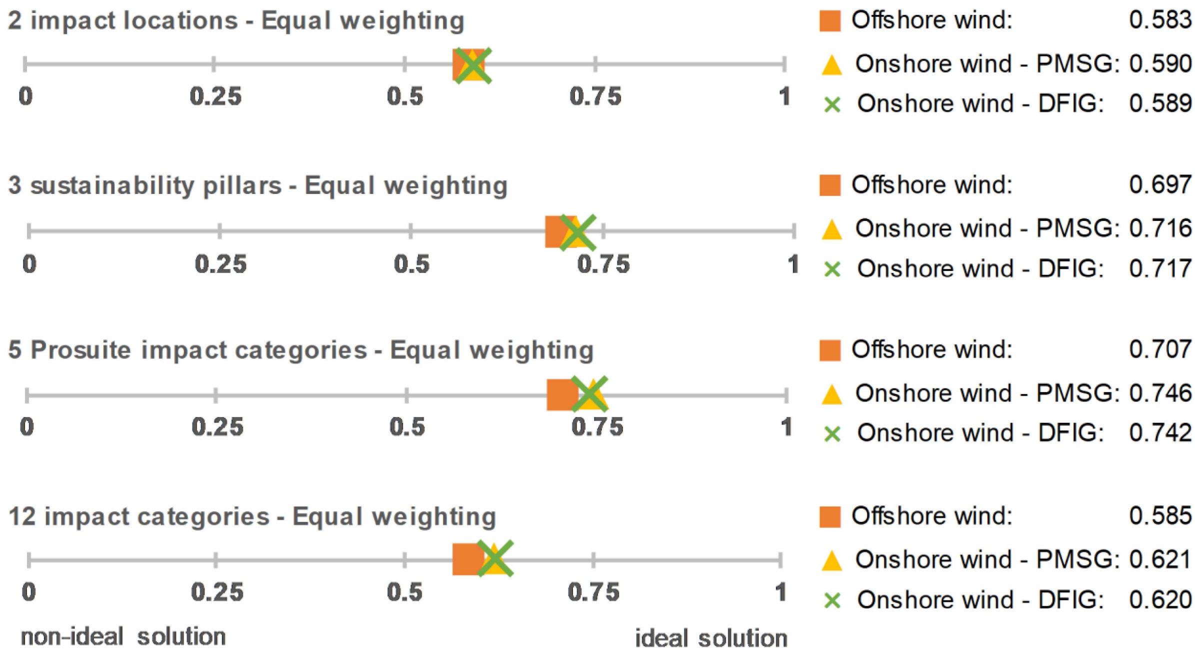

Figure 6: Sustainability indicator for three wind energy case studies considering equal weights over two, three, five and 12 aggregation dimensions

Although the NR-TOPSIS method prevents rank reversal due to the addition or deletion of alternatives [60], the ranking might not be the same when using different weighting approaches, as can be observed for the examples presented in Figure 6. This rank reversal can be fully ascribed to the influence of weighting, as will be further discussed in the following section.

3.3 Sustainability score in different weighting scenarios

The robustness of the sustainability indicator was analyzed by investigating the results of 214 weighting scenarios, including the four equal weighting scenarios. In 86% of the investigated scenarios the ranking remained the same. The onshore wind project using a PMSG was found to be the most sustainable option and in 95% of the scenarios the offshore wind project was ranked the lowest. The variability of the sustainability scores in the sensitivity analysis is presented in Figure 7. The figure shows the median and standard deviation for different weighting scenarios. The scenarios were presented according to the four ways to divide weights between either two, three, five or 12 aggregation dimensions. The figure shows that for the weighting scenarios using three or five aggregation dimensions, the median score of all wind energy cases was between 0.70 and 0.75, while it was lower for scenarios with two or 12 aggregation dimensions. The standard deviation is highest for scenarios in which the weights are distributed across the three sustainability dimensions, indicating that the score is more susceptible to changes in the weighting factors. In particular, for scenarios in which the weights are distributed across the original 12 sustainability indicators, the final score is more robust to the change in a single weighting factor, as indicated by the small deviation around the median score in Figure 7. The score of the offshore wind project shows a comparable low standard deviation for the weighting scenarios using the two aggregation dimensions, global vs. local impact. The low standard deviation in this case indicates a balance between global and local impacts, i.e. the distance to the sustainability target is approximately the same for all global indicators as for all local indicators.

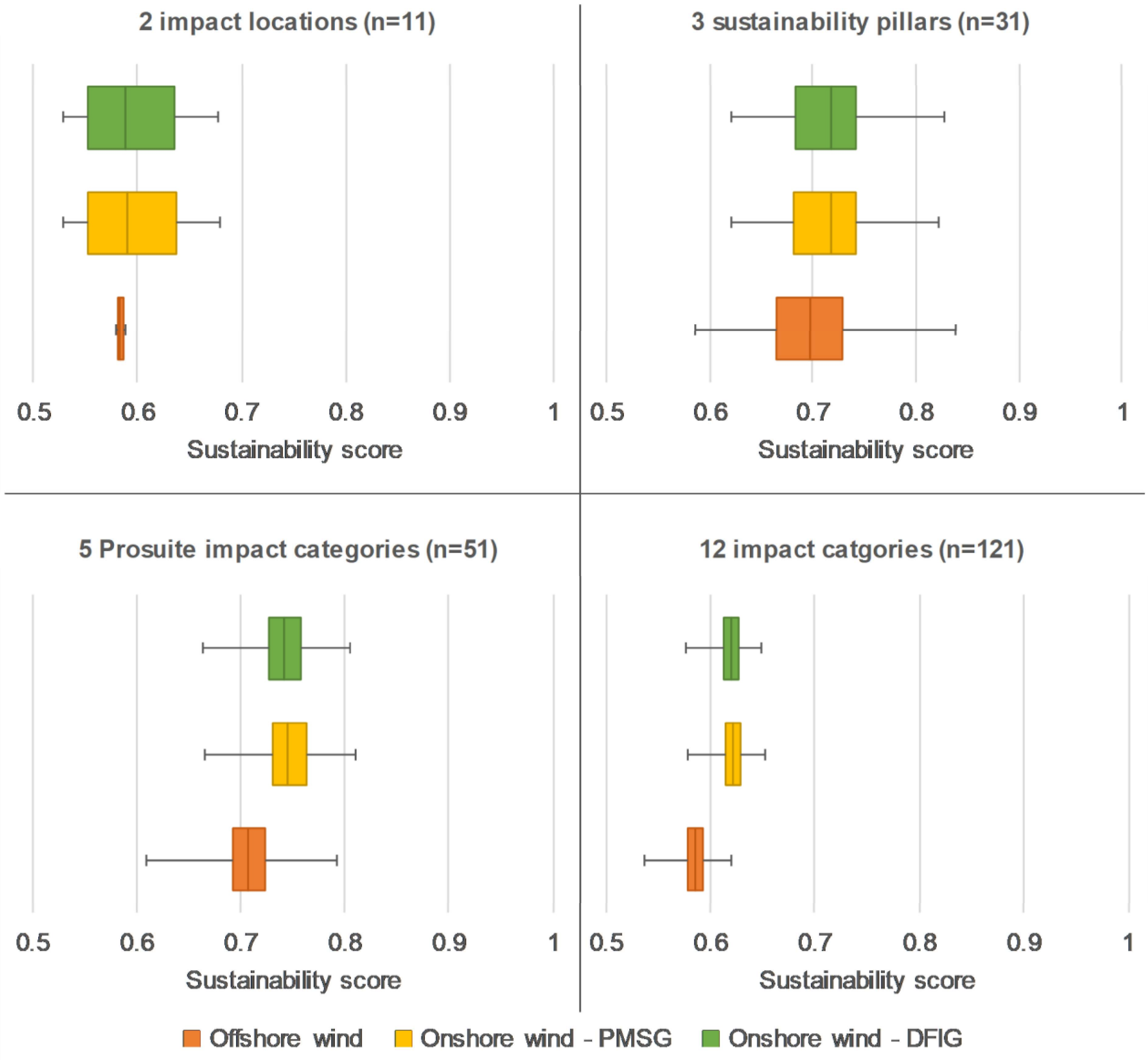

Figure 7: Median and standard deviation of the sustainability scores of wind energy case studies under different weighting scenarios. The sustainability scale reaches from 0 (non-ideal solution) to 1 (ideal solution)

Rank reversal under different weighting conditions was investigated by determining the threshold at which a variation of a single weight changed the ranking of the alternatives. Starting from the equal weighting conditions, single weights were either decreased or increased by single percentage points. For example, after determining the ranking under equal weighting of the three sustainability pillars, the weight of the environmental dimension is increased continuously until the threshold is reached at which the ranking changes. Following this procedure, the thresholds for the four ways of aggregation were determined and the results of this analysis are presented in Table 5. The table shows that under equal weighting conditions over the three sustainability pillars the onshore wind case using DFIG scored the highest, i.e. took the first place in the ranking. This ranking changed when the weight of one of the sustainability pillars was reduced by at least 17% or increased by at least 9%. Using the five Prosuite impact categories for the weighting resulted in the most stable ranking, i.e. ranks only changed if the weights of one Prosuite dimension was decreased by more than 38% or was increased by more than 80%. Considering impacts on the environment, resources, prosperity, human health, and social well-being as equally important, the onshore wind case using a PMSG was found to be the most sustainable and the offshore wind case to be the least sustainable. This high variability of single weights is in line with the finding of the sensitivity analysis that the ranking using the five Prosuite categories stayed the same in all of the scenarios. This can be explained by the good performance of the PMSG alternative in the categories 5 resource supply risks and 6 energy supply reliability. Using the Prosuite dimensions, these two categories receive relatively high weights in direct comparison with using the three sustainability pillars where both categories are aggregated in the economic dimension and receive comparably lower individual weights. The same is true for other weighting schemes where these two categories are more easily compensated by other categories.

Figure 7 already showed that the sustainability scores for the scenarios with weighting factors divided over all 12 endpoint categories did not vary much. A change of ranking appeared only when a single weight was reduced by 22% or increased by 54%. In the investigated wind energy cases the ranking of alternatives remained the same in 97% of scenarios that used weighting factor divide over 12 endpoint categories. The strong performance of the PMSG alternative in categories 5 and 6 had a minor influence on the overall results as single categories are compensated more easily with weighting factors being distributed over 12 categories.

Table 5: Ranking and sensitivity of ranking for the use of a varying number of aggregation dimensions

	Ranking under equal weighting conditions	**% of weighting scenarios with same ranking**	**Threshold at which ranking changes (in %)**	
2 impact locations	ON_PMSG > OFF > ON_DFIG	54.5	-7	+7
3 sustainability pillars	ON_DFIG > ON_PMSG > OFF	45.2	-17	9
5 Prosuite impact categories	ON_PMSG > ON_DFIG > OFF	96.1	-38	80
12 endpoint impact categories	ON_PMSG > ON_DFIG > OFF	96.7	-22	+54

Notes: OFF = Offshore wind, ON_PMSG = Onshore wind - PMSG, ON_DFIG = Onshore wind - DFIG

The influence of weighting on the ranking of alternatives should not be ignored. The default option for this framework would be to weight the 12 endpoint categories equally, but the sensitivity analysis shows the weighting over that many categories comes with the risk of the results being highly sensitive to changes in single weights, i.e. less robust results. Moreover, this effect is intensified if high weighting factors coincide with a wide spread of results, based on reference points used in the normalization step. As weighting factors are in most cases based on subjective preferences, the use of a sensitivity analysis is recommended in any case, in order to determine the influence of these factors on the final results. Using the proposed reference points to determine the distance to the sustainability target, the intermediary aggregation and weighting over the five Prosuite impact categories showed the most robust results. Moreover, the ranking of the wind energy alternatives using the Prosuite weighting scenario matched the ranking found for the majority of the weighting scenarios. Based on the sensitivity analysis using 214 weighting scenarios, the onshore wind energy project using PMSG was found to be the most sustainable alternative but only with a marginal difference to the other alternatives due to the similarity of investigated technologies.

4 Conclusion

While it is important to meet the policy goals regarding the reduction of greenhouse gas emissions, the larger sustainability, i.e. the side-effects of shifting to different energy sources needs to be investigated. However, communicating the results of a sustainability assessment to the public and to decision makers is a challenge. Although studies of different energy solutions use MCDA to identify the best solution for a given case, there is no absolute measure of sustainability in the energy sector. In order to generate comparable results for the assessment of energy projects, the use of a distance-to-sustainability target approach was proposed to aggregate to a single score sustainability indicator. The proposed indicator meets the communication challenge as it gives a combined result for a range of sustainability impacts and indicates the distance to an ideal solution, namely a sustainability goal.

The aggregation procedure was tested on a case study of wind energy projects. Three types of wind parks were compared including one case of an offshore wind park and two cases of onshore wind parks using two different generator types.

The dashboard of 12 sustainability categories showed no clear "winner" but rather that each wind project type had its strengths and weaknesses. This can also be attributed to the three wind energy cases scoring close for many of the indicators. The dashboard results were further aggregated and weighted within the NR-TOPSIS method. In comparison with other commonly used MCDA methods, NR-TOPSIS was useful in establishing a fixed sustainability scale and positioning energy case studies on this scale. The resulting sustainability scores illustrated the distance of the alternatives to the defined ideal solution. The advantage of this distance-to-sustainability-target approach is, firstly, that the distance between alternatives can be used to simplify the decision problem, and secondly, that it highlights the potential for improvement for each alternative. However, users need to be aware of the influence of the sustainability reference points and the weighting factors on the final results. The sustainability reference points used in this framework were validated by experts in the field of sustainability assessment. However, the values need to be updated regularly to reflect current technology benchmarks and policy targets, and this should be done in cooperation with different stakeholder groups in order to avoid biases. The sustainability reference points could also be chosen to represent absolute limits which is also done in environmental LCA studies [82] or the assessment of planetary boundaries [83,84].

Four ways of aggregating the 12 endpoint indicators to a single score were investigated, either directly using the 12 indicators or by using intermediate aggregation dimensions. The analysis showed that the choice and number of aggregation dimensions not only impacted the sustainability score but also the ranking of alternatives. Accordingly, there should be a clear motivation for whether and how weighting factors are applied. In the case of this sustainability assessment framework, the motivation arose from the problem that the three sustainability dimensions were represented by an unequal number of indicators.

Based on the four ways of grouping the endpoint indicators, a sensitivity analysis with 214 weighting scenarios was conducted, starting from an equal weighting scenario and then a step-wise increase and decrease of single weighting factors. In these scenarios, the most robust results were achieved by using weighting factors divided over the five Prosuite impact categories, i.e. weights could be divided between the natural environment, exhaustible resources, prosperity, human health, and social well-being. Moreover, weighting between the three sustainability pillars, which is a common approach in sustainability research, showed high sensitivity to changing weights. This can be attributed to the high number of economic and social indicators that were summarized into their respective pillars. Part of the information conveyed by the single economic and social endpoint indicators is lost, which would be better retained when using more dimensions at the aggregation level. However, these results apply to the wind energy case study which consisted of three alternatives with mostly similar impacts. The application of the framework to more energy technologies would further contribute to exploring the sensitivity of results due to weighting.

The sustainability dashboard showed that the onshore wind energy project using DFIG performed best in six of the 12 endpoint categories. However, the analysis of the aggregated results using NR-TOPSIS under different weighting scenarios showed a different result. In 88% of the 214 investigated weighting scenarios the onshore wind energy project using PMSG was found to be the most sustainable solution. This shows the advantage of using a MCDA method such as NR-TOPSIS over the interpretation solely based on the results of the sustainability dashboard. With the NR-TOPSIS method, a distance-to-sustainability-target approach was followed to consider both the ranking of alternatives for each endpoint category and the individual distance to the ideal solution for the decision making on energy technologies. As the wind energy case studies, especially the onshore alternatives, showed quite similar performances for the majority of endpoints indicators, the final sustainability scores of the alternatives lay close together. The advantage of the best ranked alternative was mostly marginal. To make the difference between the investigated wind energy projects clearer, impact categories that are specific to wind energy projects, could be included in the assessment. Thus uncertainty could be reduced for decision makers who decide between projects with similar sustainability scores. Since the proposed framework aimed to make sustainability comparable for a range of energy sector applications, this step was not taken.

Finally, the proposed aggregation framework for a sustainability assessment should be expanded to different energy case studies. The comparison of different technologies or even different energy mix scenarios on the proposed sustainability scale could provide additional insights for decision makers on energy transition strategies.

Assessing sustainability is a complex matter and it is not sufficient to concentrate on one impact category or one area of protection only. The holistic evaluation of energy technologies and the communication of sustainability impacts and targets for the energy sector is essential for planning and facilitating the European energy transition. The effective communication of sustainability, using in this case a single score sustainability indicator, should not be an afterthought but an integrative part of every sustainability assessment. The proposed aggregation method using NR-TOPSIS can provide both the public and decision makers with an easily understandable measure of the sustainability of energy technologies. This is a necessary step for informed decision-making on the energy transition and the future energy system that equally serves the economy, the society and the environment.

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