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Integrated life cycle sustainability assessment using fuzzy inference: a novel FELICITA model

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Abstract

This paper presents a new FELICITA (Fuzzy Evaluation for Life Cycle Integrated Sustainability Assessment) model which integrates life cycle assessment (LCA), life cycle costing (LCC) and social LCA (SLCA) into a fuzzy inference framework. The input data for the model are sustainability indicators estimated through LCA, LCC and SLCA. These are first normalised, then fuzzified, processed using the Mamdani fuzzy inference system and finally defuzzified using the centre-of-area method. This results in three composite indicators, one each for LCA, LCC and SLCA, providing crisp numerical values. This process is then repeated, using the composite indicators as the inputs to obtain an overall life cycle sustainability indicator for each alternative being considered in the decision-making process. These results are used to rank alternatives of interest and identify the most sustainable option(s). The application of the model is illustrated by a case study considering different electricity technologies. FELICITA is particularly useful in helping deal with imprecise (fuzzy) information often encountered in sustainability assessments and it can be used as a practical tool for decision making and policy development related to sustainable development.

Keywords: fuzzy logic, life cycle assessment, life cycle costing, life cycle sustainability assessment, social life cycle assessment

1. Introduction

Assessing sustainability is a complex task requiring an integrated life cycle approach and consideration of environmental, economic and social issues (Azapagic & Perdan, 2005a; Kloeppfer, 2008). Life cycle assessment (LCA), life cycle costing (LCC) and social LCA (SLCA) are suitable tools for evaluating environmental, economic and social sustainability of different systems and their use is growing. However, their integration into a common methodological framework is still scarce. One of the reasons for that is the nature of the indicators used in these tools, with some being quantitative and others qualitative, making their aggregation difficult (Zamagni, 2012). A further issue is the ambiguous or imprecise information often associated with data, sustainability indicators and stakeholder value judgements (Azapagic & Perdan, 2005b). Moreover, multiple, often conflicting indicators make it difficult to compare and rank different alternatives of interest.

Multi-criteria decision analysis (MCDA) can help to deal with the latter issue and has proved a useful tool in sustainability evaluations. However, most studies focus on using MCDA in LCA, for example (Domingues, et al., 2015; Zanghelini, et al., 2018; Boggia, et al., 2018). The need to deal with imprecise, uncertain values has led to the utilisation of fuzzy logic in sustainability assessments, but has also so far been confined mainly to LCA applications, e.g. (Weckenmann & Schwan, 2001; Liu, et al., 2012). A number of studies also used fuzzy mathematical programming (Ilagan & Tan, 2011; Pishvaei & Razmi, 2012), fuzzy analytic

hierarchy process (Chan, et al., 2013; Yi, et al., 2013; Zheng, et al., 2011) and fuzzy TOPSIS (Kucukvar, et al., 2014; Ulukan & Kop, 2009; Wang, et al., 2014). Another notable group of studies has used fuzzy numbers and arithmetic inference (Groen, et al., 2014; Heijungs & Tan, 2010; Reza, et al., 2013). A few studies considered fuzzy inference (Herva, et al., 2012; Rezvan, et al., 2014), mainly as a way of predicting environmental impacts through adaptive neuro-fuzzy inference systems (Khoshnevisan, et al., 2014a; Khoshnevisan, et al., 2014b; Lee, et al., 2012) or to aggregate environmental impacts and facilitate life cycle impact assessment (Afrinaldi & Zhang, 2014; González, et al., 2002; Rahimi & Weidner, 2008). Fuzzy logic has also been used to help deal with non-stochastic uncertainty and integrate environmental with economic and social aspects (Kouloumpis, et al., 2008) but without incorporating a life cycle approach. As far as we are aware, there are no studies that have used fuzzy logic for sustainability assessment from a life cycle perspective.

To address this gap, this paper proposes a novel FELICITA (Fuzzy Evaluation for Life Cycle Integrated Sustainability Assessment) model which uses fuzzy inference to help deal with imprecise and uncertain information in sustainability assessments. The fuzzy inference approach has been selected because stakeholders and decision makers can related better to the verbal IF-THEN rules than mathematical expressions that require a more precise set of values. Underpinned by a life cycle approach, the model brings together LCA, LCC and SLCA to enable integrated life cycle sustainability assessments (LCSA) of technologies, products or services. The application of the model is illustrated by a case study assessing the sustainability of different electricity-generation options.

After a brief overview of fuzzy inference, the next section describes the FELICITA model. The application of the model is illustrated in Section 3 and the conclusions are drawn in Section 4.

2. Methods

2.1. Fuzzy inference

Fuzzy logic is used to describe the ‘degrees of truth’ when the values of variables cannot be determined exactly, as often encountered in sustainability assessments. These variables are termed ‘fuzzy’ and linguistic (descriptive) instead of numerical values are used to define them. For example, the ambient temperature can be characterised as hot if it is 30 °C or above and cold if it is 0 °C. In classical (Boolean) logic, the ‘truth’ values of temperature can only be cold or hot, expressed as 0 and 1, respectively. Thus, Boolean logic cannot deal with ‘half-truths’. However, it is often necessary to deal with the values in between – for instance, if the temperature is 25 °C, it is not cold but it is also not as hot as 30 °C. Fuzzy logic uses functions, called membership functions, whose values range from 0 to 1, to denote the ‘degree of truth’ for the input variables. For the above example, the membership function $\mu(t)$ can be defined as follows:

$$\mu(t) = \begin{cases} 0, & 0 \leq t < 20 \\ 0.1 \cdot (t - 20), & 20 \leq t \leq 30 \\ 1, & t \geq 30 \end{cases} \quad (1)$$

where t is temperature. According to eqn. (1), all temperatures below 20 °C will have a degree of membership of 0 and those equal to or higher than 30 °C a degree of membership of 1. The temperatures in between will be equal to $0.1 \cdot (t-20)$; for instance, the fuzzy value for the temperature of 25 °C is equal to 0.5. This process of allocating a specific degree of membership of a linguistic value to the input values is known as fuzzification.

Fuzzy inference can be used as an aid in situations described in the example of the ambient temperature, by applying fuzzy logic to convert imprecise inputs into crisp outputs and aid decision making. In a fuzzy inference system (FIS), the input values are first fuzzified by applying membership functions and a set of rules, called the rule base, usually in the form “IF-THEN”. The result is a fuzzy set with specific degrees of membership for the output linguistic variable that needs to be processed in the next and last step of the FIS, which is called defuzzification. Here, the output fuzzy set is defuzzified to provide crisp numerical outputs that are easier to interpret than their fuzzy equivalents. There are many fuzzy inference systems (FIS), with Mamdani being most widely used owing to its simple ‘min-max’ operations (Mamdani, 1977). Many approaches are also available for the defuzzification process but the centre-of-area (Sugeno, 1985) and mean of maxima methods are most often applied (Zimmerman, 2001).

2.2. The FELICITA model

The FELICITA model uses fuzzy inference to help evaluate life cycle sustainability of different options or alternatives. As outlined in Figure 1, it consists of the following three main steps:

1. preparation of inputs;
2. aggregation of individual sustainability indicators into composite LCA, LCC and SLCA indices and ranking of alternatives; and
3. aggregation of composite indicators into an overall life cycle sustainability index and ranking of alternatives.

The above steps are described in more detail in the next sections. The model was developed using the Fuzzy Logic Design module in Matlab (The Mathworks (Inc), 2016) and is available from the authors on request.

2.2.1. *Step 1: Preparation of inputs*

The first step of the model involves preparation of the inputs for the process that follows. The inputs represent the sustainability indicators estimated through LCA, LCC and SLCA. They can first be subjected to a logarithmic transformation, particularly if the values of the sustainability indicators for different alternatives being considered span several orders of magnitude; however, this is optional (and thus not shown in Figure 1). This is followed by normalisation of input data based on a linear interpolation between the most and the least desirable values for each sustainability indicator considered. These values can be obtained by consulting experts, policy targets and/or other relevant sources of information. Alternatively, they can be based on the minimum or maximum values in the range, depending on the desirable value for different sustainability indicators. For example, the desirable value for global warming potential will always be the lowest in the range while that for employment will be the highest. If the lowest value is desirable, then the normalised value $x_{a,c}$ of indicator c for alternative a can be calculated using the following equation:

$$x_{a,c} = \frac{c_{\max} - z_{a,c}}{c_{\max} - c_{\min}} \quad (2)$$

where $c_{\max}$ is the maximum value for that indicator for all the alternatives considered, $z_{a,c}$ is the actual value of the indicator and $c_{\min}$ the minimum value for that indicator for all the alternatives considered. If the desirable value is the maximum in the range, the normalised value is equal to:

$$x_{a,c} = \frac{z_{a,c} - c_{\min}}{c_{\max} - c_{\min}} \quad (3)$$

Figure 1 Schematic representation of the FELICITA model

2.2.2. Step 2: Composite LCA, LCC and SLC indicators and ranking of alternatives

The second step involves three stages: fuzzification, fuzzy inference and defuzzification (Figure 1), followed by ranking of alternatives on LCA, LCC and SCLA. As mentioned in Section 2.1, fuzzification (step 2a in Figure 1) relies on predefined membership functions of the form defined in eqn. (1) to convert the normalised indicators into fuzzy values. In the base configuration of the model, triangular membership functions (TMF) are used; it is also possible to use other functions, such as Gaussian membership functions (GMF). This is followed by the application of a FIS to aggregate the individual sustainability indicators into composite LCA, LCC and SLCA indices, based on predefined IF-THEN rules and linguistic values (step 2b). The FELICITA model applies the Mamdani FIS using the “AND” operator, defined as ‘minimum’. The computed consequences are then aggregated using the ‘maximum’ operator, assuming that all rules have equal weight of 1; for more details on the Mamdani method, see (Zimmerman, 2001). For example, if there are two LCA indicators used as inputs, e.g. global warming potential and depletion of resources, they are first fuzzified using the membership functions to describe their performance using the appropriate linguistic values (e.g. ‘Bad’, ‘Average’ and ‘Good’). The “AND” operator is then applied to obtain a composite LCA indicator describing the overall performance on both indicators. For instance, if both indicators are ‘Good’, the composite LCA indicator can be described as ‘Very good’. However, if both are ‘Bad’, then the composite indicator is ‘Very bad’, etc. The model uses a symmetric rule base for the inference which means that the number of rules that

give the linguistic value ‘Good’ as an outcome is the same as the ones that give the outcome ‘Bad’.

The result of this process is a fuzzy set for each composite LCA, LCC and SLCA indicator which then has to be defuzzified (step 2c) to return a crisp numerical value for each composite indicator for each alternative. The defuzzification method used in the FELICITA model is the centre of area (COA) which is defined by eqn. (4) (Zimmerman, 2001):

$$u^{COA} = \frac{\int_u^U u \cdot \mu(u) du}{\int_u^U \mu(u) du} \quad (4)$$

where u^{COA} is the crisp value derived as the output of the defuzzification process for each composite indicator, $\mu(u)$ is the membership function for each linguistic value (e.g. ‘Very bad’, ‘Bad’, ‘Average’, ‘Good’ and ‘Very good’) of the output fuzzy set and $u \in U$ is the maximum degree of membership which belongs to the set U of all the degrees of membership that correspond to the specific linguistic value.

The alternatives considered in the decision-making process can then be ranked on their environmental, economic and social sustainability based on the results obtained for the composite LCA, LCC and SLCA indicators, respectively (step 2d). This helps to understand the relative performance of different alternatives for different sustainability dimensions and identify improvement opportunities.

2.2.3. Step 3: Overall LCSA indicator and ranking of alternatives

This step is similar to step 2, but rather than using the full set of LCA, LCC and SLCA indicators, the inputs here are the crisp numerical values for the composite LCA, LCC and SLCA indices. These are first fuzzified and then aggregated into an overall LCSA index using the membership functions and linguistic values. These differ from those determined in step 2 in that they use five linguistic values for the fuzzification of input values (‘Very bad’, ‘Bad’, ‘Average’, ‘Good’ and ‘Very good’) instead of three (‘Bad’, ‘Average’ and ‘Good’). As a result, the number of rules used increases from $3^3=27$ to $5^3=125$. This is followed by defuzzification to obtain crisp numerical values for the LCSA indicator for each alternative, enabling their ranking for the overall life cycle sustainability.

Further details on the methodology and mathematical formulations underpinning the estimations in the above three steps can be found in the next section which illustrates how FELICITA can be applied in practice. A case study related to a sustainability assessment of different electricity options is used for these purposes.

3. Applying FELICITA: A case study

For illustration, five sources of electricity are considered: coal, natural gas, nuclear, offshore wind and solar photovoltaics (PV). The input data for FELICITA comprise the results of LCA, LCC and SLCA which have been sourced from Stamford and Azapagic (2012). The following environmental, economic and social indicators are considered (for definitions, see (Stamford & Azapagic, 2012)):

- LCA: recyclability of power plant construction materials, global warming potential, ozone layer depletion potential, acidification potential, eutrophication potential and photochemical ozone creation potential;
- LCC: capital cost, operating & maintenance costs and fuel cost; and
- SLCA: worker injuries, large accident fatalities and direct employment.

Figure 2 depicts the decision tree developed in the FELICITA model for the sustainability evaluation of the electricity options.

Figure 2 The FELICITA decision tree for the sustainability assessment of electricity options

3.1. Step 1: Preparation of inputs

In this case study, preparation of inputs involves use of LCA, LCC and SLCA data from a published source (Stamford & Azapagic, 2012). The selection of the indicators mentioned in the previous section was guided by two principles: to keep the illustration simple and yet to demonstrate the capability of the model. For simplicity, only three indicators are considered each for LCC and SLCA and for the capability, a larger number of LCA indicators is included to show the ability of the model to deal with a larger number of inputs. Through the hierarchical structure applied, the number of the inputs for different sustainability aspects does not influence the LCSA results. The original input data are shown in Table 1.

The first step was to identify the most and the least desirable values, by finding the minimum and maximum values among all the alternatives for each criterion, as shown in the last two columns of Table 1. It should be noted that for the impacts ‘Recyclability’ and ‘Direct employment’ the most desirable value is the maximum and the least desirable the minimum value, while for the rest of the impacts, it is the opposite. Using eqn. (3) for the impacts

‘Recyclability’ and ‘Direct employment’ and eqn. (2) for the rest of the impacts the sustainability indicators were normalised to obtain the values in Table 2. Note that there was no logarithmic transformation of data normalised directly, prior to the normalisation as this is an optional step (see Section 2.2.1).

Table 1 Input data in step 1 of the FELICITA model: LCA, LCC and SLCA indicators for different electricity technologies

Impacts	Coal	Natural gas	Nuclear	Offshore wind	Solar PV	Min	Max
Recyclability (ratio)	0.84	0.89	0.81	0.99	1.00	0.81	1.00
Global warming potential (kg CO ₂ -Equiv./kWh)	1.07	0.38	0.01	0.01	0.09	0.01	1.07
Ozone layer depletion potential (µg R11-Equiv./kWh)	4.25	12.70	0.54	0.60	17.50	0.54	17.50
Acidification potential (g SO ₂ -Equiv./kWh)	1.78	0.148	0.044	0.0829	0.436	0.044	1.78
Eutrophication potential (g PO ₄ -Equiv./kWh)	0.22	0.06	0.01	0.06	0.07	0.01	0.22
Photochemical oxidants creation potential (mg C ₂ H ₄ -Equiv./kWh)	140	27.3	4.96	8.49	67.2	4.96	140
Capital cost (£/MWh)	42.30	11.20	75.00	109.40	282.62	11.20	282.62
Operating and maintenance costs (£/MWh)	11.95	6.00	14.30	36.70	19.35	6.00	36.70
Fuel cost (£/MWh)	20.10	48.50	5.30	0.00	0.00	0.00	48.50
Worker injuries (injuries/TWh)	4.50	0.54	0.59	2.30	4.84	0.54	4.84
Large accident fatalities (fatalities/PWh)	20.70	5.08	0.00	0.77	1.14	0.00	20.70
Direct employment (person-years/TWh)	55.60	26.60	55.90	311.00	537.00	26.60	537.00

Table 2 Normalised sustainability indicators for the fuzzification process in step 2 of the FELICITA model

Impacts	Coal	Natural gas	Nuclear	Offshore wind	Solar PV
Recyclability	0.82	0.90	0.85	0.37	0.00
Global warming potential	0.19	0.65	0.84	0.68	0.51
Ozone layer depletion potential	0.01	0.20	0.91	0.77	0.58
Acidification potential	0.12	1.00	0.28	0.38	0.37
Eutrophication potential	0.54	0.38	0.87	0.81	0.46
Photochemical oxidants creation potential	0.30	0.58	0.85	0.74	0.53
Capital cost	0.89	1.00	0.76	0.64	0.00
Operating and maintenance costs	0.81	1.00	0.73	0.00	0.57
Fuel cost	0.59	0.00	0.89	1.00	1.00
Worker injuries	0.08	1.00	0.99	0.59	0.00
Large accident fatalities	0.00	0.75	1.00	0.96	0.94
Direct employment	0.97	0.99	0.00	1.00	0.90

3.2. Step 2: Composite LCA, LCC and SLCA indicators and ranking of alternatives

As mentioned in Section 2.2.2, the FIS used to aggregate the sustainability indicators into the composite LCA, LCC and SLCA indicators utilises a TMF, symmetric rule base for the inference and three linguistic values defined as ‘Bad’, ‘Average’ and ‘Good’. For the fuzzification, the membership functions for these linguistic values are defined by the following equations, based on eqn. (1):

$$\mu_{Bad}(x) = \begin{cases} 1, & x \leq 0 \\ -2 \cdot x + 1, & 0 < x < 0.5 \\ 0, & x \geq 0.5 \end{cases} \quad (5)$$

$$\mu_{Average}(x) = \begin{cases} 0, & 0 \leq x \\ 2 \cdot x, & 0 < x \leq 0.5 \\ -2 \cdot x + 2, & 0.5 \leq x < 1 \\ 0, & x \geq 1 \end{cases} \quad (6)$$

$$\mu_{Good}(x) = \begin{cases} 0, & x \leq 0.5 \\ 2 \cdot x - 1, & 0.5 < x < 1 \\ 1, & x \geq 1 \end{cases} \quad (7)$$

Based on these equations, the normalised input for each sustainability indicator has been transformed into a fuzzy set by obtaining the corresponding membership function for every linguistic value. For example, for the sustainability indicator ‘Capital cost’, the normalised input for coal electricity is 0.89 (see Figure 3) and the result of the fuzzification is the fuzzy set:

$$Capital\ cost_{coal} = \{(Bad, 0.00), (Average, 0.23), (Good, 0.77)\}$$

Figure 3 Example fuzzification graph for the indicator ‘Capital cost’

Tables with the results of the fuzzification process for all the sustainability indicators can be found in Table S1 of the Supplementary Information (SI).

Their fuzzy outputs are in turn defined by five linguistic values: ‘Very bad’, ‘Bad’, ‘Average’, ‘Good’ and ‘Very good’. Using five linguistic values for the outputs rather than three allows for a finer distinction between the inference process fuzzy outputs of each alternative. This becomes more apparent from Figure 4 that shows that each linguistic value triangle base is half the length that of the three linguistic value set.

Figure 4 Graph for five linguistic values set

Concerning the FIS, firstly an ‘IF-THEN’ rule base was created for each composite indicator. This rule base contains rules such as: IF indicator ‘Capital cost’ is ‘Bad’ and indicator ‘Operation & maintenance costs’ is ‘Bad’ and indicator ‘Fuel cost’ is ‘Bad’, THEN the ‘LCC’ composite indicator is ‘Very bad’. For LCC and SLCA which have three inputs (indicators), the rule base consists of $3^3 = 27$ rules, as the one presented in Table 3. Similar rule bases were used for the LCA and SLCA composite indicators and these results can be

found in Table S2 in the SI. It is worth noting that the LCA composite indicator has six inputs instead of three and, hence, the rule base consists of $3^6 = 729$ rules instead of 27. Rules r can be described by the following equation:

$$\text{Rule } r: \text{IF } x_1 \text{ is } A_1^{j_1} \text{ and } x_2 \text{ is } A_2^{j_2} \text{ and ... and } x_n \text{ is } A_n^{j_n}, \text{ THEN } u \text{ is } A^j \quad (8)$$

where x_i is the normalised value for the sustainability indicator (linguistic variable) i , $A_i^{j_i}$ is the j th term ('Bad', 'Average', 'Good') of linguistic variable i that corresponds to the membership function $\mu_i^{j_i}(x_i)$ and A^j is the j th term ('Very bad', 'Bad', 'Average', 'Good', 'Very good') of linguistic variable (LCA, LCC or SLCA) that corresponds to the membership function $\mu^j(u)$.

Table 3 Three-input rule base for LCC

Rule r	IF the 'Capital cost' is:	And the 'Operation & maintenance' cost is:	And the 'Fuel cost' is	THEN the LCC is
1	Bad	Bad	Bad	Very bad
2	Bad	Bad	Average	Very bad
3	Bad	Bad	Good	Bad
4	Bad	Average	Bad	Very bad
5	Bad	Average	Average	Bad
6	Bad	Average	Good	Average
7	Bad	Good	Bad	Bad
8	Bad	Good	Average	Average
9	Bad	Good	Good	Good
10	Average	Bad	Bad	Very bad
11	Average	Bad	Average	Bad
12	Average	Bad	Good	Average
13	Average	Average	Bad	Bad
14	Average	Average	Average	Average
15	Average	Average	Good	Good
16	Average	Good	Bad	Average
17	Average	Good	Average	Good
18	Average	Good	Good	Very good
19	Good	Bad	Bad	Bad
20	Good	Bad	Average	Average
21	Good	Bad	Good	Good
22	Good	Average	Bad	Average
23	Good	Average	Average	Good
24	Good	Average	Good	Very good
25	Good	Good	Bad	Good
26	Good	Good	Average	Very good
27	Good	Good	Good	Very good

Based on the fuzzification undertaken in Step 1 before, the degree of membership of the input values in the rule antecedent was then determined (Zimmerman, 2001). Using Mamdani 'AND' operator, defined as 'minimum', the degree of match a_r of rule r is calculated as:

$$a_r = \min_{i=1, \dots, n} \{ \mu_i^{j_i}(x_i^{input}) \} \quad (9)$$

where $\mu_i^{j_i}(x_i^{input})$ is the degree of membership of the specific value of x_i^{input} that is used as input for the specific rule r and the j th term of indicator i .

Applying eqn. (5) - (9) for LCC gives the degrees of membership and the degrees of match shown in Table 4. The values for SLCA and LCA were calculated in a similar manner.

Table 4 Degrees of membership, degrees of match and linguistic value outputs for the LCC input indicators related to coal electricity

Rule r	$\mu_{capital\ cost}^{j_{capital\ cost}}$	$\mu_{operation\ cost}^{j_{operation\ cost}}$	$\mu_{fuel\ cost}^{j_{fuel\ cost}}$	a_r	Linguistic value output j_{LCC}
1	0.00	0.00	0.00	0.00	Very bad
2	0.00	0.00	0.83	0.00	Very bad
3	0.00	0.00	0.17	0.00	Bad
4	0.00	0.39	0.00	0.00	Very bad
5	0.00	0.39	0.83	0.00	Bad
6	0.00	0.39	0.17	0.00	Average
7	0.00	0.61	0.00	0.00	Bad
8	0.00	0.61	0.83	0.00	Average
9	0.00	0.61	0.17	0.00	Good
10	0.23	0.00	0.00	0.00	Very bad
11	0.23	0.00	0.83	0.00	Bad
12	0.23	0.00	0.17	0.00	Average
13	0.23	0.39	0.00	0.00	Bad
14	0.23	0.39	0.83	0.23	Average
15	0.23	0.39	0.17	0.17	Good
16	0.23	0.61	0.00	0.00	Average
17	0.23	0.61	0.83	0.23	Good
18	0.23	0.61	0.17	0.17	Very good
19	0.77	0.00	0.00	0.00	Bad
20	0.77	0.00	0.83	0.00	Average
21	0.77	0.00	0.17	0.00	Good
22	0.77	0.39	0.00	0.00	Average
23	0.77	0.39	0.83	0.39	Good
24	0.77	0.39	0.17	0.17	Very good
25	0.77	0.61	0.00	0.00	Good
26	0.77	0.61	0.83	0.61	Very good
27	0.77	0.61	0.17	0.17	Very good

Therefore, at this point, the LCC output for each electricity option is a fuzzy set that consists of the linguistic values ('Very bad', 'Bad', 'Average', 'Good' and 'Very Good') but not of a unique degree of membership corresponding to each of these. For example, the degree of membership in the linguistic value 'Good' for the LCC of coal can take the values: 0, 0.17, 0.23 and 0.39. That is dealt with one remaining calculation which is the application of the maximum operator using eqn. (10):

$$\mu^{j_{LCC}} = \max\{a_r^{j_{LCC}}\} \quad (10)$$

where $\mu^{j_{LCC}}$ is the degree of membership in the linguistic value of LCC, j_{LCC} , which can be 'Very bad', 'Bad', 'Average', 'Good' and 'Very good' and $a_r^{j_{LCC}}$ is the degree of match for every rule r that gives j_{LCC} .

That gives as an output a fuzzy set with the five linguistic variables and a unique degree of membership, which in the example of LCC for coal electricity is:

$$\widetilde{LCC} = \{(Very\ bad, 0), (Bad, 0), (Average, 0.23), (Good, 0.39), (Very\ good, 0.61)\}$$

The fuzzy sets that result from the application of the FIS for LCA, LCC and SLCA for each alternative can be found in Table S3 in the SI.

Finally, in order to get a crisp value as an output for each composite indicator LCA, LCC and SLCA, the COA defuzzification method was applied using eqn. (4). As illustrated in Figure 5, during the defuzzification process, the degrees of membership for the respective linguistic variables are used to find their corresponding values on the x-axis. For example, the 0.61 membership degree of the linguistic variable ‘Very good’ corresponds to a value of 0.9 on the x-axis. The COA method requires the calculation of the shaded area and the centre of area as well. For this reason the whole shaded area, defined by the degrees of membership for the respective linguistic variables as explained before, is broken down into right triangles and rectangular whose surface and centre of gravity are easy to calculate. For the eight distinct shapes shown in Figure 5, let us denote the area of each shape as A_i , and the coordinate of the centre of gravity for x-axis as C_i . Then, based on eqn.(4), the defuzzified value for LCC is calculated as follows:

$$LCC_{Coal} = \frac{\sum_{i=1}^8 C_i * A_i}{\sum_{i=1}^8 A_i} = 0.71$$

Figure 5 Defuzzification graph based on the five linguistic values of LCC for coal electricity shown in Figure 4.

The results for all the indicators are shown in Table 5 where the electricity options are ranked for the composite LCA, LCC and SLCA indicators. As indicated in the table, nuclear power ranks top for two of the three indicators, scoring 0.92 for LCA and 0.74 for SLCA, out of the maximum value of 1. Offshore wind follows closely for these two indicators, with the difference in their respective scores being small: 0.05 for LCA and 0.01 for SLCA. Natural gas is the best alternative for LCC (0.75), followed narrowly by coal and nuclear (0.71 each). The worst options are coal for LCA and SLCA and solar PV for LCC. While solar PV is only 0.04 points behind the second worst option (offshore wind), coal is decidedly worse than gas electricity, with a difference in their scores of 0.4 for LCA and 0.5 for SLCA. This allows decision makers to identify sustainability aspects for which different alternatives could be improved. The scores can also be used to find out the relative difference between them and test the robustness of the conclusions. For example, although nuclear power ranks top for SLCA, its score (0.74) is quite close to offshore wind (0.73) and solar PV (0.71) so that further improvements in social sustainability may be needed for nuclear to ensure its ranking for social sustainability is robust. It is worth bearing in mind that these findings are used here for illustrative purposes rather than a discussion on the actual sustainability of different technologies – the results would be different for different indicators considered.

Table 5 Ranking of electricity options for the composite LCA, LCC and SLCA indicators (step 2 in FELICITA) as well as the overall LCSA indicator (step 3)

Composite LCA indicator	Composite LCC indicator	Composite SLCA indicator	Overall LCSA indicator
1. Nuclear (0.92)	1. Natural gas (0.75)	1. Nuclear (0.74)	1. Nuclear (0.80)
2. Offshore wind (0.87)	2. Coal (0.71)	2. Offshore wind (0.73)	2. Offshore wind (0.73)
3. Solar PV (0.64)	3. Nuclear (0.71)	3. Solar PV (0.71)	3. Solar PV (0.634)
4. Natural gas (0.60)	4. Offshore wind (0.58)	4. Natural gas (0.63)	4. Natural gas (0.627)
5. Coal (0.20)	5. Solar PV (0.54)	5. Coal (0.13)	5. Coal (0.38)

3.3. Step 3: Overall LCSA indicator and ranking of alternatives

In the final step, FIS is applied again to aggregate the composite LCA, LCC and SLCA indicators into an overall life cycle sustainability assessment (LCSA) indicator. Tables that show the rule base used as well as the resulting output fuzzy set for LCSA can be found in Tables S2 and S3 in the SI. The same linguistic values for the outputs obtained in step 2 ('Very bad', 'Bad', 'Average', 'Good' and 'Very good') are used in order to facilitate the comparison with the results obtained for LCA, LCC and SLCA in the previous steps. This enables the ranking of the electricity options based on their overall sustainability as given in Table 5. The best option overall is nuclear power, scoring 0.80. This is due to its strong performance for the environmental and social aspects considered in the study. The next best option is offshore wind with 0.73. Solar PV and natural gas are very close in the third and the fourth position, with solar scoring 0.634 and natural gas 0.627, while electricity from coal is the worst alternative with a score of 0.38.

As can also be seen in Table 5, the ranking of the options for the LCSA is the same as for LCA and SLCA but not for LCC, which means that an alternative could be ranking first for the overall sustainability even if it is not the best option for all life cycle aspects. For example, nuclear power is ranked first for the overall as well as for the environmental and social sustainability, but comes third for the economic aspect. This is possible because the score for the third position for the LCC (0.71) is very close to the scores achieved by other technologies for the second (0.71) and the first position (0.75). On the contrary, the score that brings nuclear to the first position for LCA (0.98) is much higher from the second (0.87) and third (0.64) position.

3.4. Sensitivity analysis

The following aspects of the FELICITA model can be changed to accommodate different user requirements: the type of the membership function, the rule base and the defuzzification method. The effects of these changes on the results of the case study are explored in the following sections to demonstrate further features of the FELICITA model.

3.4.1. *Different types of membership function*

As mentioned earlier, the basic configuration of the model uses TMF but it is also possible to use GMF within FELICITA. The results obtained using the latter are compared to the TMF results in Table 6. It can be seen that the LCA rankings remain the same for both functions but they differ for LCC for the top three positions and SLCA for the top two. However, the difference in the scores between the two functions is relatively small (<0.03). The ranking remains the same for LCSA for the first two and the last positions, with the only change found for the third and fourth places, but again the difference in the scores is small (<0.02). Thus, for this particular case study, the use of TMF or GMF does not make a difference in the outcome of the analysis. However, this may not apply for other systems being evaluated.

Hence, it is recommended to carry out sensitivity analysis routinely to examine the effect on the results of using different membership functions.

Table 6 Ranking of electricity options using Triangular and Gaussian membership functions

LCA <i>TMF^a</i>	<i>GMF^b</i>	LCC <i>TMF^a</i>	<i>GMF^b</i>	SLCA <i>TMF^a</i>	<i>GMF^b</i>	LCSA <i>TMF^a</i>	<i>GMF^b</i>
1.Nuclear (0.92)	1.Nuclear (0.86)	1. Natural gas (0.75)	1. Coal (0.74)	1. Nuclear (0.74)	1. Offshore wind (0.73)	1.Nuclear (0.80)	1.Nuclear (0.74)
2.Offshore wind (0.87)	2.Offshore wind (0.83)	2. Coal (0.71)	2. Nuclear (0.73)	2. Offshore wind (0.73)	2. Nuclear (0.71)	2.Offshore wind (0.73)	2.Offshore wind (0.72)
3.Solar PV (0.64)	3.Solar PV (0.64)	3. Nuclear (0.71)	3. Natural gas (0.71)	3. Solar PV (0.71)	3. Solar PV (0.70)	3.Solar PV (0.63)	3.Natural gas (0.65)
4.Natural gas (0.60)	4.Natural gas (0.63)	4. Offshore wind (0.58)	4. Offshore wind (0.53)	4. Natural gas (0.63)	4. Natural gas (0.62)	4.Natural gas (0.63)	4.Solar PV (0.64)
5.Coal (0.20)	5.Coal (0.21)	5. Solar PV (0.54)	5. Solar PV (0.50)	5. Coal (0.13)	5. Coal (0.15)	5.Coal (0.38)	5.Coal (0.41)

^a Triangular membership function, ^b Gaussian membership function.

3.4.2. Different rule bases

As also mentioned earlier, a symmetric rule base was used for the inference. Here we consider if and how the results might change if the optimistic or pessimistic rule base is used instead. The former provides more ‘Good’ than ‘Bad’ outcomes and the latter does the opposite. Using different rule bases allows decision makers and stakeholders to express different preferences according to their value system (neutral, optimistic or pessimistic), thus helping to tailor the decision analysis to suit the participants.

The results in Table 7 indicate that using the optimistic and symmetric rule bases leads to the same rankings of the electricity options but those for the pessimistic base differ, mainly for the top two positions (nuclear and offshore wind). As expected, the scores for the pessimistic rule base are generally lower and those for the optimistic are higher than for the symmetric base.

Table 7 Ranking of electricity options for different rule bases

Assessment type	Rule base	Electricity options				
LCA	Symmetric	1. Nuclear (0.92)	2. Offshore wind (0.87)	3. Solar PV (0.64)	4. Natural gas (0.60)	5. Coal (0.20)
	Optimistic	1. Nuclear (0.92)	2. Offshore wind (0.87)	3. Solar PV (0.72)	4. Natural gas (0.68)	5. Coal (0.23)
	Pessimistic	1. Offshore wind (0.83)	2. Nuclear (0.75)	3. Solar PV (0.62)	4. Natural gas (0.58)	5. Coal (0.09)
LCC	Symmetric	1. Natural gas (0.75)	2. Coal (0.71)	3. Nuclear (0.71)	4. Offshore wind (0.58)	5. Solar PV (0.54)
	Optimistic	1. Natural gas (0.92)	2. Coal (0.82)	3. Nuclear (0.82)	4. Offshore wind (0.76)	5. Solar PV (0.75)
	Pessimistic	1. Nuclear (0.59)	2. Coal (0.58)	3. Natural gas (0.50)	4. Offshore wind (0.33)	5. Solar (0.29)
SLCA	Symmetric	1. Nuclear (0.74)	2. Offshore wind (0.73)	3. Solar PV (0.71)	4. Natural gas (0.63)	5. Coal (0.13)
	Optimistic	1. Nuclear (0.91)	2. Offshore wind (0.88)	3. Solar PV (0.87)	4. Natural gas (0.78)	5. Coal (0.22)
	Pessimistic	1. Offshore wind (0.53)	2. Nuclear (0.53)	3. Solar PV (0.46)	4. Natural gas (0.38)	5. Coal (0.13)
LCSA	Symmetric	1. Nuclear (0.80)	2. Offshore wind (0.73)	3. Solar PV (0.63)	4. Natural gas (0.63)	5. Coal (0.38)
	Optimistic	1. Nuclear (0.91)	2. Offshore wind (0.91)	3. Solar PV (0.85)	4. Natural gas (0.82)	5. Coal (0.46)
	Pessimistic	1. Offshore wind (0.55)	2. Nuclear (0.54)	3. Natural gas (0.38)	4. Solar PV (0.37)	5. Coal (0.21)

3.4.3. Different defuzzification methods

In addition to the COA defuzzification method used for the case study, many other methods can be used to defuzzify the outcomes of a fuzzy inference process (Zimmerman, 2001). Here we consider the following: the bisector, the smallest of maximum (SOM); the middle of maximum (MOM) and the largest of maximum (LOM); for definitions, see (The Mathworks (Inc), 2016). Using different defuzzification methods can influence the results significantly, particularly where several levels of aggregation are required (as in sustainability assessments) since defuzzification influences the input values in the subsequent steps. This is illustrated in Table 8. Generally, the COA and bisector methods produce lower scores than SOM, MOM and LOM, respectively. The COA and the bisector method rank the options in the same order across the different composite indicators, with small differences in their respective scores (<0.06). However, the results differ for SOM, MOM and LOM. Nevertheless, nuclear power is the best and coal the worst alternative for all five defuzzification methods. For the other alternatives, the differences in the scores and the resulting rankings obtained by different methods can be used to identify opportunities for improvements relative to the better-performing options.

Table 8 Ranking of electricity options using different defuzzification methods

Assessment type	Defuzzification method ^a	Ranking of electricity options				
LCA	COA	1. Nuclear (0.92)	2. Offshore wind (0.87)	3. Solar PV (0.64)	4. Natural gas (0.60)	5. Coal (0.20)
	Bisector	1. Nuclear (0.93)	2. Offshore wind (0.90)	3. Solar PV (0.65)	4. Natural gas (0.63)	5. Coal (0.18)
	SOM	1. Nuclear (1)	2. Offshore wind (0.89)	3. Solar PV (0.64)	4. Natural gas (0.63)	5. Coal (0)
	MOM	1. Nuclear (1)	2. Offshore wind (0.95)	3. Natural gas (0.75)	4. Solar PV (0.75)	5. Coal (0.05)
	LOM	1. Nuclear (1)	2. Offshore wind (1)	3. Natural gas (0.75)	4. Solar PV (0.86)	5. Coal (0.10)
LCC	COA	1. Natural gas (0.75)	2. Coal (0.71)	3. Nuclear (0.71)	4. Offshore wind (0.58)	5. Solar (0.54)
	Bisector	1. Natural gas (0.75)	2. Coal (0.74)	3. Nuclear (0.73)	4. Offshore wind (0.55)	5. Solar (0.52)
	SOM	1. Coal (0.91)	2. Nuclear (0.89)	3. Natural gas (0.75)	4. Solar (0.47)	5. Offshore wind (0.44)
	MOM	1. Coal (0.96)	2. Nuclear (0.95)	3. Natural gas (0.75)	4. Offshore wind (0.50)	5. Solar (0.50)
	LOM	1. Coal (1)	2. Nuclear (1)	3. Natural gas (0.75)	4. Offshore wind (0.56)	5. Solar (0.53)
SLCA	COA	1. Nuclear (0.74)	2. Offshore wind (0.73)	3. Solar PV (0.71)	4. Natural gas (0.63)	5. Coal (0.13)
	Bisector	1. Nuclear (0.75)	2. Offshore wind (0.74)	3. Solar PV (0.73)	4. Natural gas (0.63)	5. Coal (0.09)
	SOM	1. Nuclear (0.73)	2. Solar PV (0.73)	3. Offshore wind (0.71)	4. Natural gas (0.63)	5. Coal (0)
	MOM	1. Natural gas (0.75)	2. Nuclear (0.75)	3. Offshore wind (0.75)	4. Solar PV (0.75)	5. Coal (0.02)
	LOM	1. Natural	2. Offshore	3. Nuclear	4. Solar PV	5. Coal

		gas (0.87)	wind (0.79)	(0.77)	(0.77)	(0.03)
LCSA	COA	1. Nuclear (0.80)	2. Offshore wind (0.73)	3. Solar PV (0.63)	4. Natural gas (0.63)	5. Coal (0.38)
	Bisector	1. Nuclear (0.86)	2. Offshore wind (0.75)	3. Solar PV (0.67)	4. Natural gas (0.67)	5. Coal (0.32)
	SOM	1. Nuclear (0.89)	2. Offshore wind (0.64)	3. Solar PV (0.64)	4. Natural gas (0.63)	5. Coal (0.17)
	MOM	1. Nuclear (0.98)	2. Natural Gas (0.75)	3. Offshore wind (0.75)	4. Solar PV (0.75)	5. Coal (0.25)
	LOM	1. Nuclear (1)	2. Natural gas (0.87)	3. Solar PV (0.86)	4. Offshore wind (0.81)	5. Coal (0.34)

^aSOM: smallest of maximum; MOM: middle of maximum; LOM: largest of maximum.

4. Conclusions

This paper has presented a new FELICITA model which uses fuzzy inference to help decision makers and stakeholders identify most sustainable alternatives on a life cycle basis. The model integrates all three dimensions of sustainability and uses the results of LCA, LCC and SLCA to evaluate the overall sustainability of different systems or human activities. Its application has been demonstrated by assessing the life cycle sustainability of different electricity options. Additionally, a number of sensitivity analyses were performed to demonstrate the versatility of the model.

By using fuzzy inference, FELICITA helps to overcome the issues in sustainability assessments associated with imprecise or uncertain information related to indicators and other inputs. Moreover, it can deal with a differing number of indicators within the three sustainability aspects without affecting the overall results. The outputs from the model can be used to identify relative differences in sustainability performance among the alternatives being considered, helping to identify areas for improvement for each option. The model can also avoid the need for elicitation of preferences for different indicators and aspects of sustainability, reducing the subjectivity in the decision-making process. However, it can still accommodate different stakeholder preferences and perspectives through the choice of different rule bases (neutral, optimistic or pessimistic). Its further advantage is that it can be easily replicated and adjusted to reflect various changes in the assessment process.

Some of the disadvantages of the model are related to the fuzzy inference system in general. These include the need for careful definition of the rules and the membership functions; a change in the membership function can require a change in the rules and the other way round; and each parameter affects the others. Still, fuzzy rules are more expressive than crisp rules and fewer of them are needed. Moreover, the modular nature of the rules makes their development easier. Sensitivity analysis can help to examine the effect on the results of using different membership functions.

Therefore, the FELICITA model can serve as a useful tool for integrated life cycle sustainability assessments. It can be used by companies for integrated sustainability assessments of their products and services as well as by policy makers to examine the consequences of policies on the overall sustainability.

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Integrated life cycle sustainability assessment using fuzzy inference: a novel FELICITA model

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Supplementary Information

S1 Results of the fuzzification process

Table S1. Fuzzified inputs for different electricity options

Impacts	Coal	Natural gas	Nuclear
Recyclability	{ (Bad,0.67) , (Average,0.33) , (Good,0) }	{ (Bad,0.13) , (Average,0.87) , (Good,0) }	{ (Bad,1) , (Average,0) , (Good,0) }
Global warming potential	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.7) , (Good,0.3) }	{ (Bad,0) , (Average,0) , (Good,1) }
Ozone layer depletion potential	{ (Bad,0) , (Average,0.44) , (Good,0.56) }	{ (Bad,0.43) , (Average,0.57) , (Good,0) }	{ (Bad,0) , (Average,0) , (Good,1) }
Acidification Potential (AP)	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.12) , (Good,0.88) }	{ (Bad,0) , (Average,0) , (Good,1) }
Eutrophication potential	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.49) , (Good,0.51) }	{ (Bad,0) , (Average,0) , (Good,1) }
Photochemical oxidants creation potential	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.33) , (Good,0.67) }	{ (Bad,0) , (Average,0) , (Good,1) }
Capital cost	{ (Bad,0) , (Average,0.23) , (Good,0.77) }	{ (Bad,0) , (Average,0) , (Good,1) }	{ (Bad,0) , (Average,0.47) , (Good,0.53) }
Operating and maintenance costs	{ (Bad,0) , (Average,0.39) , (Good,0.61) }	{ (Bad,0) , (Average,0) , (Good,1) }	{ (Bad,0) , (Average,0.54) , (Good,0.46) }
Fuel costs	{ (Bad,0) , (Average,0.83) , (Good,0.17) }	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.22) , (Good,0.78) }
Worker injuries	{ (Bad,0.84) , (Average,0.16) , (Good,0) }	{ (Bad,0) , (Average,0) , (Good,1) }	{ (Bad,0) , (Average,0.02) , (Good,0.98) }
Large accident fatalities	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.49) , (Good,0.51) }	{ (Bad,0) , (Average,0) , (Good,1) }
Direct employment	{ (Bad,0.89) , (Average,0.11) , (Good,0) }	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0.89) , (Average,0.11) , (Good,0) }

Impacts	Offshore wind	Solar photovoltaics (PV)
Recyclability	{ (Bad,0) , (Average,0.04) , (Good,0.96) }	{ (Bad,0) , (Average,0) , (Good,1) }
Global warming potential	{ (Bad,0) , (Average,0.01) , (Good,0.99) }	{ (Bad,0) , (Average,0.15) , (Good,0.85) }
Ozone layer depletion potential	{ (Bad,0) , (Average,0.01) , (Good,0.99) }	{ (Bad,1) , (Average,0) , (Good,0) }
Acidification potential (AP)	{ (Bad,0) , (Average,0.04) , (Good,0.96) }	{ (Bad,0) , (Average,0.45) , (Good,0.55) }
Eutrophication potential	{ (Bad,0) , (Average,0.46) , (Good,0.54) }	{ (Bad,0) , (Average,0.55) , (Good,0.45) }
Photochemical oxidants creation potential	{ (Bad,0) , (Average,0.05) , (Good,0.95) }	{ (Bad,0) , (Average,0.92) , (Good,0.08) }
Capital cost	{ (Bad,0) , (Average,0.72) , (Good,0.28) }	{ (Bad,1) , (Average,0) , (Good,0) }
Operating and maintenance costs	{ (Bad,1) , (Average,0) , (Good,0) }	{ (Bad,0) , (Average,0.87) , (Good,0.13) }
Fuel costs	{ (Bad,0) , (Average,0) , (Good,1) }	{ (Bad,0) , (Average,0) , (Good,1) }
Worker injuries	{ (Bad,0) , (Average,0.82) , (Good,0.18) }	{ (Bad,1) , (Average,0) , (Good,0) }
Large accident fatalities	{ (Bad,0) , (Average,0.07) , (Good,0.93) }	{ (Bad,0) , (Average,0.11) , (Good,0.89) }
Direct employment	{ (Bad,0) , (Average,0.89) , (Good,0.11) }	{ (Bad,0) , (Average,0) , (Good,1) }

S2 Rule bases

Table S2 Three-input rule bases for composite indicators for life cycle assessment (LCA), life cycle costing (LCC), social LCA (SLCA) and life cycle sustainability assessment (LCSA)

Rule r	If the LCA composite indicator is:	And the LCC composite indicator is:	And the SLCA composite indicator is:	Then, the LCSA is:
1	Very bad	Very bad	Very bad	Very bad
2	Very bad	Very bad	Bad	Very bad
3	Very bad	Very bad	Average	Very bad
4	Very bad	Very bad	Good	Bad
5	Very bad	Very bad	Very good	Bad
6	Very bad	Bad	Very bad	Very bad
7	Very bad	Bad	Bad	Very bad
8	Very bad	Bad	Average	Bad
9	Very bad	Bad	Good	Bad
10	Very bad	Bad	Very good	Average
11	Very bad	Average	Very bad	Very bad
12	Very bad	Average	Bad	Bad
13	Very bad	Average	Average	Bad
14	Very bad	Average	Good	Average
15	Very bad	Average	Very good	Average
16	Very bad	Good	Very bad	Bad
17	Very bad	Good	Bad	Bad
18	Very bad	Good	Average	Average
19	Very bad	Good	Good	Average
20	Very bad	Good	Very good	Average
21	Very bad	Very good	Very bad	Bad
22	Very bad	Very good	Bad	Average
23	Very bad	Very good	Average	Average
24	Very bad	Very good	Good	Average
25	Very bad	Very good	Very good	Good
26	Bad	Very bad	Very bad	Very bad
27	Bad	Very bad	Bad	Very bad
28	Bad	Very bad	Average	Bad
29	Bad	Very bad	Good	Bad
30	Bad	Very bad	Very good	Average
31	Bad	Bad	Very bad	Very bad
32	Bad	Bad	Bad	Bad
33	Bad	Bad	Average	Bad
34	Bad	Bad	Good	Average
35	Bad	Bad	Very good	Average
36	Bad	Average	Very bad	Bad
37	Bad	Average	Bad	Bad
38	Bad	Average	Average	Average
39	Bad	Average	Good	Average
40	Bad	Average	Very good	Average
41	Bad	Good	Very bad	Bad
42	Bad	Good	Bad	Average
43	Bad	Good	Average	Average
44	Bad	Good	Good	Average
45	Bad	Good	Very good	Good
46	Bad	Very good	Very bad	Average
47	Bad	Very good	Bad	Average
48	Bad	Very good	Average	Average
49	Bad	Very good	Good	Good
50	Bad	Very good	Very good	Good
51	Average	Very bad	Very bad	Very bad
52	Average	Very bad	Bad	Bad
53	Average	Very bad	Average	Bad
54	Average	Very bad	Good	Average
55	Average	Very bad	Very good	Average

56	Average	Bad	Very bad	Bad
57	Average	Bad	Bad	Bad
58	Average	Bad	Average	Average
59	Average	Bad	Good	Average
60	Average	Bad	Very good	Average
61	Average	Average	Very bad	Bad
62	Average	Average	Bad	Average
63	Average	Average	Average	Average
64	Average	Average	Good	Average
65	Average	Average	Very good	Good
66	Average	Good	Very bad	Average
67	Average	Good	Bad	Average
68	Average	Good	Average	Average
69	Average	Good	Good	Good
70	Average	Good	Very good	Good
71	Average	Very good	Very bad	Average
72	Average	Very good	Bad	Average
73	Average	Very good	Average	Good
74	Average	Very good	Good	Good
75	Average	Very good	Very good	Very good
76	Good	Very bad	Very bad	Bad
77	Good	Very bad	Bad	Bad
78	Good	Very bad	Average	Average
79	Good	Very bad	Good	Average
80	Good	Very bad	Very good	Average
81	Good	Bad	Very bad	Bad
82	Good	Bad	Bad	Average
83	Good	Bad	Average	Average
84	Good	Bad	Good	Average
85	Good	Bad	Very good	Good
86	Good	Average	Very bad	Average
87	Good	Average	Bad	Average
88	Good	Average	Average	Average
89	Good	Average	Good	Good
90	Good	Average	Very good	Good
91	Good	Good	Very bad	Average
92	Good	Good	Bad	Average
93	Good	Good	Average	Good
94	Good	Good	Good	Good
95	Good	Good	Very good	Very good
96	Good	Very good	Very bad	Average
97	Good	Very good	Bad	Good
98	Good	Very good	Average	Good
99	Good	Very good	Good	Very good
100	Good	Very good	Very good	Very good
101	Very good	Very bad	Very bad	Bad
102	Very good	Very bad	Bad	Average
103	Very good	Very bad	Average	Average
104	Very good	Very bad	Good	Average
105	Very good	Very bad	Very good	Good
106	Very good	Bad	Very bad	Average
107	Very good	Bad	Bad	Average
108	Very good	Bad	Average	Average
109	Very good	Bad	Good	Good
110	Very good	Bad	Very good	Good
111	Very good	Average	Very bad	Average
112	Very good	Average	Bad	Average
113	Very good	Average	Average	Good
114	Very good	Average	Good	Good
115	Very good	Average	Very good	Very good
116	Very good	Good	Very bad	Average
117	Very good	Good	Bad	Good
118	Very good	Good	Average	Good

119	Very good	Good	Good	Very good
120	Very good	Good	Very good	Very good
121	Very good	Very good	Very bad	Good
122	Very good	Very good	Bad	Good
123	Very good	Very good	Average	Very good
124	Very good	Very good	Good	Very good
125	Very good	Very good	Very good	Very good

S3 Composite indicators obtained using the fuzzy inference system (FIS)

Table S3 LCA, LCC, SLCA and LCSA composite indicators obtained through the FIS for different electricity technologies

Electricity option	Composite indicator	Fuzzy set
Coal	LCA	{ (Very bad,0.56) , (Bad,0.33) , (Average,0) , (Good,0) , (Very good,0) }
	LCC	{ (Very bad,0) , (Bad,0) , (Average,0.23) , (Good,0.39) , (Very good,0.61) }
	SLCA	{ (Very bad,0.81) , (Bad,0.11) , (Average,0) , (Good,0) , (Very good,0) }
	LCSA	{ (Very bad,0.15) , (Bad,0.47) , (Average,0.53) , (Good,0) , (Very good,0) }
Natural gas	LCA	{ (Very bad,0) , (Bad,0.12) , (Average,0.43) , (Good,0.51) , (Very good,0.30) }
	LCC	{ (Very bad,0) , (Bad,0) , (Average,0) , (Good,1) , (Very good,0) }
	SLCA	{ (Very bad,0) , (Bad,0) , (Average,0.49) , (Good,0.51) , (Very good,0) }
	LCSA	{ (Very bad,0) , (Bad,0) , (Average,0.49) , (Good,0.51) , (Very good,0) }
Nuclear	LCA	{ (Very bad,0) , (Bad,0) , (Average,0) , (Good,0) , (Very good,1) }
	LCC	{ (Very bad,0) , (Bad,0) , (Average,0.22) , (Good,0.47) , (Very good,0.53) }
	SLCA	{ (Very bad,0) , (Bad,0) , (Average,0.02) , (Good,0.89) , (Very good,0.11) }
	LCSA	{ (Very bad,0) , (Bad,0) , (Average,0.03) , (Good,0.32) , (Very good,0.68) }
Offshore wind	LCA	{ (Very bad,0) , (Bad,0) , (Average,0.01) , (Good,0.04) , (Very good,0.54) }
	LCC	{ (Very bad,0) , (Bad,0) , (Average,0.72) , (Good,0.28) , (Very good,0) }
	SLCA	{ (Very bad,0) , (Bad,0) , (Average,0.07) , (Good,0.82) , (Very good,0.18) }
	LCSA	{ (Very bad,0) , (Bad,0) , (Average,0.08) , (Good,0.52) , (Very good,0.31) }
Solar PV	LCA	{ (Very bad,0) , (Bad,0) , (Average,0.45) , (Good,0.55) , (Very good,0.08) }
	LCC	{ (Very bad,0) , (Bad,0) , (Average,0.87) , (Good,0.13) , (Very good,0) }
	SLCA	{ (Very bad,0) , (Bad,0) , (Average,0.11) , (Good,0.89) , (Very good,0) }
	LCSA	{ (Very bad,0) , (Bad,0) , (Average,0.46) , (Good,0.54) , (Very good,0) }