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ORIGINAL PAPER

A quantitative framework for sustainability assessment

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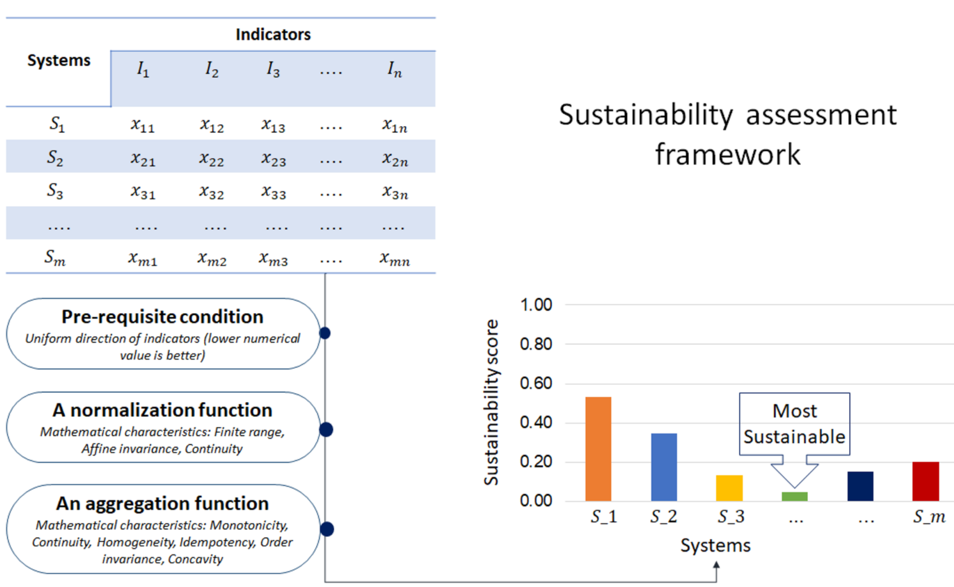
Abstract

The present climate change crisis forced humanity to opt for sustainable development. Sustainability assessment is vital to determine the relative superiority among alternatives, characterized by multiple sustainability indicators to ensure sustainable development. Various methods, such as the Euclidean distance method, geometric mean method, and elimination et choice translating reality, have been suggested in the literature to identify the most sustainable option among alternatives. These diverse approaches adopt different normalization and aggregation formulations (the two most significant steps of any sustainability assessment), leading to conflicting results. This paper proposes a generalized sustainability framework to quantitatively identify the most suitable alternative. The proposed framework incorporates various mathematical characteristics of normalization and aggregation processes and identifies mathematical functions that satisfy these characteristics. Based on the desired characteristics, the proposed approach identifies the min–max normalization function and a novel antinorm-based aggregation function as one of the appropriate functions for a quantitative sustainability framework. To illustrate the applicability of the proposed framework, different case studies are adopted from the literature: sustainable power plants for electricity generation in Portugal, sustainable feedstocks for the biodiesel supply chain, and sustainable negative emission technologies. The results are compared with those reported in the literature, and the efficacy of the suggested framework is demonstrated. The proposed framework may be utilized for multi-criteria decision-making.

Graphical abstract



Keywords Sustainability assessment · Multi-criteria decision-making · Normalization function · Aggregation function

Extended author information available on the last page of the article

Introduction

The last decade experienced a global average growth of 1.3% annually in greenhouse gas emissions, with a record emission of 58.1 gigatons of carbon dioxide (CO_2) equivalent in 2019 (UNEP 2021). It leads to the problem of global warming and affects our climate system. Hundreds of billions of dollars are lost in climate-related disasters, affecting economic growth (UNDP 2023a). On the other hand, the overexploitation of natural resources is disturbing the overall balance in nature (Hitchcock and Willard 2006). Furthermore, expanding desertification, severe water scarcity in many areas, etc., pose significant challenges to human survival (UNDP 2023b). It is essential to maintain proper balances between the economy, society, and environment for the inclusive development of human civilization. The world must adopt a sustainable pathway with appropriate technological interventions to maintain economic growth and societal welfare while satisfying ecological harmony. United Nations defined seventeen sustainable development goals (SDGs) to bring back this harmony and drive the welfare of humanity in a sustainable way. Sustainability assessment can play a vital role in identifying the best option among alternatives. The sustainability assessment offers the decision-makers a tool to determine the actions for making society sustainable (Ness et al. 2007). Sustainability is not a single-dimensional quantity that can be measured easily; instead, it is a combination of several dimensions of environmental, economic, and social (Pollesch and Dale 2015).

Sustainability can be represented through multiple data points or indicators. In literature, multiple approaches to defining indicators are presented, such as visualizing future conditions and paths, comparing places and situations. (Gallopin 1996). In general, indicators point out the state, level, purpose, and performance of a system (or a process or a product). Indicators are considered to be the core of any conceptual framework for sustainability assessment (Begic and Afgan 2007). Different indicators from environmental, economic, and social domains collectively provide the performance of a system toward sustainability (Sikdar et al. 2012). Sustainability assessment helps compare multiple systems, identified based on multiple parameters or indicators, and ranking them on a relative scale. Normally, the preference ranking of different systems cannot be determined using an individual indicator. For example, a system may be identified as sustainable based on one indicator and not sustainable based on another indicator. Therefore, it is necessary to integrate all indicators to determine the preference ranking of different systems toward sustainability. The aggregated value of all indicators should represent the overall measure toward assessing the relative sustainability (Sikdar et al. 2017). In literature, different sustainability assessment methods have been proposed to integrate multiple indicators to identify a relative ranking among various systems and applied for numerous applications.

The importance of sustainability assessment has been observed in various practical applications. Applications of different sustainability assessments include wastewater treatment systems (Balkema et al. 2002), energy planning (Beccali et al. 2003), dyeing systems (Shonnard et al. 2003), mining and minerals industry (Azapagic 2004), selection of energy system (Begic and Afgan 2007), water and resources management (Lai et al. 2008), comparing coating formulations, processes for making chlorine, and processes for hexamethylene diamine (Sikdar 2009), renewable energy system planning (Kaya and Kahraman 2010), biodiesel supply chain (Mata et al. 2011), automotive shredder residues, and automobiles fender design (Sikdar et al. 2012), ecological river assessment (Langhans et al. 2014), biodiesel logistic chain in six countries (Dos Santos and Brandi 2015), bioenergy sustainability (Pollesch and Dale 2015), corporate management (Garcia et al. 2016), building performance evaluation (Jovanovic et al. 2018), power plants in Portugal (Kabayo et al. 2019), negative emission technologies (Tan et al. 2019), energy storage technologies (Tapia et al. 2022), etc.

Sustainability assessment methods may be classified as qualitative and quantitative approaches (see Fig. 1). The unweighted color gradient method and the scaled spider diagram method are the qualitative approaches for sustainability assessment. Kabayo et al. (2019) used an unweighted color gradient method to visualize the sustainable performance ranking of the electricity generation systems in Portugal. A scaled spider diagram is the most common way to represent a system on a two-dimensional graph (Shonnard et al. 2003). Systems can be visually compared on a scaled spider diagram. Though it provides a visual representation, it does not provide the proper direction for ranking different systems toward sustainability (Sikdar et al. 2017). The area within the scaled spider diagram may be used as a quantitative measure of overall sustainability. However, the area within the scaled spider diagram depends on the order of indicators and thus, making it ambiguous as a quantitative tool. These qualitative methods provide pictorial representations but are unable to distinguish the most sustainable system, especially when the indicator values are close to each other.

In the past few decades, various quantitative methods, including multi-criteria decision-making (MCDM) approaches (Turkson et al. 2020), were proposed to integrate multiple indicators to identify a sustainable system. Diaz-Balteiro et al. (2017) identified more than 15 widely accepted MCDM methods from the literature for sustainability assessment as they exhibit the applicability of handling conflicting indicators simultaneously. A few quantitative

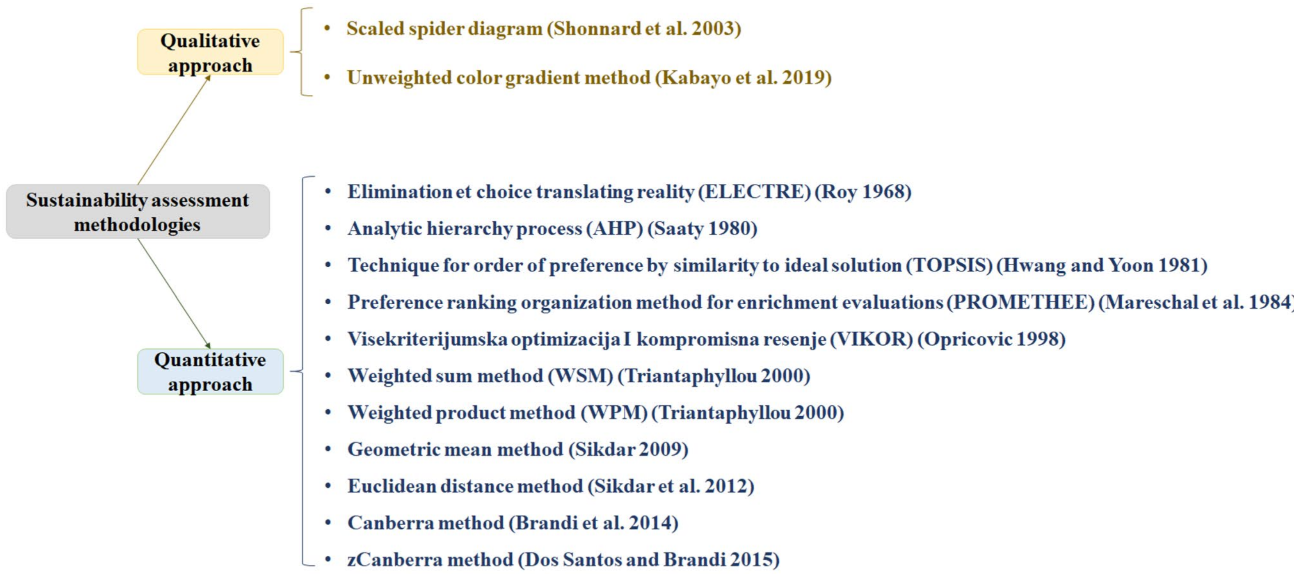


Fig. 1 Classification of sustainability assessment methods with a few approaches

methods are mentioned in Fig. 1. These quantitative methods use different mathematical formulations and procedures that may produce a conflicting ranking of existing systems. The elimination et choice translating reality (ELECTRE) method (Roy 1968) uses a pairwise comparison (or binary relation) between the systems for each indicator. It eliminates the less favorable systems using an aggregate dominance matrix to rank the order of systems. Triantaphyllou (2000) discussed that the ELECTRE method might fail to recognize the most sustainable option in case of incomplete binary relations. Like ELECTRE, the preference ranking organization method for enriched evaluations (PROMETHEE) also uses a pairwise comparison between the systems for each indicator (Maresschal et al. 1984). The PROMETHEE aggregates the preference functions (degree by which one system is preferred to another) using the weighted sum method (WSM), and determines the index for finding the most sustainable system. In comparison, the PROMETHEE method is considered by some researchers as an efficient method (Siksnelyte-Butkiene et al. 2020). The Analytic hierarchy process (AHP) method (Saaty 1980) is more popular than ELECTRE and PROMETHEE (Pohekar and Ramachandran 2004). The AHP begins with a hierarchical structure of problem definition and provides a judgment matrix to quantify the relative importance of indicators. The AHP uses the WSM to aggregate the indicators (Jain et al. 2020). Moreover, The AHP is used to quantify the indicators and assign weights to indicators. The technique for order of preference by similarity to ideal solution (TOPSIS) method (Hwang and Yoon 1981) identifies the relative superiority of a system as the ratio of Euclidean distances from the ideal and the non-ideal solutions. The visekriterijumska optimizacija I kompromisna resenje (VIKOR) method (Opricovic 1998) is an extension of the TOPSIS method and provides the compromising solution with weights of indicators. Within the VIKOR framework, the WSM and a maximization function are used to rank different systems (Tzeng and Huang 2011). Sikdar et al. (2009) proposed geometric mean to aggregate different indicators. It may be noted that the applicability of the geometric mean is restricted to only indicators with positive values. Sikdar et al. (2012) suggested the Euclidean distance for aggregation of the indicators. Brandi et al. (2014) used the Canberra distance method to measure the closeness and farness of systems to a reference system. Dos Santos and Brandi (2015) modified the Canberra distance function into the zCanberra distance function to handle the interval scale transformation.

Different MCDM methods are critically evaluated and compared in the literature. Diaz-Balteiro et al. (2017) performed critical and comparative analyses of multiple MCDM techniques. Kumar et al. (2017) discussed the strengths and weaknesses of multiple MCDM methods. Mulliner et al. (2016) differentiated the results of multiple MCDM methods using statistical correlations. Lee and Chang (2018) discussed the dependency of some of the MCDM methods on the weights of indicators. Recently, Li et al. (2020) suggested applying multiple MCDM methods simultaneously and choosing the most favorable result. It should be noted that these comparisons highlight the inconsistency among the methods and the ambiguity to decision-makers.

Instead of focusing purely on the comparisons of results, it is desired to focus on the mathematical aspects of these quantitative methods as they primarily differ in their mathematical treatment. Each method has different mathematical formulations, leading to inconsistency in the results. There are two most significant steps in these MCDM methods: the usage of a normalization function and an aggregation function. The normalization function makes the indicators comparable. The aggregation function produces the sustainability score for comparison and ranking. Trojanowska and Necka (2020) discussed eight normalization functions and four aggregation functions. It is noticed that multiple normalization and aggregation functions make the assessments inconsistent.

The main objective of this work is to identify appropriate normalization and aggregation functions with a set of axioms for sustainability assessment. This paper proposes desired mathematical characteristics (or axioms) and identifies a suitable framework to determine the most sustainable system using an appropriate quantitative method. In the proposed framework, the mathematical characteristics of the normalization function (finite range, affine invariance, and continuity) and aggregation function (monotonicity, continuity, homogeneity, idempotency, order invariance, and concavity) have been introduced. These desired characteristics differentiate various normalization and aggregation functions from the literature. Based on the identified mathematical characteristics, the proposed framework rationalizes the importance of the min–max normalization function and identifies p-antinorm aggregation function for sustainability assessment. The paper identifies p-antinorm functions as a generic aggregation functions for the first time. Significant contributions of this work are as follows:

- A new quantitative framework for sustainability assessment is proposed, which shows the mathematical characteristics of normalization and aggregation functions.
- The defined mathematical characteristics (axioms) allow decision-makers to identify the most suitable normalization and aggregation functions.
- The physical significance of each axiom is discussed to address the complexity of the multi-dimensional sustainability analysis.
- The efficacy of the proposed framework is demonstrated with multiple case studies.
- The proposed framework can be applied to multi-criteria decision-making.

In the later part of this paper, the proposed approach has been illustrated with three case studies with a summary of the result obtained: the power plants for electricity generation, the feedstock options for biodiesel production, and the negative emission technologies. Overall, the paper provides direction to identify the most sustainable system among the alternatives with a novel multi-dimensional quantitative method.

Problem statement

Decision-makers must assess the overall sustainability of different available options and choose the best alternative to achieve sustainability. Given m number of alternatives, characterized by n indicators, a decision-maker must follow a quantitative assessment method to identify the most sustainable option. Though the selection of indicators depends upon the decision-makers, it should be ensured that all three components of sustainability, i.e., environment, economic, and social, are adequately represented. The formal problem of sustainability assessment of several systems, characterized by various indicators, is stated as follows:

- A set of m systems (also called alternatives or options), denoted by $\{S_1, S_2, \dots, S_m\}$, is given.
- A set of n quantitative indicators (also called attributes or criteria), denoted by $\{I_1, I_2, \dots, I_n\}$, is available.
- A numerical performance score $x_{ij} (\in \mathbb{R})$ of system S_i for indicator I_j is known. It is assumed that indicators follow an inverse scale, i.e., lower numerical values are preferred for sustainability.
- The objective is to select and identify the most sustainable system through an appropriate sustainability assessment framework. A novel sustainability assessment framework is proposed in this paper to achieve this goal.

In this work, a quantitative sustainability assessment framework is proposed. All performance scores (x_{ij}) are represented by numerical values to perform the quantitative analysis. If some indicators are non-quantitative, different approaches, such as the analytic hierarchy process (Saaty 1980), should be adopted to convert them to quantitative values. Furthermore, as defined in the problem statement, lower numerical values of the performance scores are preferred for the proposed sustainability assessment. Performance scores, where higher values may be desirable for sustainability, should be multiplied by − 1 (Sikdar et al. 2017). Multiplication by − 1 reverses the directionality of preference, ensuring that all the performance scores are uniformly directed. The proposed sustainability assessment framework identifies a real-valued function that accounts for different performance scores for a system and produces a sustainability score (f) for relative ranking among the alternatives. The objective of a decision-maker is to identify the system having the minimum sustainability score.

$$min\{f_1, f_2, f_3, \dots, f_i, \dots, f_m\} \tag{1}$$

where f_i denotes the sustainability score of i^{th} system, and the minimum value of f_i helps to identify the most sustainable option. Note that the sustainability score does not provide the physical information of the system related to sustainability. It is used to measure the differences in the sustainability scores of different systems and helps in ranking the systems through comparative analysis. The proposed approach identifies the most sustainable system through a relative sustainability assessment by ranking different systems.

Sustainability assessment framework

Analysis of the indicators

All quantitative performance scores x_{ij} $\forall j (= 1, 2, \dots, n)$ are analyzed simultaneously for relative sustainability assessment. Performance scores may have numerical values on variant scales with different units. This poses a problem in comparing and analyzing different performance scores as larger-value performance scores can dominate the smaller-value scores. By transforming these performance scores dimensionless and within a given finite range, they can be made comparable. Normalization is applied for a specified finite range to make indicators dimensionless.

In literature, there exist many normalization functions. While using different normalization functions for any application, different rankings of systems can be obtained. These results may be conflicting in nature and may lead to inconsistent conclusions. Therefore, there is a need to identify an appropriate normalization function to avoid such inconsistent conclusions. A preferred normalization function should satisfy a set of desired mathematical characteristics (axioms). The desired mathematical characteristics of a normalization function are:

i. Finite range
ii. Affine invariance
iii. Continuity

The physical significances of these characteristics are described below.

Finite range

It may be noted that the performance scores of different indicators may be represented with different units with different numerical values. A significantly large value dominates over other small values, and this may lead to minimal contributions of other indicators in determining the final sustainability score. To avoid this, the normalization function is desired to transform all performance scores to a finite range for an appropriate comparison.

The normalization function should map the performance scores to a defined finite real-valued interval $[a, b]$, where a is the most preferred score, and b is the least preferred score for sustainability. Note, a and b are finite real numbers with $0 \leq a < b$. Typically, the finite interval is considered as $[0, 1]$ with $a = 0$ and $b = 1$. The normalization function may be expressed as:

$$y_{ij} = N\left(x_{ij}\right) \quad \text{with} \quad N\left(x_{ij}\right) : \mathbb{R} \to [0, 1] \tag{2}$$

In Eq. (2), $y_{ij} \in [0, 1]$ represents the normalized performance score of the i^{th} system for the j^{th} indicator.

Affine invariance

The change of units of measurement of any indicator may change the numerical values of the performance scores. In most cases, the relationship of different units of measurement is related to each other through a known affine equation. The mathematical form of an affine transformation is represented as follows:

$$x'_{ij} = cx_{ij} + d \tag{3}$$

where c and d are real-valued constants with positive c. A normalization function should be invariant to such affine transformations as scaling or change of units should not affect the normalized performance scores. In other words, normalized performance scores of x'_{ij} and x_{ij} should be identical.

$$N(x'_{ij}) = N(x_{ij}) \tag{4}$$

Continuity

It is expected that a small change in the performance score (x_{ij}) should lead to a small change in the normalized performance score (y_{ij}). Mathematically, this condition can be satisfied whenever the normalization function is continuous. Normalization function $(N : \mathbb{R} \to [0, 1])$ is continuous at all $x^*_{ij} \in \mathbb{R}$, if for every $\epsilon > 0$, there exists $\delta > 0$ such that for all $x_{ij} \in \mathbb{R}$:

$$\left|x_{ij} - x^*_{ij}\right| < \delta \Rightarrow \left|N(x_{ij}) - N(x^*_{ij})\right| < \epsilon \tag{5}$$

where, δ and ϵ are very small quantities.

Assessment of normalization function

Finite range, affine invariance, and continuity are the required characteristics of a normalization function. These characteristics can help identify a desired normalization function from different normalization functions reported in the literature. A list of normalization functions from the literature is identified in Table 1 and analyzed based on the required characteristics.

It may be noted from Table 1 that the min–max and the zCanberra normalization functions satisfy all the required characteristics. It may also be noted that for the zCanberra normalization function, the range depends on a user-specified reference value. This may lead to variations in the results due to the subjective decision of the reference value. On the other hand, the min–max normalization function is the most efficient and widely accepted in literature for sustainability assessment, and it follows all the required characteristics for normalization. The min–max normalization function is the most preferred among other existing normalization functions. To define the range of the min–max normalization function as $[a, b]$, the generalized min–max normalization function is shown in Eq. (6).

Table 1 List of normalization functions from the literature and their characteristics

Name (Reference)	$N(x_{ij})$	Mathematical characteristics		
		Finite Range	Affine invariance	Continuity
Max-difference ratio (Körth 1969)	$1-\left\lvert\frac{\underbrace{\max}_{1\le i\le m}(x_{ij})-x_{ij}}{\underbrace{\max}_{1\le i\le m}(x_{ij})}\right\rvert$	No $(-\infty, 1]$	No	No
Min–max (Weitendorf 1976)	$\frac{x_{ij}-\underbrace{\min}_{1\le i\le m}(x_{ij})}{\underbrace{\max}_{1\le i\le m}(x_{ij})-\underbrace{\min}_{1\le i\le m}(x_{ij})}$	Yes $[0, 1]$	Yes	Yes
Euclidean ratio (Nijkamp and Van-Delft 1977)	$\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$	Yes $[-1, 1]$	No	Yes
Sum ratio (Voogd 1983)	$\frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$	No $(-\infty, \infty)$	No	No
Mean ratio (Krajnc and Glavič 2005)	$\frac{x_{ij}}{\underbrace{\mathrm{mean}}_{1\le i\le m}(x_{ij})}$	No $(-\infty, \infty)$	No	No
Logarithmic (Zavadskas and Turskis 2008)	$\frac{\ln(x_{ij})}{\ln(\prod_{i=1}^{m} x_{ij})}$	No $(-\infty, \infty)$	No	No
Canberra (Brandi et al. 2014)	$\frac{\left\lvert x_{ij}-\underbrace{\mathrm{ref}}_{j}(x_{ij})\right\rvert}{\lvert x_{ij}\rvert+\left\lvert\underbrace{\mathrm{ref}}_{j}(x_{ij})\right\rvert}$	Yes $[0, 1]$	No	No
Vector space (Olinto 2014)	$\frac{x_{ij}}{\left\lvert\underbrace{\max}_{1\le i\le m}(x_{ij})\right\rvert+\left\lvert\underbrace{\min}_{1\le i\le m}(x_{ij})\right\rvert}$	Yes $[-1, 1]$	No	Yes
Subjective (Pinar et al. 2014)	Assign score between 0 and 1	Yes $[0, 1]$	-	No
zCanberra (Dos Santos and Brandi 2015)	$\frac{\left\lvert x_{ij}-\underbrace{\mathrm{ref}}_{j}(x_{ij})\right\rvert}{\left\lvert x_{ij}-\underbrace{\mathrm{mean}}_{1\le i\le m}(x_{ij})\right\rvert+\left\lvert\underbrace{ref}_{j}(x_{ij})-\underbrace{\mathrm{mean}}_{1\le i\le m}(x_{ij})\right\rvert}$	Yes Range depends on a reference value	Yes	Yes
Converting (Pollesch and Dale 2016)	$converter \times x_{ij}$	No $(-\infty, \infty)$	-	Yes
Max ratio (Pollesch and Dale 2016)	$\frac{x_{ij}}{\underbrace{\max}_{1\le i\le m}(x_{ij})}$	No $(-\infty, \infty)$	No	No

$$N\left(x_{ij}\right) = \left[a + \left(\frac{x_{ij} - \underbrace{\min}_{1 \le i \le m}\left(x_{ij}\right)}{\underbrace{\max}_{1 \le i \le m}\left(x_{ij}\right) - \underbrace{\min}_{1 \le i \le m}\left(x_{ij}\right)}\right)(b-a)\right] \quad (6)$$

Analysis of the systems

To analyze the sustainability of given alternatives, all indicators are assumed to be independent. Each independent indicator (j) may be assigned a weight (w_j) to the overall sustainability score. Weight (w_j) defines the importance of the j^{th} indicator with respect to other indicators for the sustainability score. All existing indicators are essential to sustainability; however, some may have higher importance than others. Mathematically, $w_j \; \forall j (= 1, 2, \ldots, n)$ is greater than zero, and the sum of all weights is unity.

$$\sum_{j=1}^{n} w_j = 1, w_j > 0 \; \forall j (= 1, 2, \ldots, n) \quad (7)$$

In general, systems $S_i \; \forall i (= 1, 2, \ldots, m)$ cannot be assigned a preference order for sustainability with more than one indicator ($n > 1$). To compare different systems with multiple indicators, an aggregation function is required. An aggregation function ($f : \mathbb{R}^n \to \mathbb{R}$) calculates the sustainability score of a system to compare with other systems. As the range of normalization function has been considered between 0 and 1 (including 0 and 1), the aggregation function (f) for sustainability maps from $[0, 1]^n$ to $[0, 1]$.

Similar to normalization functions, many aggregation functions are proposed in the literature. The sustainability scores and ranking of available systems depend on the aggregation function adopted. This may create ambiguity in identifying the most sustainable system. Similar to the normalization function, the required mathematical characteristics (axioms) are defined to identify a preferred aggregation function:

i. Monotonicity
ii. Continuity
iii. Homogeneity
iv. Idempotency
v. Order invariance
vi. Concavity

The physical significances of these characteristics are described below.

Monotonicity

It is expected that an increment (or decrement) in the normalized performance score (y_{ij}) should lead to an increment (or decrement) in the sustainability score of i^{th} system. In other words, the aggregation function should be monotonic in each indicator. Monotonicity in each indicator is shown in Eq. (8), where $y_{ij}, y'_{ij} \in [0, 1]$.

$$y_{ij} \le y'_{ij} \Rightarrow f\left(y_{i1}, y_{i2}, \ldots, y_{ij}, \ldots, y_{in}\right) \le f\left(y_{i1}, y_{i2}, \ldots, y'_{ij}, \ldots, y_{in}\right), \forall j \quad (8)$$

Continuity

Similar to the normalization function, it is expected that a small variation in the normalized performance score (y_{ij}) should lead to a small variation in the sustainability score. Therefore, for sustainability measurement, the aggregation function should be continuous. An aggregation function ($f : [0, 1]^n \to [0, 1]$) is continuous at all $Y^* \in [0, 1]^n$ if for every $\epsilon > 0$, there exists $\delta > 0$ such that for all $Y \in [0, 1]^n$

$$\|Y - Y^*\|_2 < \delta \Rightarrow \|f(Y) - f(Y^*)\|_2 < \epsilon \quad (9)$$

where, δ and ϵ are very small quantities and $\| \cdot \|_2$ denotes the Euclidean norm.

Homogeneity

It is expected that if all indicators are scaled down simultaneously by a positive constant (λ), then the sustainability score also should be multiplied by the same constant (λ). The aggregation function should follow this property, also called homogeneity. The mathematical form of the homogeneity property is represented in Eq. (10).

$$f\left(\lambda y_{i1}, \lambda y_{i2}, \lambda y_{i3}, \ldots, \lambda y_{in}\right) = \lambda f\left(y_{i1}, y_{i2}, y_{i3}, \ldots, y_{in}\right) \quad (10)$$

Idempotency

It may be possible that all the normalized performance scores $y_{ij} \; \forall j (= 1, 2, \ldots, n)$ for a system have the same numerical value. In such a case, the aggregation function is desired to produce an identical numerical value. This property is known as the idempotency (Grabisch et al. 2009) of the aggregation function and is defined as follows:

$$y_{i1} = y_{i2} = \cdots = y_{in} = h \Rightarrow f\left(y_{i1}, y_{i2}, \ldots, y_{in}\right) = h \quad (11)$$

where $h \in [0, 1]$ is a constant.

Order invariance

The order of the normalized performance scores should not affect the sustainability score. Otherwise, it may affect the implications of sustainability assessment. For every permutation $\sigma = (\sigma(1), \sigma(2), \ldots, \sigma(n))$ over $j\,(= 1, 2, \ldots, n)$ of normalized performance scores (y_{ij}), the sustainability score should be the same.

$$f\left(y_{i1}, y_{i2}, \dots, y_{in}\right) = f(y_{i\sigma(1)}, y_{i\sigma(2)}, \dots, y_{i\sigma(n)}) \tag{12}$$

Concavity

Slight improvement (Δy_{ij}) in the normalized performance score (y_{ij}) for i^{th} system can make i^{th} system to be more sustainable as the sustainability score decreases. Additional improvements in the normalized performance score should reduce the sustainability score more to encourage improvements in the performance of the system. For example, twice improvement ($2\Delta y_{ij}$) in the normalized performance score is expected to make i^{th} system to be more than or equal to twice sustainable, and mathematically, it can be expressed as:

$$\begin{aligned} &f\left(y_{i1}, y_{i2}, \dots, y_{ij}, \dots, y_{in}\right) - f\left(y_{i1}, y_{i2}, \dots, y_{ij} - 2\Delta y_{ij}, \dots, y_{in}\right) \\ &\quad \geq 2\left(f\left(y_{i1}, y_{i2}, \dots, y_{ij}, \dots, y_{in}\right) - f\left(y_{i1}, y_{i2}, \dots, y_{ij} - \Delta y_{ij}, \dots, y_{in}\right)\right) \end{aligned} \tag{13}$$

If the aggregation function is twice differentiable, Eq. (13) leads to the conclusion that the second derivative of aggregation should be less than or equal to zero.

$$f''\left(y_{i1}, y_{i2}, \dots, y_{ij}, \dots, y_{in}\right) \leq 0 \tag{14}$$

In general, the aggregation function is expected to be concave.

Assessment of aggregation function

As discussed above, the aggregation function for sustainability assessment is desired to be monotonic, continuous, homogeneous, idempotent, order invariance, and concave. A list of aggregation functions, applied in the literature, is categorized in Table 2. In literature, 1-norm and 2-norm functions are the widely used aggregation functions for various applications. However, p-norm ($p > 1$) functions do not follow the concavity property. Similarly, the aggregation function associated with the TOPSIS approach does not follow the homogeneous property. It also does not satisfy the concavity property in general. On the other hand, p-antinorm ($p \leq 1$) function satisfies all the desired properties of the aggregation function. Therefore, p-antinorm ($p \leq 1$) aggregation function can be appropriate for sustainability assessment by determining the sustainability score. It may be noted that the p-antinorm function is identical to the geometric mean function as $p \to 0$. However, precautions should be taken to use the p-antinorm function with $p \leq 0$, as the inverse of the performance score is involved in calculating the sustainability score. In such a case, the range of the normalization function should be positive, excluding 0. In this paper, the p-antinorm function is proposed as the most suitable aggregation function for sustainability assessment.

Table 2 List of aggregation functions with their characteristics

Name (Reference)	$f\left(y_{i1}, y_{i2}, \dots, y_{in}\right)$	Mathematical characteristics					
		Monotonicity	Continuity	Homogeneous	Idempotency	Order invariance	Concavity
p-norm	$\left(\frac{\sum_{j=1}^{n}(w_j y_{ij})^p}{\sum_{j=1}^{n} w_j^p}\right)^{\frac{1}{p}}$, $(p > 1)$	Yes	Yes	Yes	Yes	Yes	No
2-norm (Sikdar 2012)	$\sqrt{\frac{\sum_{j=1}^{n}(w_j y_{ij})^2}{\sum_{j=1}^{n} w_j^2}}$	Yes	Yes	Yes	Yes	Yes	No
1-norm (Krajnc and Glavič 2005)	$\frac{\sum_{j=1}^{n} w_j y_{ij}}{\sum_{j=1}^{n} w_j}$	Yes	Yes	Yes	Yes	Yes	Yes
p-antinorm (this work)	$\left(\frac{\sum_{j=1}^{n}(w_j y_{ij})^p}{\sum_{j=1}^{n} w_j^p}\right)^{\frac{1}{p}}$, $(p \leq 1)$	Yes	Yes	Yes	Yes	Yes	Yes
Weightage geometric mean (Triantaphyllou 2000)	$\prod_{j=1}^{n} y_{ij}^{w_j}$	Yes (if $y_{ij} \neq 0$)	Yes	Yes	Yes	Yes	Yes
TOPSIS (Hwang and Yoon 1981)	$\frac{\sqrt{\sum_{j=1}^{n}(w_j y_{ij})^2}}{\sqrt{\sum_{j=1}^{n}[w_j(1-y_{ij})]^2} + \sqrt{\sum_{j=1}^{n}(w_j y_{ij})^2}}$	Yes	Yes	No	Yes	Yes	No

Illustrative case studies

The proposed sustainability assessment method determines the appropriate ranking of existing systems with their preferences for sustainability. A flowchart of the proposed framework is shown in Fig. 2. It derives the results for the sustainability assessment with six steps as follows:

Step 1: The performance scores (x_{ij}). The proposed approach starts with the quantitative performance scores (x_{ij}) of each system S_i for each indicator I_j. Quantitative performance scores (x_{ij}) should clearly define the overall impact of j^{th} indicator on i^{th} system.

Step 2: Uniform direction of all indicators. It is required to check the directionality of preferences of all indicators with lower numerical values representing more sustainability. Otherwise, performance scores should be multiplied by –1 to align uniform directionality.

Step 3: Determine normalized performance scores $\left(N\left(x_{ij}\right)\right)$. Normalize performance scores (x_{ij}) using the min–max normalization function (Eq. 6).

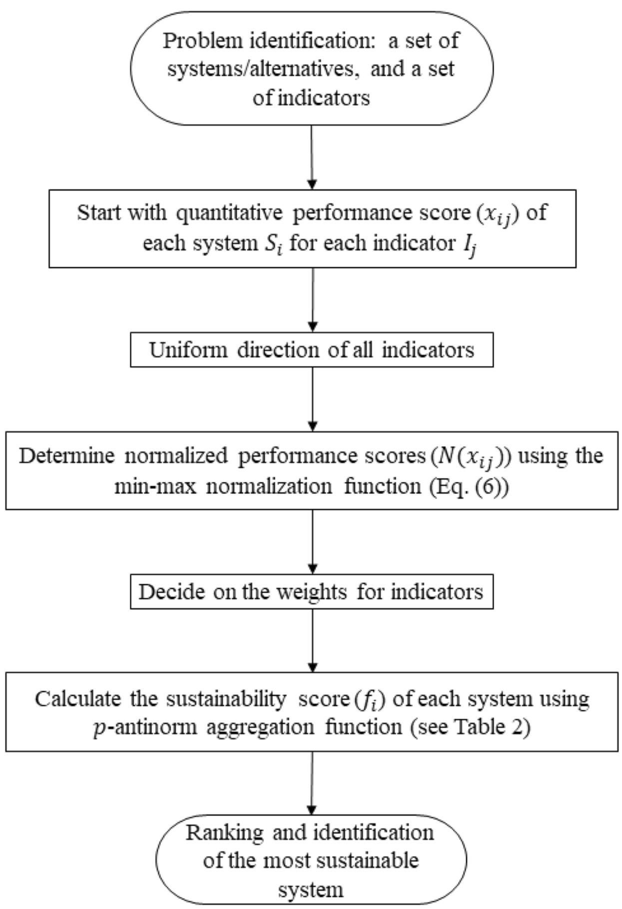


Fig. 2 Flowchart of the proposed framework for sustainability assessment

Step 4: Decide on the weights for indicators. Determine the weights (w_j) for all indicators, following Eq. (7). In case of no preference, equal weights for all indicators are to be assumed.

Step 5: Calculate the sustainability score (f_i) *of each system.* Aggregate all normalized performance scores of each system using p-antinorm (see Table 2) to determine respective sustainability scores.

Step 6: Ranking and identification of the most sustainable system. Using the sustainability score, rank all the systems and identify the most sustainable option with the minimum sustainability score.

The applicability of the proposed methodology is illustrated with three sustainability assessments: power plants, feedstocks for biodiesel production, and negative emission technologies.

Case study 1: Sustainability assessment of power plants

The demand for global electricity has increased significantly over the years, with a total electricity generation of over 26,000 TWh in 2019 (Mathew 2022). Electricity usage has a beneficial influence on economic growth, while its generation has a detrimental impact on the environment. To address the global warming issue, the electricity sector should be decarbonized. It is necessary to make energy sector planning for sustainable development (Atabaki et al. 2022).

This case study focuses on the sustainability assessment of power plants in Portugal, considering six different types of power plants ($S_1, S_2, \ldots, S_6$) such as coal, natural gas, large hydro, small hydro, wind, and solar PV (Kabayo et al. 2019). These power plants have been compared with 16 quantified indicators ($I_1, I_2, \ldots, I_{16}$), viz., metal depletion, fossil fuel depletion, ozone depletion, global warming, terrestrial acidification, aquatic acidification, freshwater eutrophication, freshwater scarcity footprint, freshwater ecotoxicity, human toxicity carcinogenic, human toxicity non-carcinogenic, domestic employment, total employment, dependence on fossil fuels, capacity factor, and levelized cost of electricity. Performance scores (x_{ij}), based on the life cycle analysis, are listed in Table 3 (Kabayo et al. 2019). Note that Table 3 has been represented as a transposed of the original data index, with rows representing the various indicators and columns representing the power plants. In the original case study, Kabayo et al. (2019) used the unweighted color gradient scale to find the most sustainable power generation option.

All indicators follow the inverse scale (i.e., lower values are preferred) except for domestic employment, total employment, and capacity factor. These three indicators are multiplied by – 1 for uniform directionality. Some intermediate steps are shown in Supplementary information.

Table 3 Performance scores of various power plants for electricity generation in Portugal (Kabayo et al. 2019)

Electricity generation systems →	Coal	Natural gas	Large hydro	Small hydro	Wind	Photovoltaic
Metal depletion $\frac{\text{kg Fe eq.}}{\text{MWh}}$	3.10	1.10	2.20	2.00	18.60	13.90
Fossil fuel depletion $\left(\frac{\text{kg oil eq.}}{\text{MWh}}\right)$	238.10	154.80	1.30	0.90	4.40	13.40
Global warming $\left(\frac{\text{kg } CO_2 \text{ eq.}}{\text{MWh}}\right)$	965.00	444.00	14.00	4.00	16.00	50.00
Ozone depletion $\left(\frac{\text{kg CFC}-11\text{ eq.}}{\text{MWh}}\right)$	5×10^{-6}	6×10^{-5}	5×10^{-7}	3×10^{-7}	2×10^{-6}	9×10^{-6}
Terrestrial acidification $\left(\frac{\text{kg } SO_2 \text{ eq.}}{\text{MWh}}\right)$	2.62	0.31	0.03	0.02	0.11	0.33
Freshwater eutrophication $\left(\frac{\text{kg } PO_4^{3-} \text{ eq.}}{\text{MWh}}\right)$	4×10^{-1}	2×10^{-3}	1×10^{-3}	1×10^{-3}	2×10^{-2}	3×10^{-2}
Aquatic acidification $\left(\frac{\text{kg } SO_2 \text{ eq.}}{\text{MWh}}\right)$	3.14	0.38	0.03	0.02	0.12	0.36
Freshwater ecotoxicity $\left(\frac{\text{CTUh}}{\text{MWh}}\right)$	0.50	0.03	0.03	0.01	0.11	0.54
Freshwater scarcity footprint $\left(\frac{m^3}{\text{MWh}}\right)$	1.50	12.10	615.60	0.60	1.30	23.90
Human toxicity carcinogenic $\left(\frac{\text{CTUh}}{\text{MWh}}\right)$	6×10^{-9}	6×10^{-9}	5×10^{-10}	4×10^{-10}	2×10^{-9}	3×10^{-9}
Human toxicity non-carcinogenic $\left(\frac{\text{CTUh}}{\text{MWh}}\right)$	1×10^{-9}	7×10^{-11}	4×10^{-11}	2×10^{-11}	2×10^{-10}	2×10^{-9}
Domestic employment $\left(\frac{\text{person−years}}{\text{MWh}}\right)$	8.7×10^{-5}	1×10^{-4}	1.6×10^{-4}	4.7×10^{-4}	2×10^{-4}	9.9×10^{-4}
Total employment $\left(\frac{\text{person−years}}{\text{MWh}}\right)$	6.4×10^{-4}	3.8×10^{-4}	1.8×10^{-4}	5.2×10^{-4}	2.8×10^{-4}	1.2×10^{-3}
Dependence on fossil fuels (% relative to coal-based generation)	100.00	67.10	0.50	0.40	1.80	5.60
Capacity factor (%)	77.40	21.70	21.90	30.80	29.00	20.70
Levelized cost of electricity $\left(\frac{\text{USD}}{\text{MWh}}\right)$	87.50	129.70	113.20	92.50	63.60	76.90

Indicator values are normalized using the min–max normalization function (Eq. (6)) with $a = 0$ and $b = 1$. All normalized performance scores are mentioned in Table A3 (see Supplementary information). All indicators are considered with equal weights ($w_j = 0.0625\ \forall j$). Indicators are aggregated with p-antinorm ($p \leq 1$) function. As discussed in Sub-section "Assessment of aggregation function," when the data index includes the zero value of any normalized performance score, p should be positive ($p > 0$). In this case study, an intermediate value of $p = 0.5$ is used in p-antinorm aggregation function for calculating the sustainability scores of systems. The sustainability scores of each power plant are compared in Fig. 3 (numerical values are tabulated in Table A4 (see Supplementary information)).

The proposed approach analyzes all 16 quantitative indicators simultaneously for assigning the ranking of available power plants. It is noted that among conventional energy sources such as coal-based and natural gas-based power plants, natural gas is a more sustainable option for electricity generation. Among these six power plants, small hydro is the most sustainable option, followed by large hydro, wind, solar PV, natural gas, and coal. The result is consistent with Kabayo et al. (2019).

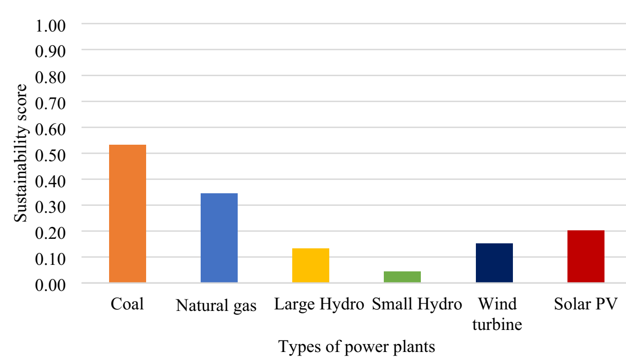


Fig. 3 Sustainability scores of different types of power plants (case study 1)

It may be noted that the decision-makers can select the indicators based on their objectives and apply the proposed approach to identify the appropriate option. For example, the decision maker may minimize overall resource utilization

Table 4 Performance scores of various feedstock options for biodiesel production (Mata et al. 2011)

Feedstock options ↓	Life cycle energy efficiency	Fossil energy ratio	Land-use intensity $\left(\frac{m^2\ year}{MJ\ fuel}\right)$	Carbon footprint $\left(\frac{kg\ CO_2\ eq.}{MJ\ fuel}\right)$	Emissions from carbon stock changes by land use $\left(\frac{kg\ CO_2\ eq.}{MJ\ fuel}\right)$
Palm oil	1.28	1.28	0.05	0.04	0.08
Sunflower	1.04	1.04	0.28	0.05	0.70
Rapeseed methyl ester	2.90	1.15	0.31	0.04	0.78
Rapeseed ethyl ester	2.97	1.32	0.31	0.07	0.78
Soybean	0.41	0.41	0.46	0.13	1.66
Microalgae	1.84	0.56	0.01	0.14	0.01

and consider indicators such as metal depletion and fossil fuel depletion. In such a case, small hydro is identified as the most sustainable option. On the other hand, if the decision maker only considers social aspects, indicators such as domestic employment and total employment should be considered. The wind-based power plant is the most appropriate in this case.

Case study 2: Sustainability assessment of feedstocks for biodiesel production

In the era of industrialization, the requirement for fossil fuels has increased significantly (Basha et al. 2009), and they occupy about 87% of the total global energy market (Nayab et al. 2022). Fossil fuels are responsible for climate change and associated problems. Biodiesel can be an alternate option for transportation fuel with easy availability and low carbon emission (Topare et al. 2022). For overall sustainability, it is required to examine the environmental and economic indicators of biodiesel (Janaun and Ellis 2010) through an appropriate selection of feedstocks (Nayab et al. 2022).

Mata et al. (2011) used the geometric mean with ratio normalization for the sustainability assessment of feedstock options for biodiesel production. Six feedstock options, such as palm oil (S_1), sunflower (S_2), rapeseed methyl ester (S_3), rapeseed ethyl ester (S_4), soybean (S_5), and microalgae (S_6) were considered. These feedstocks have different input–output processing for biodiesel production. The sustainable feedstock option was identified based on multiple indicators ($I_1, I_2, \ldots, I_5$), viz., life cycle energy efficiency, fossil energy ratio, land-use intensity, carbon footprint, and emissions from carbon stocks change. Performance scores for this case study are shown in Table 4. Note that the indicators life cycle energy efficiency and fossil energy ratio do not follow the inverse scale. These two indicators are multiplied by – 1 for the uni-directionality of all indicators. Some intermediate steps are shown in Supplementary information.

To identify the most sustainable feedstock option, the proposed approach is followed. The central focus of this case study leads toward the discussion on the impact of the parameter (p) for measuring the sustainability score. In the previous case study, an intermediate value ($p = 0.5$) is used in p-antinorm aggregation function, although the value of the parameter (p) is defined between 0 and 1 ($0 < p < 1$). In this case study, sustainability scores are measured using the various values of the parameter (p) from 0 to 1 with a step size of 0.25. Instead of zero, a very small positive value of p ($p = 0.1$) is considered. Note that p-antinorm function with $p \to 0$ returns zero as a sustainability score in case of having any normalized performance score be zero. The sustainability scores of feedstock options for various values of (p) in p-antinorm function are shown in Table 5 and Fig. 4. From Fig. 4, it can be concluded that palm oil is the most sustainable feedstock option among sunflower, rapeseed methyl ester, rapeseed ethyl ester, soybean, and microalgae using all different values of (p) in p-antinorm aggregation function. The applicability of the proposed method represents that the selection of parameter (p) does not create ambiguity in the result. Decision-makers can choose any value of p between 0 and 1 for p-antinorm function with any qualitative preferences.

It is also noted that Mata et al. (2011) assessed microalgae as the most sustainable alternative using ratio normalization and geometric mean aggregation functions. The ratio normalization function fails to provide a consistent result with the unit conversion of any indicator. As discussed in Sub-section"Assessment of aggregation function," the geometric mean function is identical to p-antinorm function with $p \to 0$. The result is different due to the usage of a different normalization function. Conflicting results are identified using the various available methods in the literature. The Canberra distance method uses the Canberra function for normalization (see Table 1) and the 1-norm for aggregation (see Table 2). The Canberra distance method identifies microalgae as the most sustainable option. On the other hand, the zCanberra method assessed palm oil as the most sustainable option using the zCanberra normalization function (mentioned in Table 1) and the 1-norm aggregation function. Furthermore, the TOPSIS method, with the Euclidean ratio normalization function (see Table 1) and the TOPSIS aggregation function (discussed in Table 2), identifies

Table 5 Sustainability scores of various feedstock options for biodiesel production

Sustainability scores (f) using various methods		Palm oil	Sunflower	Rapeseed methyl ester	Rapeseed ethyl ester	Soybean	Microalgae
p-antinorm ($0 \leq f \leq 1$)	$p = 0.10$	0.0117	0.3661	0.0231	0.0028	0.9792	0.0044
	$p = 0.25$	0.0496	0.3790	0.0975	0.0596	0.9794	0.0943
	$p = 0.50$	0.0932	0.3995	0.1759	0.1677	0.9796	0.2659
	$p = 0.75$	0.1303	0.4185	0.2287	0.2388	0.9798	0.3790
	$p = 1.00$	0.1671	0.4360	0.2695	0.2867	0.9800	0.4553
Mata et al. (2011) ($-\infty \leq f \leq \infty$)		1.0000	2.4745	1.9703	2.1335	5.7056	0.6740
Canberra method ($0 \leq f \leq 1$)		0.3714	0.5227	0.3985	0.4369	0.7516	0.2389
zCanberra method ($0 \leq f \leq 1$)		0.2423	0.7572	0.4676	0.5285	1.0000	0.5699
TOPSIS method ($0 \leq f \leq 1$)		0.1950	0.2502	0.2823	0.2973	0.4158	0.2500

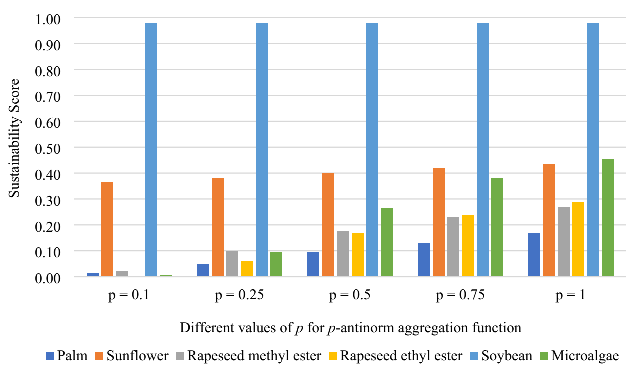


Fig. 4 Effect of p on the sustainability scores of various feedstock options for bio-diesel production (case study 2)

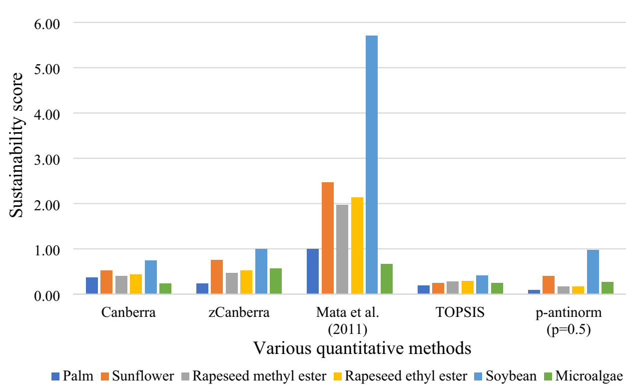


Fig. 5 Sustainability scores of various feedstock options using various quantitative approaches

palm oil as the most sustainable option. The sustainability scores are calculated using various methods and compared in Table 5 (also shown in Fig. 5). It can be concluded that the min–max normalization function and p-antinorm aggregation function follows all mathematical characteristics for sustainability assessment, and therefore, palm oil may be considered the most sustainable feedstock.

Case study 3: Sustainability assessment of negative emissions technologies

Deployments of negative emission technologies are required to meet the Paris Agreement limits of global warming (Smith et al. 2016), especially during the energy system transition. Negative emission technologies (NETs) can remove carbon dioxide (CO_2) from the atmosphere and help decarbonize the energy system. Large-scale deployment of NETs is restricted due to high investment costs, negative influence on water requirements, and parasitic energy needs (Honegger and Reiner 2018). This example focuses on the selection of appropriate NET for sustainable development.

Tan et al. (2019) analyzed the sustainability assessment of negative emission technologies (NETs) ($S_1, S_2, \ldots, S_6$) such as bioenergy with CO_2 and storage, afforestation and reforestation, biochar application, direct air capture, soil carbon sequestration, and enhanced weathering. A similar case study has been adopted with the relative performance scores of each technology for four indicators (I_1, I_2, I_3, I_4), e.g., sequestration potential, water requirement, energy requirement, and specific cost. The relative performance scores (x_{ij}) of each system ($S_i\ \forall\, i (= 1, 2, \ldots, 6)$) for given indicators ($I_j\ \forall\, j (= 1, 2, 3, 4)$) are mentioned in Table 6. The relative performance score (Tan et al. 2019) signifies the value of 0 as the least preferred option for sustainability and 1 as the most preferred option for sustainability. To reverse the directionality of preferences, the adopted performance scores are multiplied by –1. These uniformly directed data are normalized using the min–max normalization function (Eq. 6). Some intermediate steps are shown in Supplementary information.

After getting normalization performance scores, it is necessary to determine the weights of all indicators. In both previous studies, equal weights are assumed. Determining the weights of indicators is a part of subjectivity and depends upon decision-makers. However, different weights of all indicators can affect the result of sustainability assessment. This case

Table 6 Relative performance scores of negative emission technologies (Tan et al. 2019)

Negative emission technologies ↓	Sequestration potential	Water requirement	Energy requirement	Specific cost
Bioenergy with CO_2 and storage	0.63	0.00	0.64	0.98
Afforestation and reforestation	0.72	0.73	0.79	1.00
Soil carbon sequestration	0.00	1.00	0.79	1.00
Biochar application	0.22	1.00	1.00	0.86
Direct air capture	0.63	0.96	0.00	0.61
Enhanced weathering	1.00	1.00	0.07	0.00

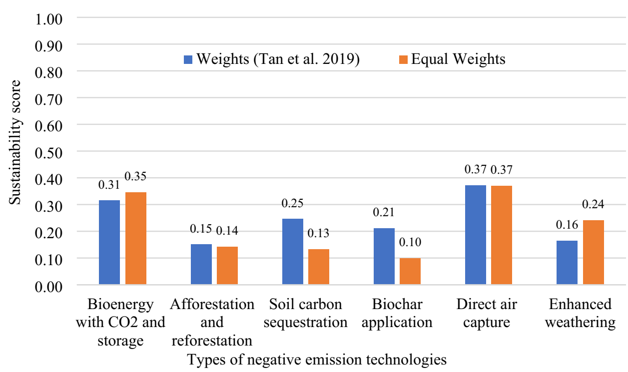


Fig. 6 Impact of weights on sustainability scores of various negative emission technologies (case study 3)

study uses two different weights: weights defined by Tan et al. (2019) and equal weights. Tan et al. (2019) associated $w_1 = 0.6$, $w_2 = 0.1$, $w_3 = 0.1$ and $w_4 = 0.2$ to all indicators (sequestration potential, water requirement, energy requirement, and specific cost). For equal weights, w_j would be equal to 0.25 for all j. The p-antinorm function with $p = 0.5$ is used to aggregate the normalized performance scores with both associated weights. Sustainability scores (with both associated weights) of negative emission technologies are compared in Fig. 6.

The proposed approach identifies afforestation and reforestation as the most sustainable negative emission technology with weights. This is consistent with the results of Tan et al. (2019). However, when all indicators have equal weights, the proposed approach identifies biochar application as the most sustainable negative emission technology. It may be observed that the sustainability assessment is sensitive toward the weights. It is suggested that decision-makers should clearly define the weights of all indicators with an involved understanding and appropriate knowledge of the problem.

Conclusions

With various complexities with the choice of normalization and aggregation functions in sustainability assessment, more than 15 MCDM methods are widely accepted in the literature for establishing the ranking of available systems (Diaz-Balteiro et al. 2017). These methods exhibit the applicability of handling conflicting indicators simultaneously. However, various quantitative methods cause the problem of getting consistent results for the sustainability assessment of multi-dimensional systems. It has been concluded in the literature that not a single method can be considered the best method for sustainability assessment. Beyond the discussion on the weakness and strengths of various MCDM methods, this paper has developed an axiomatic sustainability assessment method with desired mathematical properties to identify the most sustainable system or alternative among the existing systems or alternatives. This paper proposes a generalized framework with mathematical properties (or axioms), which compiles the information from the significant steps of MCDM methods (such as normalizing the indicator and aggregating the performance scores). The proposed characteristics signify one of the most significant normalization functions (i.e., min–max normalization function) and aggregation functions (i.e., p-antinorm aggregation function. The foundation of the proposed axioms is based on the physical aspects of sustainability, establishing a crucial and novel framework for sustainability assessment.

Furthermore, the proposed method is supported by three energy- and environmental-related case studies with diverse dimensions. In the first case study, small hydro is identified as Portugal's most sustainable power plant for electricity generation. The second case study identifies palm oil as the most sustainable feedstock option for biodiesel production. The result also concludes that the proposed approach provides a consistent result for various values of p $(0 < p < 1)$. Afforestation and reforestation, and biochar are identified as the most sustainable negative emission technologies in the last case study. This case study shows the sensitivity of indicator weights in identifying the most sustainable option.

As demonstrated through multiple case studies, the proposed framework can significantly help decision-makers, researchers, and scientists handle the complexity of multi-dimension systems (where more than one parameter is required for making decisions). It is also noted that the proposed framework has some limitations. The proposed framework is restricted to precise performance scores (where the exact performance scores of indicators are known), and the proposed functions are limited to the independence of indicators. Future work is directed to overcome these limitations.

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Declarations

Conflict of interest The authors declare no competing interests.

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