

# Approach to Sustainability Assessment of Renewable Energy Technologies combining Fuzzy Logic with the Integrative Sustainability Triangle

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## Abstract

*The expansion of renewable energy technologies is a supporting pillar of the energy revolution. Its goal is the sustainable transformation of the current energy system. Despite being positively acknowledged as low-emission technologies, current renewable energy technologies have negative impacts on ecological, economic and social environments throughout their life cycles. Comprehensive, practicable methods for sustainability assessment are a key factor in supporting decision makers in building a sustainable energy system. Existing methods, like Life Cycle Assessment or Multi-Criteria-Decision-Analysis methods have shortcomings concerning completeness, processing of fuzziness, and representation of results. In this paper, the holistic Fuzzy Logic Approach for Sustainability Assessment Based on the Integrative Sustainability Triangle (Fuzzy-IST) is proposed to eliminate these deficits. Quantitative and qualitative Basic Sustainability Indicators of all sustainability dimensions and life cycle phases are hierarchically processed in a multi-stage fuzzy system. Thus, seven crisp Sustainability Dimension Indices, six Life Cycle Sustainability Indices and a General Sustainability Index are calculated and visualized in a color-coded Integrative Sustainability Triangle and life cycle diagram, providing a straightforward interpretation of the results. Thus, deficits in all sustainability dimensions and life cycle phases can easily be identified and actions to improve the overall sustainability of renewable energy technologies can be deduced.*

## 1. Introduction

Our time's major societal issues include climate change, scarce resources, especially fossil fuels, and increasing environmental awareness. These, in turn, fuel the energy revolution – i.e. the change to a sustainable energy system – which is a widely recognized political, social and technological goal. The expansion of renewable energy technologies (RET) and improved energy efficiency are the supporting pillars of the energy revolution [1]. On the one hand, RET have positive impacts on ecological, economic and social environments throughout their life cycle. These include low emissions, low resource consumption and job

growth. On the other hand, negative impacts, such as noise pollution, fluctuating energy production and effects on biodiversity challenge RET's good reputation [2–4].

There are various approaches for sustainability assessments, which are developed for investigating the influence of positive and negative impacts on the overall sustainability of RET. The existing approaches include, but are not limited to, Life Cycle Sustainability Assessments (LCSA) and Multi-Criteria-Decision-Analyses (MCDA). While differing in focus, effort for data acquisition and implementation, and presentation of results, all approaches have benefits and shortcomings. [2,5–7]

The objective of this paper is to introduce and describe a novel, integrated approach for sustainability assessment of RET. The holistic *Fuzzy Logic Approach for Sustainability Assessment Based on the Integrative Sustainability Triangle (Fuzzy-IST)* includes qualitative and quantitative sustainability indicators that represent all dimensions of sustainability and all life cycle phases of the assessed RET. In the following Chapter 2, an overview of the state of the art of techniques used in sustainability assessment for RET is given. In Chapter 3, the proposed method is described and conclusions are drawn in the final Chapter 4.

## 2. State of the Art

Sustainability is affected by diverse aspects of ecology, economy and social issues. Therefore, it is characterized as a complex and multi-dimensional construct. To process the complexity, adequate models, measures and tools for capturing and assessing sustainability are necessary [8]. The objective of a sustainability assessment is to provide decision makers with the necessary information and context required to support them in defining short- and long-term actions necessary for sustainable development [6,8,9]. The following sections give an overview of the systematization concepts of sustainability, indicators and indices, as well as methods for sustainability assessment.

### 2.1. Systematization Concepts for Sustainability

In order to successfully carry out a sustainability assessment, it is essential to answer one question

first: What is sustainability [10]? As of yet there is no undisputed definition, merely a commonly accepted notion of sustainability. First introduced in the 18<sup>th</sup> century, this notion was developed from an approach to careful arboriculture, into a holistic concept that tries to reconcile human economic activities with the carrying capacity and exhaustibility of the natural environment and human needs – today and in the future [1]. Based on this notion there are three dimensions to sustainability: ecology, economy and social issues. These dimensions have interdependencies and intersections [11]. Due to its multi-dimensional properties, there are several approaches to systemizing sustainability.

The three sustainability dimensions are either considered separately or integrated. For instance, the triple-bottom-line (TBL) approach systemizes ecology, economy and social issues as three pillars standing side-by-side, carrying sustainability as a roof, implying a separation of the different dimensions [12]. Another TBL-based modelling approach uses intersecting circles to represent the dimensions so as to emphasize their overlaps [12]. Systemizing the sustainability dimensions in a triangle allows for the continuous classification of elements, like for example indicators or fields of action, between two dimensions. All of these systematization concepts are based on separate, partially intersecting sustainability dimensions [12].

Integrative systematization approaches represent the complexity of sustainability – i.e. the interdependencies and connections of all three dimensions [12]. The Integrative Sustainability Triangle (IST) further extends the classical sustainability triangle by adding discrete fields inside the triangle (see Figure 1).

There are four types of fields within the IST. The first type is related to only one dimension (*social, ecological, economic*). The second type is mainly related to one dimension but is slightly influenced by the other dimensions as well (*mainly social, mainly*

*ecological, mainly economic*). The third type concerns two dimensions respectively (*social-ecological, social-economic, ecological-economic*), while the fourth type is influenced by all three dimensions nearly equally (*social-ecological-economic*). This allows for a classification of elements, such as indicators or fields of action, in and between all three dimensions. This approach is based on Gibb's Triangle, which is used to visualize three-component mixtures in chemistry or material sciences [11].

The IST does not only systemize the three core dimensions; it also provides a structured visualization of sustainability. Furthermore, it facilitates the allocation of elements to the different fields. By connecting the elements with arrows, interdependencies can be depicted. By using a color-code, levels of attainment within fields can be visualized [11].

## 2.2. Indicators and Indices

Methods for sustainability assessment are classically based on sustainability indicators. Indicators include “*results from the processing (to various extents) and interpretation of primary data*” [10]. Sustainability is a complex and, at times, subjective field based on different perspectives. In order to process these characteristics, quantitative and qualitative indicators must be considered in sustainability assessments [6]. Depending on their application and the availability of data, the indicators are generally based on theories, empirical analyses, pragmatism or intuition [10].

Sustainability indicators are either assessed separately or combined with one another. Indices are combined indicators that are based on the transformation and aggregation of sub-indicators with different units, to a single, dimensionless number [10]. The author of [4] proposes a hierarchical aggregation of Basic Sustainability Indicators (BSI) to a General Sustainability Index (GSI), shown in Figure 2. The aggregation is facilitated by scaling, normalization and weighting methods. By using normalization, quantitative and qualitative sustainability indicators, that can have different specific units or be dimensionless, are made comparable. The complexity of the sustainability assessment is reduced by combining indicators [4,14].

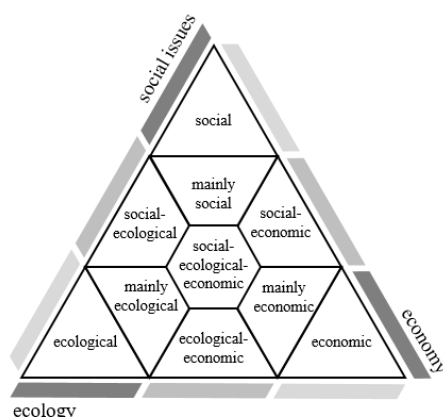


Figure 1. Integrative Sustainability Triangle [12]

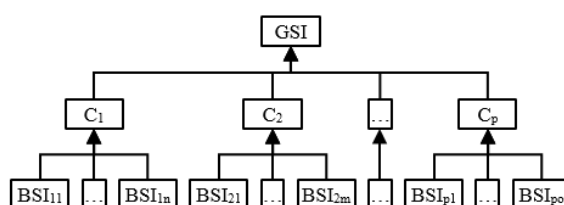


Figure 2. Hierarchical aggregation of BSI [4]

## 2.3. Methods for Sustainability Assessment

Existing models, measures and tools for sustainability assessment analyze sustainability and sustainable development from diverse angles and with wide-ranging focuses. They are based on different scales, elements and aspects that consider various levels, including product, process, company and political levels, which in turn can be further divided into regional, national or international levels [9,14].

### 2.3.1. Life Cycle Approaches

One popular method for sustainability assessment is Life Cycle Analysis (LCA). This approach is based on analyses of material and energy flows and their impacts over the entire life cycle of the object under investigation. Life cycle phases of RET include *planning, resource extraction, manufacturing, logistics & installation, operation & maintenance* as well as the *end-of-life* [5].

LCA historically focuses on ecological indicators, such as material consumption, emissions and land use. In recent years, new life cycle approaches have emerged that focus on the other two sustainability dimensions. Thus, on one hand, Life Cycle Costing (LCC) focuses on economic aspects by considering all monetary costs throughout the life cycle in the set system. On the other hand, Social Life Cycle Assessment (S-LCA) focuses on social aspects by incorporating the social impacts of material and energy flows in the analysis. LCA, LCC and S-LCA are all based on ISO 14040 and ISO 14044 [5].

The author of [14] proposes a framework for the combination of LCA, LCC and S-LCA in order to reach a LCSA. He underlines the importance of an integrated assessment by interpreting the results of each life cycle approach next to the others, rather than simply summing them up. As of yet there is no universal standard for LCSA [5]. Whilst S-LCA is equipped to process qualitative and quantitative data, LCA and LCC are solely based on quantitative indicators, which facilitates the mathematical calculations necessary for the assessment, but it might be considered incomplete due to relevant qualitative indicators being omitted [5,10]. For all life cycle approaches the costs of data acquisition, consolidation and processing are high [15].

### 2.3.2. Multi-Criteria-Decision-Analysis

MCDA approaches are commonly used in sustainability assessments in order to process quantitative and qualitative inputs for all sustainability dimensions and to also help reduce the effort for application [16]. They are not standardized,

thus indicators, indices, system boundaries, depth and focus of the analysis must be chosen individually. Examples of MCDA approaches include, but are not limited to: Analytical Hierarchy/Network Process (AHP/ANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Grey Relational Analysis (GRA), ELimination Et Choice Translating Reality (ELECTRE), Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) and Fuzzy Logic approaches [2].

The AHP is based on creating a ranking – i.e. a hierarchy of elements – by pairwise comparison. This ranking is either used directly as a comparative assessment of alternatives, or to deduce weights of the considered elements [4]. The ANP is the generalization of the AHP. It is suited to problems in which elements are interconnected by complex relationships, thus a network of elements can be investigated [2]. Both approaches are subject to uncertainties connected to an unbalanced scale of judgement, an imprecise ranking and subjective preferences of the respective user [4].

The general idea of TOPSIS is that the optimal alternative has the highest score for all the criteria taken into consideration. Thus, the alternative with the shortest geometrical distance to the ideal solution and simultaneously the largest geometrical distance to the least favorable solution is deemed the most advantageous choice. The ideal solution is comprised of the solutions containing the maximum scores in all criteria, and respectively the worst solutions are comprised of the minimum scores. While the mathematical equations used in TOPSIS are of low complexity, the results are not as robust as those of other approaches. [7]

The idea of GRA is similar to TOPSIS but, in addition to looking at the geometrical distances between the ideal and least favorable solutions, error intervals and other parameters are included as well. Multiple assessment criteria are evaluated simultaneously. Due to complex mathematical calculation rules, the definition of the assessment formula is time and process intensive [4,7]

The ELECTRE method is characterized by a two-step approach. Firstly, hierarchical relationships between the alternatives being considered are constructed. The focus here is on dominance between alternatives. Secondly, graphs are created based on pairwise comparisons, concordance and discordance indices, as well as threshold values. These graphs are then used to determine the final ranking of the alternatives. The method is suitable for decision-making situations with few criteria, but multiple alternatives. Both qualitative and quantitative criteria can be included. Due to the complexity of the assessment process, one or more advantageous alternatives are chosen [2,7].

PROMETHEE is also based on a ranking principle, but it is less complex and easier to use than ELECTRE. The method is based on weighted hierarchical relationships related to inputs and outputs of the considered system. Similar to other methods, the alternatives are compared pairwise. However, in addition to simply using preferences to compare alternatives, distances between alternatives are also considered [7].

Fuzzy Logic is based on the assumption that objects can be attributed to more than one set, the attribution is therefore fuzzy. It emulates the human mind, which extracts qualitative information from numerical, categorical or linguistic data and rates, summarizes and processes this information to make decisions and assessments [17]. Fuzzy Logic provides mathematical tools with the ability to process crisp as well as fuzzy inputs in order to create crisp outputs. Due to the complexity of sustainability, not all indicators can be measured quantitatively and thus have to be estimated or assigned qualitative values. This uncertainty and subjectivity – i.e. fuzziness of inputs – can be processed in a fuzzy system to provide a crisp, absolute output value [17].

### 2.3.3. Requirements for a Holistic Method for Sustainability Assessment

Existing approaches to sustainability assessment provide several starting points for improvement and optimization. For instance, LCA only takes quantitative indicators of the ecological dimension into account. The combination with LCC and S-LCA is an initial step towards an integrated assessment in the form of LCSA, though the costs of data acquisition, consolidation and processing are high [15]. In classical methods, the sustainability dimensions are considered separately, which implies a trade-off between different indicators and dimensions [3]. For an integrated assessment, all three dimensions, their intersections and relationships must be considered equally [12]. In some applications, certain life cycle phases are omitted. By including aspects of the entire life cycle, a more complete image of sustainability is provided [6].

Due to subjective or uncertain inputs, results of the assessment can be distorted [2]. By choosing an approach that is equipped to process these uncertainties, more reliable assessment results are generated [17]. Methods like GRA, ELECTRE or PROMETHEE are characterized by complex mathematical operations and thus elaborate assessment procedures [7]. By limiting the effort of those carrying out the assessment, the more attractive the sustainability assessment becomes. All the methods described provide assessment results as complex as the assessment process itself. Easily

understandable visualization techniques facilitate the interpretation of results [18]. Based on these aspects, which are described in literature, seven requirements are deduced for creating a holistic method for sustainability assessments of RET. They are summarized in Table 1.

Table 1. Requirements for holistic method for sustainability assessment [2,3,6,7,12,15,17,18]

No.	Requirement
R1	Consideration of all sustainability dimensions
R2	Separate and aggregated evaluation of sustainability dimensions
R3	Inclusion of the entire life cycle
R4	Inclusion of quantitative and qualitative aspects of sustainability
R5	Processing of uncertainties and subjectivity of inputs and calculations
R6	Balancing level of detail and effort of data procurement, -consolidation and -processing
R7	Structured, clear and understandable visualization of results

## 3. Proposed Method for Sustainability Assessment

The proposed *Fuzzy Logic Approach for Sustainability Assessment Based on the Integrative Sustainability Triangle (Fuzzy-IST, see Figure 3)* is based on the combination of a multi-stage fuzzy logic approach, which, on the one hand, aggregates Basic Sustainability Indicators (BSI) into Sustainability Dimension Indices (SDI) and then into a GSI, with the IST as a tool for the systematization of indicators and a visualization of the results. On the other hand, the BSI are allocated to the different life

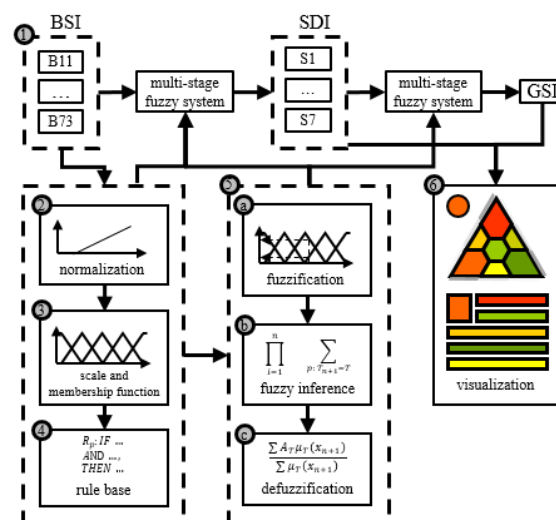


Figure 3. Process of the Fuzzy-IST

cycle phases and aggregated and visualized accordingly. The approach is further illustrated in the following sections.

### 3.1. Indicator selection

The first step of the *Fuzzy-IST* is the selection of appropriate BSI. There are several basic requirements for BSI selection. One requirement is to represent the current notion of sustainability – i.e. the three dimensions ecology, economy and social issues – and the entire life cycle of the assessment object. Furthermore, BSI should be based on current and reliable information and additionally, clearly depict the fulfillment levels of sustainability goals and indicate optimization options for the assessment object [4,20]. The statement, that more indicators increase the quality of the assessment is not without restrictions. Thus, in indicator selection, there is always a trade-off between level of detail and manageability of the sustainability assessment [6,18]. Generally, the final indicator set is variable in terms of number and type of indicators used. Depending on the application, requirements of the analysis and data availability, the BSI must be selected based on theories, empirical analysis, pragmatism or a

combination of these factors [13].

In order to fulfill the requirements mentioned above, the indicator selection is carried out in four sub-steps. Firstly, a pre-selection of BSI is conducted based on literature research regarding sustainability, the respective RET under investigation and its life cycle as well as indicators, already being used in other approaches. During the research phase, topicality and reliability of sources are to be ensured.

The resulting set of possible BSI is then systemized in a simplified IST as well as in a life cycle diagram (see Figure 6) to balance out the different sustainability dimensions and life cycle phases. The simplification of the IST is done by combining the *social/ecological/economic* with *mainly social/ ecological/economic* fields (see Figure 6) in order to facilitate the allocation of indicators, resulting in seven discrete fields. The life cycle diagram comprises the phases *planning, resource extraction, manufacturing, logistics and installation, operation and maintenance* as well as the *end-of-life*.

In the next step, interviews with experts in sustainability, sustainability assessment and/or the respective RET are conducted, in order to narrow down the number of indicators. Thus, a final set of BSI is selected based on the remaining requirements.

Table 2. Indicator set for sustainability assessment of wind power plants [20]

Dimension	No.	Indicator	Life Cycle Phase*	Measure	Unit
social	B11	Shadowing	O	Deviation from threshold	h/a
	B12	Safety	L, O	Deaths through accidents	#/GWa
	B13	Social acceptance	P, L, O, E	Expert estimation	qualitative
	B14	Situation in supply chain	All	Expert estimation	qualitative
social-ecological	B21	Land use	L, O	Space requirement	m <sup>2</sup> /GWh
	B22	Optical landscape influences	P, O	Expert estimation	qualitative
	B23	Sound emissions	O	Deviation from threshold	dB(A)
ecological	B31	Climate-relevant emissions	All	CO <sub>2</sub> -equivalent	g/kWh
	B32	Effects on biodiversity	O	No. of threatened species	#
	B33	Effects on water	R, M, L, O, E	Water usage	m <sup>3</sup> /TJ
	B34	Effects on soil	R, L, O, E	Expert estimation	qualitative
ecological-economic	B41	Resource consumption	R, M, L, O	Material use	kg/MWh
	B42	Recycling quota	E	Mass percentage	%
	B43	Recycling approaches for critical materials	E	Qualitative comparison	qualitative
economic	B51	Energy efficiency	All	Energy return on invest	dml.
	B52	Economic profitability	All	Cost of energy production	€-cent/kWh
	B53	Technical reliability	O	Technical availability	%
social-economic	B61	Jobs	All	Job growth	%
	B62	Participation, transparency and fairness	P, L, O	Expert estimation	qualitative
	B63	Political support	All	Expert estimation	qualitative
	B64	Supply security	O	Quality of prognosis	%
social-ecological-economic	B71	External costs	All	External costs	€-cent/kWh
	B72	Use of critical resources	R, M	Material usage	kg/MW
	B73	Future potential	All	Expert estimation	qualitative

\*(P = Planning. R = Ressource extraction. M = Manufacturing. L = Logistics & Installation. O = Operation. E = End-of-Life)

As a preparation for the following steps, the final BSI set again is systemized in a simplified IST and a life cycle diagram.

Table 2 shows the exemplary indicator set for the sustainability assessment of wind power plants (WPP) [20]. It contains 24 different indicators, which are allocated to the seven sustainability dimensions and intersections represented in the simplified IST as well as to the six life cycle phases. As shown in Table 2, all indicators have different measures and units. For instance, the indicator *Land use* is measured in space requirement using [m<sup>2</sup>/GWh] as a unit, while the indicator *Future potential* is measured by expert estimation using *qualitative*, linguistic values. Normalization is needed to make quantitative and qualitative indicators comparable.

### 3.2. Normalization

In step two, the indicators are normalized to facilitate the comparability and processing of BSI with different units. For normalization, three different equations are used. Equation (1) is applied if a low input value is seen as advantageous. For an advantageous high value, (2) is used whilst (3) is applied if a proximity to the target value ( $x_i^*$ ) is desired. The normalized value ( $x_i$ ) of the indicator (i) is calculated from the input value ( $x_{i,s}$ ) of the indicator (i), the upper threshold ( $U_i$ ) and the lower threshold ( $L_i$ ). The variables ( $u_i$ ) and ( $l_i$ ) determine values close to ( $x_i^*$ ). [17]

The thresholds are based on international conventions, norms, laws, guidelines, expert opinions and studies. The selected thresholds directly influence the resulting normalized values and thus the overall assessment results. Therefore, it is crucial to ensure topicality and reliability of the threshold values [17].

$$x_i = \begin{cases} 1, & x_{i,s} \leq L_i \\ \frac{U_i - x_{i,s}}{U_i - L_i}, & L_i < x_{i,s} < U_i \\ 0, & x_{i,s} \geq U_i \end{cases} \quad (1)$$

$$x_i = \begin{cases} 0, & x_{i,s} \leq L_i \\ \frac{x_{i,s} - L_i}{U_i - L_i}, & L_i < x_{i,s} < U_i \\ 1, & x_{i,s} \geq U_i \end{cases} \quad (2)$$

$$x_i = \begin{cases} 0, & x_{i,s} \leq L_i \\ \frac{x_{i,s} - L_i}{l_i - L_i}, & L_i < x_{i,s} < l_i \\ 1, & l_i \leq x_{i,s} \leq u_i \\ \frac{U_i - x_{i,s}}{U_i - u_i}, & u_i < x_{i,s} < U_i \\ 0, & x_{i,s} \geq U_i \end{cases} \quad (3)$$

After normalization, each indicator is represented by a dimensionless value between 0 and 1. A value below 0.5 has a negative impact on the sustainability of the indicator being considered, a value above 0.5 on the other hand has a positive impact. The closer

Table 3. Thresholds for normalization of BSI for sustainability assessment of wind power plants [20]

No.	Unit	$L_i$	$U_i$	Eq.	Explanation
B11	h/a	0	30	(1)	Threshold of max. permitted duration of shadowing per year and measuring point
B12	#/GWa	0	0.135	(1)	Average number of deaths through accidents in coal industry**
B13	qualitative	0	8	(2)	Self-defined, qualitative scale with 8 = complete social acceptance
B14	qualitative	0	8	(2)	Self-defined, qualitative scale with 8 = Very good situation in supply chain
B21	m <sup>2</sup> /GWh	0	12,600	(1)	Average land use for energy production from biomass**
B22	qualitative	0	8	(1)	Self-defined, qualitative scale with 8 = very high negative influence on landscape
B23	dB(A)	- 35	0	(1)	Distance from threshold of max. permitted sound emissions at the measuring point
B31	g/kWh	0	980	(1)	Average climate-relevant emissions of energy production from coal**
B32	#	0	96	(1)	Max. number of endangered species and presence of increased hazard
B33	m <sup>3</sup> /TJ	0	15,100	(1)	Average water usage and alteration in hydroenergy**
B34	qualitative	0	8	(1)	Self-defined, qualitative scale with 8 = very high negative impact on soil
B41	kg/MWh	0	11,271	(1)	Average material usage of energy production from lignite**
B42	%	0	100	(2)	Max. possible recycling quota
B43	qualitative	0	1	(2)	Self-defined, discrete scale for recycling approaches
B51	dmnl.	1	94	(2)	Average energy return on invest of hydroenergy**
B52	€-cent/kWh	0	21	(1)	Average cost of energy production in photovoltaics**
B53	%	0	100	(2)	Max. possible technical reliability
B61	%	0	13	(2)	Job growth in wind energy industry 2013 to 2014**
B62	qualitative	0	8	(2)	Self-defined, qualitative scale with 8 = complete participation, transparency and fairness
B63	qualitative	0	8	(2)	Self-defined, qualitative scale with 8 = complete political support
B64	dmnl.	0	7.53	(1)	Variation coefficient of deviation from prognosis for photovoltaics in 2014**
B71	€-cent/kWh	0	10.75	(1)	Average external costs of energy production from lignite**
B72	kg/MW	0	217.5	(1)	Average material usage of rare earths in gearless wind power plants
B73	qualitative	0	8	(2)	Self-defined, qualitative scale with 8 = very high future potential

the value is to 0.5, the lower the positive or negative impact. Table 3 shows the exemplary normalization thresholds for the BSI set for WPP (see Table 2), the corresponding units, explanations and equations [20].

### 3.3. Scales and Membership Functions

The next step involves assigning scales and membership functions to each indicator. By using normalized indicators, the interval of the scale for each indicator is naturally [0,1]. For each scale, there are several discrete sets that are described in linguistic terms and overlapping triangular membership functions. Generally, the number of discrete sets is not limited, although numbers between three and nine are considered as an appropriate trade-off between the level of detail and its processibility [17].

As Fuzzy Logic tries to emulate the human mind, that is better equipped to process linguistic rather than numerical data, each discrete set is described by a linguistic term. Those terms are based on linguistic values, such as *good* or *bad*, which can be extended using modifier terms, such as *not* or *very* [17].

Each triangular membership function, that represents a discrete set, is completely defined by five parameters (see Figure 4). Parameter (p) defines the location on the x-axis at which the maximum membership grade ( $\mu_{\max}$ ) is reached. The parameters ( $\alpha$ ) and ( $\beta$ ) indicate the left hand and right hand side distance from (p) at which the minimum membership grade ( $\mu_{\min}$ ) is reached. The three points (p,  $\mu_{\max}$ ), (p -  $\alpha$ ,  $\mu_{\min}$ ) and (p +  $\beta$ ,  $\mu_{\min}$ ) build a triangle. In normal fuzzy sets, ( $\mu_{\min}$ ) is 0 and ( $\mu_{\max}$ ) is 1. [17]

The terms and membership functions indicate the extent to which the input value is attributed to the discrete sets. The overlap between membership functions represents the attribution of input values to two adjacent sets (see Figure 5). Here, the discrete sets are represented by the linguistic terms *very bad*, *bad*, *neutral*, *good* and *very good* on a scale [0,1].

### 3.4. Rule Base

In step four, the rule base is defined. It specifies the aggregation of indicators and consists of simple IF-THEN rules, which connect the linguistic variables of the indicators to one another. The rules

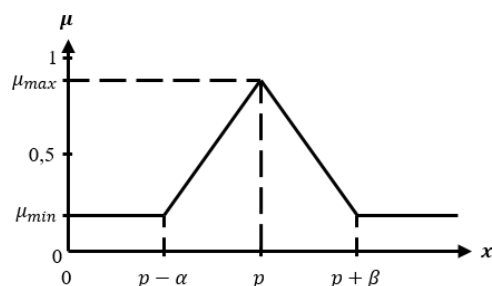


Figure 4. Triangular membership function

consist of two parts: the premise (IF) and the conclusion (THEN). In the *Fuzzy-IST*, in each aggregation step (j), ( $n_j$ ) indicators are combined.

Therefore, each premise consists of ( $n_j$ ) conditions – i.e. the assignment of input values to linguistic variables. The conditions are combined using operators of classic set theory, such as conjunction (AND) and adjunction (OR). The number of rules ( $S_R$ ) for all aggregation steps (k) is related to the number of discrete sets described in linguistic terms ( $m_j$ ) and the number of aggregated indicators ( $n_j$ ) per step [17]. If the number of discrete sets, and thus the number of linguistic terms and membership functions, is the same for all indicators of an aggregation step, the total number of rules is calculated as in (4).

$$S_R = \sum_{j=1}^k m_j^{n_j} \quad (4)$$

The number of rules increases with all three parameters, thus contributing to the rule explosion – i.e. the exponential growth of the rule base [17]. The level of detail increases with an increasing number of discrete sets for one aggregation step as facts are better represented. The same relates to the number of BSI representing sustainability. The amount of calculations – i.e. the number of aggregation steps – decreases with an increasing number of indicators being aggregated at once. In order to keep the number of rules controllable whilst maintaining a satisfactory level of detail, a trade-off has to be made between the three parameters ( $m_j$ ,  $n_j$ , k) [17].

The general form of a rule ( $R_p$ ) using conjunction is illustrated in (5). The linguistic Term ( $T_{i,p}$ ) of the indicator (i) is assigned to the normalized input value ( $x_i$ ). The conclusion comprises the linguistic term ( $T_{n+1,p}$ ) and the corresponding output value ( $x_{n+1}$ ) of the aggregated (sub-) index (n+1). For adjunction, the AND-operator in has to be exchanged with OR.

$$R_p: \text{IF } (x_1 \text{ is } T_{1,p}) \text{ AND } \dots \text{ AND } (x_n \text{ is } T_{n,p}), \\ \text{THEN } (x_{n+1} \text{ is } T_{n+1,p}) \quad (5)$$

In the *Fuzzy-IST*, as a trade-off between the level of detail and the effort required for calculation, indicators and indices are aggregated in pairs. Thus, the rule base for each aggregation step can be represented in a compact matrix form, as shown in Table 4 with the top value in each cell being ( $T_{n+1,p}$ ) and the bottom value being ( $x_{n+1,p}$ ).

The rule base shown in Table 4 is symmetrical, thus assigning the same weight to both inputs being aggregated. However, it is possible to represent differing preferences by using asymmetrical rule bases. An example is shown in

Table 5. Here, Input A is assigned a higher weight – i.e. a higher preference.

Table 5. Symmetrical rule base matrix for aggregation of two inputs

Rule base		Input B				
		VB	B	N	G	VG
Input A	VB	VB 0.00	B 0.25	B 0.25	N 0.50	N 0.50
	B	B 0.25	B 0.25	N 0.50	N 0.50	N 0.50
	N	B 0.25	N 0.50	N 0.50	N 0.50	G 0.75
	G	N 0.50	N 0.50	N 0.50	G 0.75	VG 1.00
	VG	N 0.50	N 0.50	G 0.75	VG 1.00	VG 1.00

Table 4. Asymmetrical rule base matrix for aggregation of two inputs

Rule base		Input B				
		VB	B	N	G	VG
Input A	VB	VB 0.00	B 0.25	B 0.25	N 0.50	G 0.75
	B	VB 0.00	B 0.25	N 0.50	N 0.50	G 0.75
	N	B 0.25	B 0.25	N 0.50	G 0.75	G 0.75
	G	B 0.25	N 0.50	N 0.50	G 0.75	VG 1.00
	VG	B 0.25	N 0.50	G 0.75	G 0.75	VG 1.00

Every weighting, if balanced or unbalanced, is subject to uncertainties and subjectivity. Methods, such as the AHP, aim to facilitate the deduction of objective weights. However, the weighting of sustainability indicators fuels controversial debates in the scientific community [4,18]. Therefore, the current version of the *Fuzzy-IST* uses symmetrical rule bases.

### 3.5. Fuzzification, Inference, Defuzzification

The next step is the fuzzification of input values – i.e. the translation of crisp inputs into linguistic terms using defined membership functions. A normalized input value ( $x_i$ ) is assigned to the linguistic term ( $T_{i,p}$ ) with a membership grade of

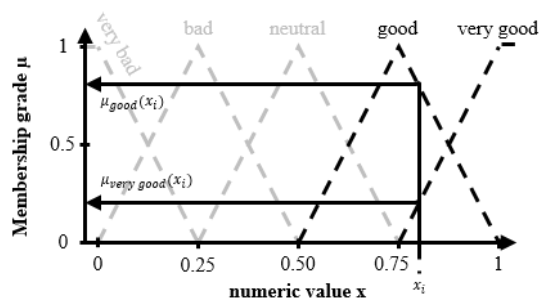


Figure 5. Fuzzification of indicator (i)

( $\mu_p(x_i)$ ). The membership grade is a real number in the interval [0,1] (see Figure 5).

The following step is the fuzzy inference – i.e. the actual calculation for the aggregation of BSI based on the rule base. In the *Fuzzy-IST*, the Takagi-Sugeno-Kang (TSK) inference is used. A hierarchical network of TSK fuzzy systems is monotonic across all aggregation stages – i.e. changes in lower stages lead to corresponding changes in upper stages [17]. For rules using conjunction, the algebraic product rule from (6) is used. For adjunction, an algebraic sum rule, as illustrated in (7), is used. If more than one rule assigns the same linguistic variable (T) to the input value ( $x_{n+1}$ ), the membership grade ( $\mu_T(x_{n+1})$ ) is calculated using (8).

$$\mu_{n+1,p}(x_{n+1}) = \prod_{i=1}^n \mu_{i,p}(x_i) \quad (6)$$

$$\mu_{n+1,p}(x_{n+1}) = 1 - \prod_{i=1}^n (1 - \mu_{i,p}(x_i)) \quad (7)$$

$$\mu_T(x_{n+1}) = \sum_{p: T_{n+1}=T} \mu_{n+1,p}(x_{n+1}) \quad (8)$$

In the next step, the defuzzification, crisp outputs are calculated from the membership values of the aggregated inputs. In the *Fuzzy-IST*, Singleton defuzzification is used. It provides clear and crisp output values with minimal calculation effort [18]. The output value ( $x_{n+1}$ ) is calculated as in (9), while ( $A_T$ ) is the numerical value of the linguistic variable (T) at ( $\mu_T = 1$ ).

$$x_{n+1} = \frac{\sum_T A_T \mu_T(x_{n+1})}{\sum_T \mu_T(x_{n+1})} \quad (9)$$

The three steps, fuzzification, inference and defuzzification, are repeated throughout the multistage hierarchical aggregation, from BSI, to SDI, to GSI, with the outputs of each stage being used as inputs for the next stage (see Figure 2). Additionally, in an analogous multistage hierarchical aggregation procedure the BSI are combined to the different life cycle phases.

### 3.6. Visualization

The sixth step is the comprehensive visualization of the results (see Figure 6). One part of the visualization is based on a simplified IST. The second part visualizes the sustainability values in different life cycle phases.

The fields representing the sustainability dimensions and their intersections are color-coded



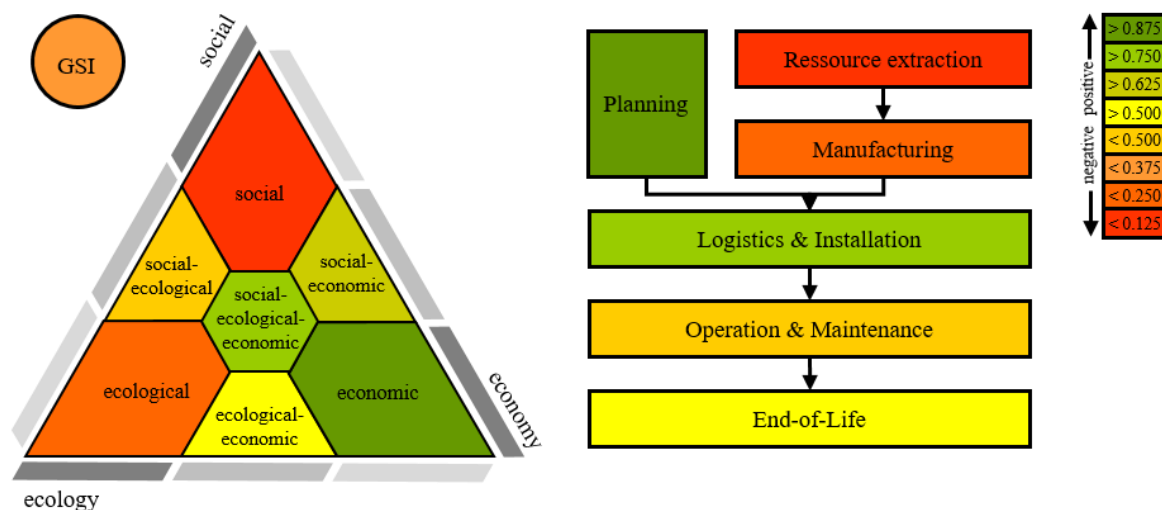


Figure 6. Visualization of the results in the color-coded simplified IST

*red – yellow – green* based on their calculated sustainability values. Low values (below 0.5) are coded *red – orange – dark yellow* and represent a negative influence on the sustainability value of the dimension being considered. The lower the calculated value, the more negative the influence on overall sustainability. High values (above 0.5) are coded *light yellow – light green – dark green* and represent a positive influence on the sustainability value of the dimension. The higher the calculated value, the more positive the influence on overall sustainability. Thus, advantageous and disadvantageous dimensions are easily identifiable and recommendations for actions can be quickly deduced. The color-coded circle in the top-left corner (see Figure 6) represents the overall sustainability – i.e. the value of the GSI.

The graphical representation of the sustainability values in the life cycle diagram uses the same color-code, as mentioned above. Again, advantageous and disadvantageous life cycle phases can be identified effortlessly and recommendations for action can be deduced.

#### 4. Results, Discussion and Conclusion

For the development of the new method, requirements (R1–R7) were determined based on the literature (see Table 1). By systemizing the BSI in the IST, all sustainability dimensions and their intersections are included in the assessment (R1). By using stepwise aggregation to create SDI and finally a GSI and representing the results of those calculations in the color-coded IST, all dimensions are made evaluable (R2). The definition phase for BSI is used to include aspects throughout the entire life cycle of the object under investigation. The BSI are also aggregated to the different life cycle phases and finally represented in a color-coded life cycle diagram (R3). By using a fuzzy logic approach,

quantitative, as well as qualitative indicators are included, and uncertainties and subjectivity are made processible (R4, R5). The effort required for data acquisition depends on the availability of data and the expertise of the user. The level of detail depends on the quality of the data, scales and membership functions (R6) [18]. The representation of results in the color-coded IST and life cycle diagram provides a structured, clear and understandable visualization of the results (R7).

The *Fuzzy-IST* has been applied to wind energy [20]. The exemplary sustainability assessment leads to an overall neutral classification result for the WPP being considered as it shows strengths and weaknesses in the various dimensions and life cycle phases. By making a trade-off between the number of aggregation steps and the number of rules in the rule base – i.e. a trade-off between level of detail and the complexity of calculations – information could be lost during aggregation. A starting point for further investigation is research into the influence of the number of aggregation steps and/or the number of linguistic terms on the results. In the past, the processing of complex mathematical operations was limited by computing power and technologies. However, in the light of recent developments, there is a chance for more complex problems to be solved, using existing and enhanced fuzzy logic approaches. The current model as applied in [20] does not consider interdependencies or weights of BSI and SDI. In order to fully integrate all sustainability dimensions and life cycle phases, further research into these aspects is needed.

Furthermore, the applicability for other RET is currently under investigation. Indicator sets for both photovoltaics and hydro power have been selected. Preliminary results show, that these sets partly overlap with the one for WPP. However, several BSI for WPP, such as *Shadowing* or *Sound Emissions*, are either not relevant for the sustainability

assessment of photovoltaics or hydro power or require differing thresholds for normalization, as legal requirements for other RET differ from those for WPP. On the one hand, individual BSI sets are needed to represent the specific characteristics of different RET. On the other hand, comparability of indicator sets must be ensured. This is facilitated by focusing on the sustainability dimensions, their intersections and the life cycle phases, as mentioned in Section 3.1.

Moreover, the transferability of the *Fuzzy-IST* to other domains, such as sustainability assessment of enterprises, is currently being investigated. For the assessment of companies of both, the automotive industry and the utility sector, again, specific indicator sets for the respective applications are required. However, the general process of the *Fuzzy-IST*, as illustrated in Section 3, can directly be transferred, indicating a broad applicability of the novel approach.

Another ongoing study shows promising results, indicating the adaptability of the approach to a completely different field – in this case performance measurement of demographic management in an automotive enterprise. Here, assessments of various measures are normalized, aggregated and visualized analogous to the process of the *Fuzzy-IST*. Thus, decision makers in the respective enterprise are provided with a solid basis for the deduction of options for action aimed at preparing the enterprise for demographic change.

To recap the results of the performed research, the *Fuzzy-IST* is suitable for investigating the positive and negative impacts of RET throughout their life cycle and in doing so overcoming deficits present in other approaches to sustainability assessment. The visualization of the results and corresponding numerical values provide comprehensive decision-making support. However, further research is needed to further improve and validate the *Fuzzy-IST*.

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