Probabilistic multicriteria environmental assessment of power plants: A global approach

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A B S T R A C T

This paper presents a probabilistic model to assess the environmental performance of power plants. The entire life-cycle is considered, from the fuel extraction to the dismantling phase. The model is based on the use of requirement trees, value functions, the analytic hierarchy process and Monte Carlo simulation. The data to feed the model were established after an extensive literature review and also after collecting more than 350 sets of life cycle assessment (LCA) results. The midpoint impact methods recommended by the International Reference Life Cycle Data System Handbook were employed. The results can be considered as representative for the world at large, including the most common types of energies. Wind and hydro power plants are the best options, with environmental indices always above 0.95, 1 and 0 being the highest and lowest levels of satisfaction. In contrast, power plants fired by coal, lignite and fuel oil are at the bottom of the ranking, with indices typically below 0.5. However, not all the renewables present high-performing environmental results. Furthermore, some non-renewable power plants can be environmentally competitive in certain situations. The model was used to assess case studies related to natural-gas and biomass power-plants, previously analysed in the literature. The environmental indices fell within the expected intervals for such technologies, which served to validate the model. This study can be useful for researchers, professionals of all kinds in the energy sector, politicians, Non-Governmental Organizations (NGOs) and the general public as well as for energy policy decision-making processes at different geographical scales.

Keywords:
Environmental assessment
Cradle to grave
Non-renewables
Renewables
Multicriteria decision method
Monte Carlo

1. Introduction

Energy is a basic instrument for facilitating the development of every modern society. It improves the living conditions as well as the well-being of populations through heating, transport, lighting [1] and air conditioning [2]. In fact, it can be considered a key aspect for economic growth and social development [3].

On the other hand, the energy sector generates a considerable number of environmental impacts at local and global levels. These have been studied since the second half of the past century due to, among other things, the appearance of global environmental politics [4]. In recent years, environmental and energy policy has grown in importance all over the world [5]. It is a well-known fact that most attention has been given to climate change and the emission of greenhouse gases. In fact, the Paris Agreement reached in 2015 and ratified by many nations [6], served to establish a goal in terms of limiting temperature increases [7]. Thereafter, the initial expectations diminished when the United States declared its intention of abandoning the agreement [8], although some authors suggest that this may represent an opportunity to consolidate global climate policy [9]. Despite the necessity of combatting climate change due to its global nature, there are other impacts that must be studied and considered in depth in the international agenda, such as acidification, biodiversity loss, air and marine pollution, among others [10].

Consequently, national governments face the challenge of meeting the growing energy demand and, at the same time, protecting the environment at national and international levels. To these should be added other economic, social and geopolitical conditioning factors as well as a considerable degree of uncertainty [11], which make decision-making difficult [12]. Therefore, it is necessary to adopt a trade-off solution to all these competing objectives. It is precisely in this matter where global energy policy must play a key role. Nevertheless, it is important to note that global energy policies must be based on scientific knowledge. There are several reasons for this. On the one hand, a risk arises if long-term policies are not founded on scientific research: they could seem to be consistent with the desired targets when they are not, leading to worse future environmental situations than the expected ones. On the other hand, once a long-term policy is adopted and implemented, it can be quite complicated (and expensive) to rectify or to introduce major amendments without drastically reducing the chances of success. Furthermore, well-intended policies applied without a deep reflection can produce the opposite effect to the desired one. The green paradox discussed by van der Ploeg and Withagen [13] or the carbon leakage effect [14] are some examples. In other words, an extensive knowledge of every possible environmental impact derived from the different types of renewable and non-renewable power plants should constitute the foundations for regional, national and global policies in terms of energy and environment.

Currently, the energy sector still depends largely on carbon-containing fuels [15], whose environmental impact is far reaching. Therefore, the expansion of renewable energies may result in improved environmental conditions, as well as providing other benefits [16].

Nevertheless, all power plants present some form of direct or indirect impact on the environment. One example of an indirect impact is when equipment for electricity generation is produced [16]. In other words, despite the fact that some renewables have zero direct emissions during the operation stage as indicated by Briones Hidrovo et al. [17], Desideri et al. [18] and

Uddin and Kummar [19], environmental impacts always occur throughout the manufacturing, installation, transport and decommissioning stages. These impacts should be analysed. In this context, the environmental impacts associated with renewable energy have yet to be thoroughly understood [20].

In recent years, many studies regarding the environmental impacts of power plants have been published. Tremeac and Meunier [21] compared the environmental impacts of two wind turbines in France. In Spain, Butnar et al. [22] analysed the environmental behaviour of two energetic crops for electricity production. The environmental impacts associated with the electricity production from biomass were also addressed by da Costa et al. [23], for the particular case of Portugal. Demir and Taşkın [24] studied the environmental impacts of different scale wind turbines in the Turkish region of Pınarbasi-Kayseri. The emissions of wind turbines were also examined in Thailand, by Uddin and Kummar [19] and in Taiwan, by Huang et al. [25]. Fantin et al. [26] performed an environmental assessment of an anaerobic digestion plant for producing electricity, located in Northern Italy. Briones Hidrovo et al. [17] estimated the amount of greenhouse gas (GHG) emissions of hydropower in Ecuador. Another assessment involving the same type of emissions for a set of large hydropower plants was made by dos Santos et al. [27], this time across different Brazilian regions. The environmental impacts of hydropower plants were also studied in Europe by Mahmud et al. [28], distinguishing between alpine and non-alpine regions.

Regarding non-renewables, Castelo Branco et al. [29] analysed the environmental behaviour of a coal-fired power plant located in North-eastern Brazil. Also in Brazil, Restrepo et al. [30] performed an environmental analysis of coal for electricity production. Similarly, de Almeida et al. [1], studied, from an environmental point of view, the behaviour of a power plant using heavy fuel oil and natural gas simultaneously. In the particular case of Spain, Martín-Gamboa et al. [31] estimated the environmental performance of combined-cycle power plants fuelled by natural gas. In the same line, the environmental impacts caused by a natural gas power plant, located in Thailand, were examined by Usapein and Chavalparit [32]. In Turkey, Şengül et al. [33] carried out an environmental analysis of different types of lignite used for electricity generation. Concerning nuclear power, Carless et al. [34] conducted a study addressing the environmental issues relating to a small modular reactor.

In the majority of cases, the studies referred to in the previous two paragraphs only cover one type of power plant in a specific place, region or country. Therefore, from these publications, it is not possible to know which types of power plants cause less environmental damage, since comparisons among different technologies are not addressed. In addition, due to the fact that only one place, region or country is analysed, it would be impossible to draw conclusions with global coverage. Added to this is the need to incorporate more environmental impacts to some of the studies, in which only the GHG emissions were considered. Furthermore, most of them do not adopt any strategies for dealing with uncertainty and variability. Nevertheless, these factors, having an effect on many of the power plants' variables, can play an important role in evaluating environmental impacts. A limited number of probabilistic studies can be found. Among these are Briones Hidrovo et al. [17], Carless et al. [34], Fantin et al. [26] and de Almeida et al. [1]. Even in these cases, there are other limitations such as the ones mentioned above.

On the other hand, there are also some studies dealing with more than one type of technology in the same region. One such study is that carried out by Bonou et al. [35], where the environmental impacts caused by wind energy in Europe were addressed, considering both onshore and offshore options. In Turkey, Atilgan and Azapagic [36] studied the environmental performance of different power plants using hard coal, lignite and gas as fuels. Subsequently, they analysed the environmental performance of certain renewables in the same country [37]. For clean non-renewable technologies, Liang et al. [38] studied the environmental impacts of some Chinese coal-fired power plants. Another case in point is Weldu et al. [39], in which the authors assessed the impacts of electricity production from the health and ecotoxicological points of view, for the province of Alberta, Canada. Coal and wood biomass were the two fuels considered. In the same vein, a deterministic approach was taken by the Spanish Institute for Energy Diversification and Saving (IDAE). Eight different types of power plants were ranked according to their contribution to environmental impacts [40]. More recently, Wang et al. [41] performed an environmental assessment of hydropower, wind and nuclear power plants in China. Despite the fact that these publications compare, at least, two different technologies in terms of environmental impacts, there are still several gaps to be filled. Firstly, the influence of uncertainty and variability on the results is not always considered. Secondly, the scope is also limited in terms of geographical coverage, since only one region is studied. In addition, some studies, such as that carried out by IDAE, do not include the decommissioning stage.

Finally, there are few studies that consider different types of power plants in a variety of world regions. Turconi et al. [42] is one of those few. The authors reviewed a great number of existing studies tackling the life cycle assessment of different renewable and non-renewable technologies. They also identified the ranges for emissions that contribute to key environmental impact categories. Nevertheless, the study considers only a limited number of environmental emissions (GHG, NO_x and SO_2), a fact which hampers the decision-making processes in the energy sector, since many leading pollutants and their corresponding environmental impacts are missing.

From all of the above it is clear that an integrated probabilistic assessment of the most relevant environmental impact categories for the more frequent types of renewable and non-renewable energies, adopting a worldwide approach, has yet to be performed. Therefore, the main research objective of the present study is to fill these gaps in current knowledge. A new probabilistic model was created for such a purpose. It was fed with data covering different types of power plants all over the world. It provided a general overview of the real environmental impacts that renewables and non-renewables can cause. These results can be useful for researchers, professionals of all kinds in the energy sector, politicians, Non-Governmental Organizations (NGOs) and the general public. They will help to change some popular misconceptions about the environmental behaviour of power plants, on the basis of scientific knowledge. In particular, the results should be taken into account by decision-makers at the time of setting and prioritising energy policies from an environmental point of view.

On the other hand, the model can be used, by professionals and researchers, to assess the environmental performance of specific power plants, real or under design. For instance, it can be applied to existing case studies with the objective of extending, or not, their service lives on the basis of their environmental indices. This is a clear example of model implementation. In fact, it was also validated by its application to two types of power plants (natural gas and biomass), previously analysed in the existing literature. It is important to note that the model can also be modified by other users to incorporate alternative environmental impact categories or to include other indicators with the objective of assessing the global sustainability of power plants, including economic, environmental, social and technical indicators. Furthermore, this study contains valuable information (input values for environmental indicators for different types of power plants, including minimum, maximum and mode) based on an extensive literature review that can serve as reference for other studies addressing the environmental dimension of power plants.

In summary, the main novelties of this paper are:

- Complete environmental analysis of 11 types of power plants, including both renewables and non-renewables.
- The use of 15 environmental impact categories (see Section 3.1 for more information).
- Implementation of a multi-criteria decision-making method (MCDM) model to group all the environmental results into a single index (see Sections 3.2 and 4 for more information).
- Use of different sets of weights to integrate the results for the environmental indicators.
- Global geographical scope, covering almost 50 countries across the world, in the five continents, including both developed and developing nations.
- Probabilistic approach based on the data collected, by using probability distributions to feed the model.
- Correlations between environmental impacts.
- Collection of environmental data that can be used by professionals and researchers at the time of developing their own studies.

This paper is organised as follows: after this Introduction, Section 2 presents a more detailed identification of our objectives as well as the main contributions. Section 3 is divided into two parts. In the first one (Section 3.1), a brief overview of life cycle assessment (LCA) methodology is provided. In Section 3.2 the MIVES-Monte Carlo method, used to construct the model of this study, is introduced. The reader will find in Section 4 specific information about the model. The results are presented and discussed in Section 5, including the application of the model to different case studies. Finally, the main conclusions, limitations, policy implications and possible future developments are summarised in Section 6.

2. Objectives and main novel contributions

The first main objective of this article is to carry out an environmental and probabilistic assessment of 11 types of power plants all over the world, six of which can be classified as non-renewables, using hard coal (C1), lignite (C2), coal gases (C3), heavy fuel oil (C4), natural gas (C5) and nuclear (C6) power. Five renewables were also considered: onshore and offshore wind (R1), photovoltaic (R2), biogas (R3), biomass (R4) and hydro (R5) power plants. This study aims to represent the majority of possible real cases. The second main objective is to provide a probabilistic model that can be used by professionals and researchers to assess the environmental performance of specific power plants.

Consequently, this work presents three original contributions. Firstly, its results cover most of the world's regions, including both developed and developing countries. Secondly, its main aim is to carry out a probabilistic assessment on key environmental impacts produced by renewable and non-renewable technologies along their life cycles, including the decommissioning stage.

Correlations between environmental impacts are also modelled. Finally, this is the first time that the results arising from a midpoint environmental life cycle assessment (LCA) technique based on the recommendations of the International Reference Life Cycle Data System Handbook (ILCD) [43] have been combined with the MIVES-Monte Carlo method (see Section 3.2) to achieve these aims. As indicated in the previous section, the model was also validated by its application to case studies related to natural gas and biomass power plants.

Certain aspects should be clarified. Carrying out an LCA for several renewable and non-renewable power plants all over the world is beyond the scope of this study. The authors did not model the hundreds or even thousands of unit processes involved in a typical LCA analysis. In fact, midpoint LCA results are the starting point for the study developed here. In a first stage, a large set of LCA results were collected by the authors from Thinkstep Energy [44] and Professional databases [45]. Then, in a second phase, the LCA data and results included in the existing literature, when possible, were also taken into account at the time of defining the input values to feed the model presented in this study. By way of example, data from de Almeida et al. [1], Tremeac and Meunier [21], Carless et al. [34], Bonou et al. [35], Wang et al. [41], Turconi et al. [42], Restrepo et al. [46], Wang and Sun [47], Nguyen [48], Agrawal et al. [49], Kourkoumpas et al. [50], Yang et al. [51], Zhao et al. [52], among others, were considered.

Regarding the Thinkstep databases, more than 350 sets of LCA results – as well as their corresponding inputs and outputs – were culled covering both renewable and non-renewable power plants and more than 40 developing and developed countries. More than 30 countries located in Europe (Finland, France, Germany, Italy, Portugal, Spain, among others) were considered, as well as 7 Asian countries (China, India, Indonesia and Japan, among others), 3 countries in the American continent (Brazil, Canada and United States), 3 countries in Oceania (Australia, Indonesia and New Zealand) and 1 African country (South Africa). By using these databases, the LCA results of multiple products or services can be obtained without modelling their entire life cycles, since they are already predetermined. Notwithstanding the above, general information about LCA will be provided in the following section.

On the other hand, it is important to emphasise the need for adopting a probabilistic approach. As previously mentioned, uncertainty and variability affect many of the power plants' variables. In other words, the same type of power plant can present considerable differences in terms of environmental performance, depending on factors such as the country's level of development, the technologies employed, the level of automation during the construction and manufacturing stages, the efficiency and experience (learning curves) during different phases, the type of fuel used and its quality, the weather conditions and the assumptions considered at the time of modelling the life-cycle stages, among many others. In fact, the influence of uncertainty and variability on the results is so important that most of the commercial LCA softwares enable users to handle it by, for example, performing a Monte Carlo simulation. A significant number of authors have emphasised the importance of studying both the uncertainty and the variability within an LCA framework. Chiu and Lo [53], Hauck et al. [54], Huijbregts et al. [55], Sastre et al. [56] and Sonnemann et al. [57] are some examples. Nevertheless, most of the existing studies still adopt a deterministic approach [55].

3. Materials and methods

3.1. *Life Cycle Assessment (LCA)*

An LCA is a standardised and internationally accepted tool to identify and assess, in an objective way, the environmental impacts that occur during the complete life cycle of a product, system, process or service [58]. LCA can be of great help to policy makers, developers, researchers and designers when it comes to detecting environmental pitfalls [59]. It provides valuable data with which technology can be improved and optimised [60].

As a way of handling the complexity of LCA, a regulatory framework was defined by ISO 14040 [61] and ISO 14044 [62]. According to these documents, an LCA usually consists of four phases: i) goal and scope definition, ii) life cycle inventory analysis, iii) life cycle impact assessment and iv) interpretation. In the first phase, the study's objective, the functional unit (FU) and the system boundaries are defined [58]. All the LCA inputs and outputs (life cycle inventory analysis) are referred to the FU. In the present study, 1 kWh of electricity generated was established as the FU.

The sets of LCA results extracted from Thinkstep databases were based on the average impacts of each type of energy system, for each country. Due to length constraints, all the input and output data lists (life cycle inventory analysis) associated with the sets of LCA results are not included here. The scope was from cradle to grave with some exceptions, which will be explained later. Further information about the power plants' boundaries was provided by Thinkstep Energy [44] and Professional databases [45]. The most important aspects are summarised below.

Regarding hard coal (C1), lignite (C2), coal gases (C3), heavy fuel oil (C4) and natural gas (C5) power plants, the exploration, production, processing and transportation phases were included in the fuel supply chain. Also considered were their construction, use and end of life phases. Different national technology standards concerning firing technology or efficiency, among other aspects, were taken into account.

As for nuclear energy (C6), the production of electricity is a country specific mix of two types of water reactors: boiling water and pressure water ones. The fuel cycle included the following phases: mining, milling, conversion, enrichment, fuel fabrication, use and end of life of the spent fuel. The construction, use and end of life stages of the power plant were also analysed.

With reference to wind energy (R1), an average country specific mix of onshore and offshore wind farms was considered. In both cases, the production, transportation, installation, operation and dismantling phases were analysed, including the removal of wind turbines and the electrical gear. Continuing with renewables, different photovoltaic (R2) technologies were also examined (mono-Silicon, multi-Silicon, amorphous-Silicon, Ribbon-Silicon, Cadmium-Telluride, and Copper-Indium-Gallium-Diselenide). In all cases, the manufacturing and use phases were included. Once again, the share of each type of technology was country specific. However, the panels' end of life was not included, because there are no common technologies to recycle or reuse them according to Thinkstep Energy [44] and Professional databases [45].

In terms of system boundaries, biogas (R3) and biomass (R4) power plants are similar to the first four non-renewable power plants. The fuel supply chain includes the same stages with the exception of the exploration one. Again, the construction, operation and end of life stages were analysed, along with a range of national technology standards.

In the case of hydro (R5) power plants, three technologies were studied: run-of river, storage and pump storage (with natural afflux). The share of the three hydro power types was country specific. The construction, installation and operation phases of these plants were included. For the electrical parts, the dismantling and removal phases were also taken into account. Nevertheless, the infrastructures' end of life, like earth dams or concrete foundations, were considered beyond the scope of this study. In fact, dismantling the civil engineering works of hydro (R5) power plants, if possible, is not executed [63].

In the third phase of an LCA, related to the life cycle impact assessment, the data compiled (life cycle inventory analysis) is grouped and employed to quantify environmental impacts, by using the corresponding set of indicators [15]. In fact, this phase can consist of up to four sub-steps (classification, characterisation, normalisation and weighting), only the first two being mandatory [62]. The sets of LCA results collected and used in this study are the results of this third phase (classification and characterisation).

Once the statistical analysis had been done, the results obtained served to establish the input values for the MIVES model (see Sections 3.2 and 4).

There are several LCA approaches that can be used, such as the one developed by the Institute of Environmental Sciences (Centrum voor Milieuwetenschappen in Nederlands, CML) of Leiden University, known as the CML method; the ReCiPe method, designed by the Netherlands National Institute for Public Health and the Environment (Rijksinstituut voor Volksgezondheid en Milieu in Dutch, RIVM), Radboud University, CML and PRé Consultants; the Tool for the Reduction and Assessment of Chemical and other Environmental Impacts (TRACI); the Method of Ecological Scarcity (also referred to by its German acronym UBP); or Ecoindicator 99, among others [64]. In this case, instead of using one of these methods, the midpoint impact methods recommended by the European Commission [43] in the ILCD Handbook were used, with only once exception: land use. In other words, the sets of LCA results extracted from Thinkstep databases and collected by the authors arise from following the ILCD recommendations for most of the environmental impacts. The authors carried out a statistical analysis of the LCA results to define several values such as the minimum, maximum, mean or modal ones, among others. The sets of LCA results, together with the statistical analysis and the extensive literature review, served to establish the input values for the different types of power plants that were assessed by means of the MIVES method (see Section 3.2). The application of the MIVES method is equivalent to the non-mandatory sub-steps in the third phase of an LCA; that is, normalisation and weighting. In summary, MIVES makes it possible to group the ILCD midpoint results for different environmental impacts into a unique value, taking into account different weights. More information about MIVES and MIVES Monte Carlo is provided in Section 3.2.

Other authors, including da Costa et al. [23], Fantin et al. [26], Usapein and Chavalparit [32], and Bonou et al. [35], whose objective and scope differed from the ones considered here, had previously followed the ILCD guidelines. The environmental impacts included in the present work were [43]: acidification (AC); climate change biogenic carbon (CC); ecotoxicity, freshwater (EF); eutrophication, freshwater (EuF); eutrophication, marine (EuM); eutrophication, terrestrial (EuT); human toxicity, cancer effects (HTC); human toxicity, non-cancer effects (HTNC); ionising radiation (IR); ozone depletion (OD); particulate matter (PM); photochemical ozone formation (POF); resource depletion, water (RDW); resource depletion, mineral, fossil and renewables (RD); and the LANCA indicator (Land Use Indicator Value Calculation in Life Cycle Assessment) [65]. Their units of measurement can be found in Table 2. As for land use, the LANCA, rather than the SOM (Soil Organic Matter), indicator was employed. Despite its usefulness, the SOM option does not take into account certain soil-related aspects such as erosion resistance [65]. There are multiple options for assessing the land use environmental impacts. However, no agreement has been reached on which one is the best indicator. In fact, the different options present advantages and disadvantages. According to Vidal-Legaz et al. [65], LANCA can be considered a good choice due to its extensive scope, environmental relevance and applicability. The reader can find in Ref. [65] more information about the different indicators related to land use, including SOM and LANCA. On the other hand, it must be added that the results presented in this study are an aggregated version of LANCA, measured in points[1].

The results are interpreted in the fourth and final stage of an LCA. That is, they are placed in context [33], usually explaining the limitations of the study and providing conclusions and recommendations [15]. In this paper, the LCA findings served to define the inputs for the MIVES model. Therefore, the interpretation phase will be carried out in connection with the MIVES results.

3.2. MIVES-Monte Carlo

The results of an LCA study are gathered in a list with the values for the different indicators, from which it is not easy, or even possible, to extract conclusions. Consequently, a method to integrate those figures is needed so that decisions can be made. The MIVES method is one of the existing options. It was previously described by Cartelle Barros et al. [66] and by de la Cruz et al. [67], among others.

MIVES is the Spanish acronym for the Integrated Value Model for Sustainability Assessment. It can be classified as a deterministic MCDM. There are several studies in which the MIVES method has been employed to support a decision-making problem in different sectors. Among these are Cartelle Barros et al. [66], Cuadrado et al. [68], de la Fuente et al. [69], de la Fuente et al. [70], del Caño et al. [71], del Caño et al. [72], Gómez et al. [73], San-José et al. [74], San-José Lombera and Cuadrado Rojo [75], San-José Lombera and Garrucho Aprea [76].

Requirement trees, value functions and the Analytic Hierarchy Process (AHP) make up the foundations of the MIVES method [67]. One of its main advantages is that indicators measured in different units can be easily compared, since all of them are transformed into a dimensionless parameter. In this kind of transformation process, nonlinearities can be considered. Furthermore, the relative importance (usually known as weight) of each element included in the requirement tree is also taken into account, either through the direct allocation of the weights, or by employing the AHP technique. The result of applying the MIVES method is a single and global index, or level of satisfaction. This parameter varies between 0 and 1, respectively the worst and best possible solutions. de la Cruz et al. [67] provide detailed information about MIVES.

On its own, MIVES does not take into account uncertainty and variability. Nevertheless, it has already been mentioned that these factors would play an important role in the present work. As a result, there was a need to combine MIVES with a procedure for handling them. Two options

[1]Personal communication of the Thinkstep team, 10/24/2017.

were available. The first one involves using Monte Carlo simulation [71]. The second is based on fuzzy arithmetic [72]. More information about these two options is provided in de la Cruz et al. [67] and in de la Cruz et al. [77], respectively.

The reader can find in Fig. 1 a flowchart summarising the main steps followed in this study, from the literature review to the achievement of results.

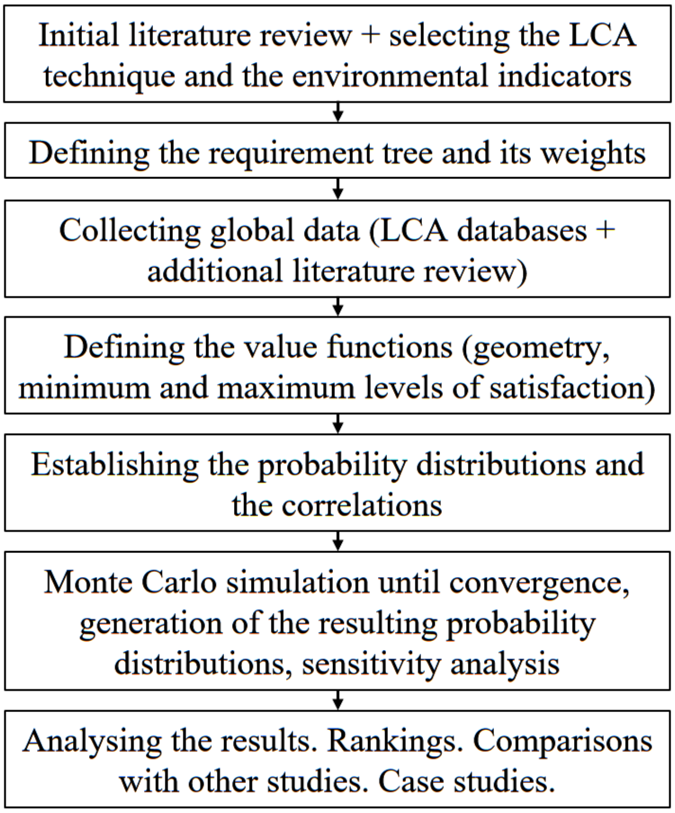

Fig. 1. Flowchart of the methodology employed

Once the first five steps have been covered, the model (Section 4) is completely defined. It is at this point that the integration between MIVES and Monte Carlo is carried out. At the time of assessing a specific alternative, in each iteration, pseudo-random numbers are generated for the indicators, according to the previously defined probability distributions (more information about the distributions used in this study can be found in Section 4), and taking into account the correlations mentioned in this paper. The pseudo-random numbers are then introduced in the corresponding value functions. Each function generates a level of satisfaction between 0 and 1, one being the maximum level. After that, the general equation of the MIVES method (Eq. 1, Section 4) is used to obtain the global index. The weights of the requirement tree (Table 1) are employed for such a purpose. This process is repeated until convergence is achieved for the global index.

4. The model

A MIVES model was constructed with the fifteen environmental indicators alluded to in Section 3.1. In this study, the Environmental Index (*ENI*) was the result of applying the MIVES method. Eq. (1) was used for its estimation [67].

$$ENI = \sum_{ind=1}^{ind=15} \alpha_{ind} \cdot \beta_{ind} \cdot \gamma_{ind} \cdot V_{ind} \quad (1)$$

In Eq. (1), α_{ind}, β_{ind} and γ_{ind} are the relative importance of the elements included in the requirement tree, while V_{ind} is the value function defined to each one of the indicators.

Table 1 presents this requirement tree. Here, for calculation purposes, the last two levels could be merged into a single one, since each criterion contains only one indicator. Nevertheless, power plants cause impacts not only on the environment, but also society and the economy. Consequently, the requirement tree here proposed should be used in future studies as part of a more comprehensive model including social, economic and technical aspects. This is the main reason why the authors decided to preserve the three characteristic levels of the MIVES method. The reader can find more information about potential future developments in Section 6.

Table 1
Requirement tree of the model. Environmental criteria and indicators.

	α_{ind}	Requirements	β_{ind}	Criteria	γ_{ind}	Indicators
ENI	100%	Environmental	7.4%	Acidification	100%	Acidification (*AC*)
			11.2%	Climate change	100%	Climate change including biogenic carbon (*CC*)
			8.2%	Ecotoxicity, freshwater	100%	Ecotoxicity, freshwater (*EF*)
			5.5%	Eutrophication, freshwater	100%	Eutrophication, freshwater (*EuF*)
			1.2%	Eutrophication, marine	100%	Eutrophication, marine (*EuM*)
			1.2%	Eutrophication, terrestrial	100%	Eutrophication, terrestrial (*EuT*)
			0.5%	Human toxicity, cancer	100%	Human toxicity, cancer (*HTC*)
			8.0%	Human toxicity, non-cancer	100%	Human toxicity, non-cancer (*HTNC*)
			6.9%	Ionizing radiation	100%	Ionising radiation (*IR*)
			7.5%	Ozone depletion	100%	Ozone depletion (*OD*)
			8.1%	Particulate matter	100%	Particulate matter (*PM*)
			7.8%	Photochemical ozone formation	100%	Photochemical ozone formation (*POF*)
			9.7%	Resource depletion, water	100%	Resource depletion, water (*RDW*)
			8.1%	Resource depletion	100%	Resource depletion, mineral, fossils and renewables (*RD*)
			8.7%	Land use	100%	Land use indicator value calculation (*LANCA*)

In the present study, the maximum level of satisfaction was not correlated with a zero environmental impact, but with a reasonably low one, taking into account the technology available.

MIVES can integrate both quantitative and qualitative indicators. Nevertheless, in this study, all of them are measured in a quantitative way. Therefore, Eq. (2) is used to define each one of the value functions V_{ind} (see Section 3.2 and de la Cruz et al. [67]).

$$V_{ind} = \frac{1 - exp\left(-m_{ind} \cdot \left(\frac{\left|P_{ind} - P_{ind,min}\right|}{n_{ind}}\right)^{A_{ind}}\right)}{1 - exp\left(-m_{ind} \cdot \left(\frac{\left|P_{ind,max} - P_{ind,min}\right|}{n_{ind}}\right)^{A_{ind}}\right)} \quad (2)$$

P_{ind} is the input of a specific indicator for the power plant under consideration. $P_{ind,min}$ is the input value that returns a $V_{ind} = 0$. $P_{ind,max}$ is the input value that returns a $V_{ind} = 1$. The different geometries of the value functions are modelled through the factors A_{ind}, m_{ind} and n_{ind}. The reader can find in de la Cruz et al. [67] further information about value functions. The value functions parameters employed in this work are shown in Table 2.

Table 2
Value functions parameters for the environmental indicators.

Indicator [a]	Parameters					Characteristics	
	$P_{ind,min}$	$P_{ind,max}$	A_{ind}	m_{ind}	n_{ind}	Trend	Shape
AC (Mole H+ eq./kWh)	7E-3	2E-5	4	5E-2	7E-3	Decreasing	Concave
CC (kg CO_2 eq./kWh)	1.2	1E-2	3.5	0.1	0.9	Decreasing	Concave
EF (CTUe/kWh)	1	0	6	5E-2	0.5	Decreasing	S-shaped
EuF (kg P eq./kWh)	1E-5	1E-8	9	0.1	1E-5	Decreasing	Concave
EuM (kg N eq./kWh)	1.6E-3	1E-5	6	0.5	1.45E-3	Decreasing	Concave
EuT (Mole N eq./kWh)	2.1E-2	1E-4	4.5	0.3	1.8E-2	Decreasing	Concave
HTC (CTUh/kWh)	1E-8	0	4.5	0.2	5.5E-9	Decreasing	S-shaped
HTNC (CTUh/kWh)	4E-8	0	4.5	0.2	2.2E-8	Decreasing	S-shaped
IR (kBq U235 eq./kWh)	1E-2	1E-4	5.5	0.2	6.5E-3	Decreasing	S-shaped
OD (kg CFC-11 eq./kWh)	4E-12	0	5	0.1	2E-12	Decreasing	S-shaped
PM (kg PM2,5 eq./kWh)	5E-4	1E-6	5	0.1	2.6E-4	Decreasing	S-shaped
POF (kg NMVOC/kWh)	3.5E-3	1E-5	5	0.1	1.7E-3	Decreasing	S-shaped
RDW (m^3 eq./kWh)	5E-2	1E-4	5	0.3	4.5E-2	Decreasing	Concave
RD (kg Sb eq./kWh)	1E-5	0	4.5	0.1	5E-6	Decreasing	S-shaped
LANCA (points/kWh)	1	0	3	0.5	0.5	Decreasing	S-shaped

[a] AC: Acidification; CC: Climate Change; EF: Ecotoxicity, freshwater; EuF: Eutrophication, freshwater; EuM: Eutrophication, marine; EuT: Eutrophication, terrestrial; HTC: Human toxicity, cancer; HTNC: Human toxicity, non-cancer; IR: ionising radiation; OD: Ozone depletion; PM: Particulate matter; POF: Photochemical ozone formation; RDW: Resource depletion, water; RD: Resource depletion; LANCA: Land use indicator value.

The values for $P_{ind,min}$ and $P_{ind,max}$ for each one of the indicators were established on the basis of the more than 350 sets of LCA results collected by the authors for the different types of power plants. In other words, once the LCA results were collected, the authors were able to identify the minimum and maximum input values for each indicator (environmental impact) and, so, to define $P_{ind,min}$ and $P_{ind,max}$. Nevertheless, it is important to clarify that $P_{ind,min}$ and $P_{ind,max}$ do not necessarily have to coincide with the global minimum and maximum values, since the authors established a high level of exigency at the time of assessing each one of the indicators. On the other hand, most of the existing MCDM methods consider a lineal relation between the input value for a specific indicator and its corresponding output (level of satisfaction). This would be tantamount to using lineal value functions in a MIVES model. Nevertheless, in practice, two times the input value for a certain indicator does not necessarily deserve half of the original level of satisfaction. There are some input values from which the resulting levels of satisfaction must decrease in a more acute way to prevent the user of the model from choosing undesirable options. This is the reason why in this study, lineal value functions were not used. In fact, the authors defined more demanding geometries that significantly penalise those alternatives that are far from the best possible scenarios. The values for A_{ind}, m_{ind} and n_{ind} were established in accordance with the above.

There is a range of quantitative weighting approaches: proxy, distance to target, panel, monetisation and technology [78]. The easiest option is to assume the same importance for all the aspects under consideration. However, it is not always advisable to do so [66]. For requirement tree branches that only have one aspect, the weight is always equal to 100% [67]. For the criteria, a set of weights was established based on the weighting factors proposed by Kupfer et al. [64]. Taking into account that the weights could bear great influence on the assessment results, additional sets of weights, mainly based on the literature, were considered in this work, as part of a sensitivity analysis. In other words, the calculation process described in this section and in Section 3.2 was repeated but, this time, using different weights for the environmental criteria (sensitivity analysis in Fig.1). For further information, the reader can consult Section 1 of Appendix A (Tables A.1-A.5).

On the other hand, the authors performed a statistical analysis of the sets of LCA results previously collected from the Thinkstep Energy [44] and Professional databases [45], identifying some parameters such as the minimum, maximum, mean, standard deviation, among others, with the objective of determining adequate distribution functions for each indicator (environmental impact) and power plant. Although more than 350 sets of results were used, for some types of power plants, the number of available results was limited (under 30). When there is scarce information available, many authors recommend the use of triangular or uniform distributions (for example: Maurice et al. [79] or Williams [80], among others) defined by expert estimation [53], instead of employing statistical, distribution fitting methods. The reader can find in Fig. 2 some examples of distribution functions. Maurice et al. [79] and Williams [80] provide more information about the advantages of these two distributions.

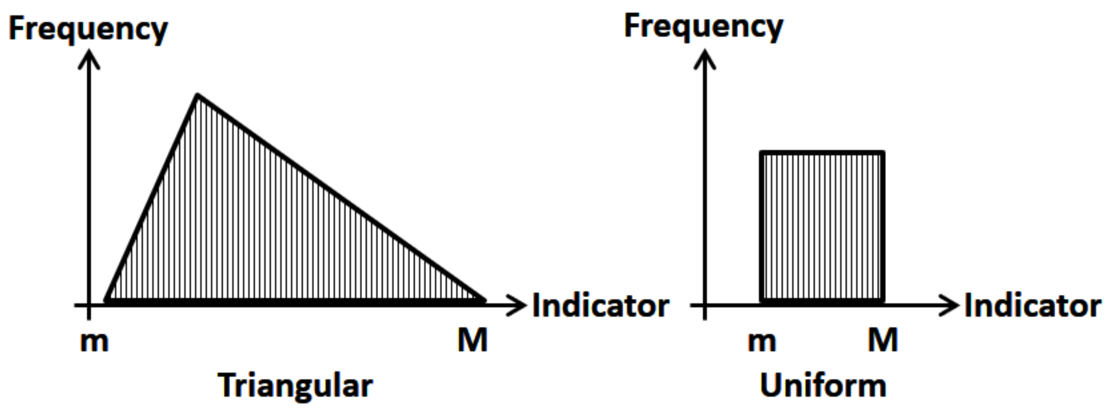

Fig. 2. Examples of simple distribution functions that can be used when the available data is limited

Furthermore, it is important to note that the LCA results collected from the Thinkstep databases are, for each country, the average values for the power plant analysed. This means that employing statistical methods to determine the distribution functions will lead to biased and non-realistic distributions, since the differences in the installed capacity for each type of power plant among different countries would be ignored. All of this has led the authors to define both closed triangular (Case 1) and uniform distributions (Case 2) (Fig. 2). Their corresponding parameters (minimum, maximum and mode for Case 1; extreme values for Case 2) for all the power plants and indicators are listed in Table 3. The minimum and maximum values were defined from the extreme values found in the sets of LCA results. The modes were established by taking into account, to an approximate degree, the installed capacity that each one of the countries included has for the different power plants. As previously alluded to, the data from the existing literature was also considered in a subsequent stage. In addition, one of the authors has more than 40 years of international experience in the energy sector. Despite all of that, there could be real cases in which the values for some indicators fell out of the intervals proposed.

Table 3
Model input values for the ILCD environmental indicators.

Alternative[a]	Distribution function	Distribution parameters	Indicators [c]														
			AC	*CC*	*EF*	*EuF*	*EuM*	*EuT*	*HTC*	*HTNC*	*IR*	*OD*	*PM*	*POF*	*RDW*	*RD*	*LANCA*
C1 Hcoal	CT[b]	Min	8.07E-4	0.838	0.0109	1.18E-8	2.59E-4	2.82E-3	2.65E-10	7.98E-9	9.78E-5	6.57E-15	3.43E-5	7.15E-4	1.19E-4	8.14E-8	0.0345
		Mode	3.5E-3	1.1	0.02	5E-8	8E-4	0.01	5E-10	2E-8	6E-4	2.2E-13	3E-4	3.5E-3	8E-3	1E-7	0.1
		Max	0.0219	1.66	0.878	1.81E-7	2.65E-3	0.029	1.13E-8	6.81E-7	3.34E-3	1.18E-12	1.5E-3	7.97E-3	0.178	2.01E-7	0.312
C2 Lign	CT[b]	Min	1.35E-3	0.919	0.0134	5.93E-9	3.06E-4	3.22E-3	5.13E-10	3.2E-8	4.83E-5	4.01E-15	5.39E-5	8.1E-4	4.1E-4	9.19E-8	0.0142
		Mode	6E-3	1.2	0.04	5E-8	6E-4	9E-3	7E-10	7E-8	1.2E-3	9E-13	3.5E-4	3E-3	0.017	1.2E-7	0.1
		Max	0.0421	1.57	0.172	8.75E-8	1.61E-3	0.0176	4.61E-9	1.63E-7	6.21E-3	8.88E-12	2.23E-3	6.6E-3	0.079	2.27E-7	0.955
C3 Clgas	CT[b]	Min	8.68E-4	0.732	3.31E-3	1.69E-8	4.29E-4	4.78E-3	1.09E-10	7.71E-10	7.02E-5	8.88E-15	2.83E-5	1.16E-3	1.34E-4	6.48E-8	0.0346
		Mode	2.5E-3	1.3	7E-3	4E-8	1.5E-3	0.01	3.5E-10	2E-9	6E-4	2E-13	6.5E-5	4E-3	0.021	1E-7	0.1
		Max	7.14E-3	1.74	0.0156	1.81E-7	3.56E-3	0.039	7.12E-10	5.3E-9	2.68E-3	1.24E-12	1.23E-4	9.3E-3	0.155	1.73E-7	0.389
C4 Hfuel	CT[b]	Min	1.15E-3	0.543	0.0298	8.56E-8	1.98E-4	2.15E-3	4.11E-10	5.56E-9	2.88E-5	3.06E-15	5E-5	6.66E-4	7.82E-5	8.88E-8	0.0125
		Mode	4E-3	0.9	0.9	2E-7	8E-4	4E-3	4E-9	2.5E-8	9E-4	5E-13	2.5E-4	2.8E-3	7E-3	2E-7	0.05
		Max	0.0299	1.3	2.36	2.9E-7	1.94E-3	0.0212	1.97E-8	6.57E-8	0.0149	6.55E-12	1.48E-3	6.79E-3	0.0758	4.48E-7	0.233
C5 Ngas	CT[b]	Min	9.63E-5	0.36	1.16E-4	3.02E-9	3.91E-5	4.45E-4	2.12E-11	5.07E-11	1.4E-5	1.22E-15	4.01E-6	1.14E-4	2.74E-5	5.49E-8	6E-3
		Mode	4E-4	0.5	9E-3	2E-8	3.5E-4	1.5E-3	1E-10	3E-10	6E-4	1.5E-14	2E-5	5E-4	6E-3	1E-7	0.05
		Max	1.91E-3	0.768	1.39	7.18E-8	7.5E-4	8.22E-3	1.39E-7	6.21E-9	9.67E-3	2.32E-12	8.97E-5	2.1E-3	0.117	9.34E-7	0.513
C6 Nucl	CT[b]	Min	3.1E-5	4.28E-3	0.0149	3.17E-8	1.16E-5	7.74E-5	3.27E-11	4.68E-10	0.245	3.95E-12	1.91E-6	2.26E-5	8.05E-5	3.46E-6	3.11E-3
		Mode	4.5E-5	5E-3	0.019	3.5E-8	1.5E-5	9.5E-5	6E-11	6E-10	0.4	1E-10	2E-6	2.8E-5	0.02	3.7E-6	0.01
		Max	7.4E-5	0.0132	0.0236	4.03E-8	1.9E-5	1.27E-4	5.58E-10	1.14E-9	0.929	1.13E-9	3.97E-6	3.63E-5	0.319	3.94E-6	0.0167
R1 Wind	CT[b]	Min	1.71E-5	5.06E-3	1.09E-3	1.15E-8	4.19E-6	4.44E-5	3.66E-11	5.57E-10	1.53E-4	5.85E-14	2.56E-6	1.17E-5	1.46E-4	7.08E-7	0.0192
		Mode	3E-5	8E-3	2E-3	2E-8	6.5E-6	6E-5	5E-11	8E-10	2.7E-4	8E-14	4E-6	2E-5	2.5E-4	1.2E-6	0.03
		Max	4.28E-5	0.0126	2.73E-3	2.88E-8	1.05E-5	1.11E-4	9.15E-11	1.39E-9	3.81E-4	1.46E-13	6.39E-6	2.92E-5	3.66E-4	1.77E-6	0.048
R2 Pvolt	CT[b]	Min	1.94E-4	0.0413	0.027	1.05E-7	3.38E-5	3.64E-4	7.23E-10	9.06E-9	4.31E-3	9.98E-13	2.36E-5	1.23E-4	8.04E-4	9.11E-6	0.173
		Mode	3.5E-4	0.07	0.04	1.8E-7	5E-5	6.4E-4	1.3E-9	1.6E-8	7.5E-3	1.75E-12	4.1E-5	2.14E-4	1.4E-3	1.59E-5	0.3
		Max	3.7E-4	0.0788	0.0516	2.01E-7	6.45E-5	6.94E-4	1.38E-9	1.73E-8	8.23E-3	1.91E-12	4.5E-5	2.34E-4	1.54E-3	1.74E-5	0.33
R3 Biog	CT[b]	Min	1.91E-3	0.128	-0.647	5.91E-6	5.39E-4	5.7E-3	-1.45E-9	-1.21E-6	5.65E-4	2.61E-14	6.82E-5	1.03E-3	7.38E-4	1.83E-8	0.125
		Mode	3.5E-3	0.22	-0.4	5E-5	2E-3	0.01	-1E-9	-8E-7	2.5E-3	2.5E-13	1.1E-4	2E-3	0.02	3E-6	111

		Max	5.79E-3	0.388	0.0196	8.61E-5	2.88E-3	0.0197	9.81E-10	1.49E-8	4.14E-3	3.75E-13	2.06E-4	3.75E-3	0.105	4.97E-6	190
R4 Biom	CT[b]	Min	9.56E-4	0.0227	2.59E-3	5.97E-8	3.33E-4	2.25E-3	1.64E-10	7.02E-9	6.25E-4	1.02E-13	4.11E-5	6.47E-4	3.6E-4	1.78E-8	5.22
		Mode	1.1E-3	0.04	0.04	1.2E-5	7E-4	5E-3	4E-10	7E-8	1.3E-3	1.5E-13	9E-5	1.5E-3	0.025	3E-7	31
		Max	5.81E-3	0.169	0.117	4.2E-5	2.16E-3	0.0213	3.36E-9	2.03E-7	5.08E-3	1.56E-12	4.03E-4	4.75E-3	0.171	2E-6	442
R5 Hydr	CT[b]	Min	4.59E-6	5.29E-3	9.97E-5	2.17E-9	1.23E-6	1.32E-5	3.65E-12	1.16E-10	2.92E-5	4.73E-15	3.57E-7	3.43E-6	2.44E-5	2.5E-7	4.71E-3
		Mode	6E-6	7E-3	2E-4	2.5E-9	2E-6	1.5E-5	4.5E-12	1.5E-10	4E-5	6E-15	5.5E-7	6E-6	3E-5	3.1E-7	7E-3
		Max	1.36E-5	0.166	2.93E-4	6.32E-9	3.67E-6	3.96E-5	1.08E-11	3.67E-10	8.34E-5	1.2E-14	1.07E-6	1.04E-5	6.59E-5	4.88E-7	0.0138

[a] C1: Hard coal, C2: Lignite, C3: Coal gases, C4: Heavy fuel oil, C5: Natural gas, C6: Nuclear, R1: Wind, R2: Photovoltaic, R3: Biogas, R4: Biomass, R5: Hydro.

[b] Closed triangular distribution.

[c] AC: Acidification; CC: Climate Change; EF: Ecotoxicity, freshwater; EuF: Eutrophication, freshwater; EuM: Eutrophication, marine; EuT: Eutrophication, terrestrial; HTC: Human toxicity, cancer; HTNC: Human toxicity, non-cancer; IR: ionising radiation; OD: Ozone depletion; PM: Particulate matter; POF: Photochemical ozone formation; RDW: Resource depletion, water; RD: Resource depletion; LANCA: Land use indicator value.

It should be clarified that there can be correlations between the indicators of a MIVES model. In this work, Spearman's rank coefficients were used. The reader can find in Lovie and Lovie [81], in Spearman [82] and in Ref. [83] more information about correlations. From the LCA sets of results, the authors estimated the Spearman correlation coefficients for the indicators of all the types of power plants. It is important to note that the absence of correlations between indicators that are correlated in practice would lead to unrealistic results, compromising the veracity of the conclusions drawn from them. More information on these coefficients is provided in Section 2 of Appendix A (Tables A.6-A.16).

5. Results and discussions

The results obtained for the Environmental Index (*ENI*) are summarised in Table 4. The cumulative probability curves for all the alternatives are shown in Fig. 3 (Case 1). It facilitates the understanding of the numerical values included in Table 4. Furthermore, it also provides an idea about the position that each power plant occupies in the environmental ranking. For example, from Fig. 3, it is clear that if one compares hard coal (C1) and biomass (R4) power plants, it is not possible to state that one alternative is always better than the other, since their cumulative probability curves present an intersection. However, biomass (R4) is more likely to surpass hard coal (C1) in terms of environmental performance, since its curve is usually positioned to the right of that of coal. Also with the objective of getting a brief overview of the results, the reader is referred to Fig. 4, where the minimum and maximum *ENIs* for Case 1 (closed triangular distributions) are shown in a bar chart. A maximum of 110,000 iterations was established. Furthermore, a study of the real convergence was also performed, by analysing the mean, standard deviation and 95th percentile for every 100 iterations. In Section 4 of Appendix A (Tables A.17-A.21), the reader can find the results obtained with other sets of weights, different from the one included in Table 1.

Table 4
Summary of the Monte Carlo simulation results for the Environmental Index (*ENI*).

Plants [a]	Cases													
	Case 1 (Closed triangular distributions)							Case 2 (Uniform distributions)						
	Parameters													
	Min	Max	Mean	S. Dev.[b]	Mode	5^{th} P.[c]	95^{th} P.[d]	Min	Max	Mean	S. Dev.[b]	Mode	5^{th} P.[c]	95^{th} P.[d]
C1 Hcoal	0.2424	0.6832	0.3767	0.0561	0.3406	0.2993	0.4787	0.2408	0.7711	0.3526	0.0713	0.3162	0.2671	0.5022
C2 Lign	0.1984	0.5566	0.3237	0.0449	0.3085	0.2538	0.4048	0.1889	0.6451	0.3032	0.0567	0.3006	0.2229	0.4085
C3 Clgas	0.4373	0.7477	0.5604	0.0380	0.5650	0.4987	0.6240	0.4300	0.7844	0.5455	0.0549	0.5386	0.4642	0.6452
C4 Hfuel	0.1941	0.6891	0.2808	0.0627	0.2154	0.2083	0.3997	0.1932	0.7558	0.2784	0.0804	0.2068	0.1999	0.4496
C5 Ngas	0.3185	0.8981	0.5859	0.0977	0.5670	0.4255	0.7461	0.3055	0.9014	0.5187	0.1103	0.5058	0.3521	0.7140
C6 Nucl	0.6881	0.7981	0.6963	0.0084	0.6947	0.6912	0.7074	0.6874	0.7956	0.6966	0.0125	0.6949	0.6894	0.7111
R1Wind	0.9587	0.9881	0.9749	0.0060	0.9758	0.9642	0.9843	0.9587	0.9881	0.9741	0.0085	0.9875	0.9604	0.9869
R2 Pvolt	0.6228	0.7519	0.6692	0.0275	0.6442	0.6331	0.7219	0.6226	0.7523	0.6833	0.0374	0.6253	0.6280	0.7445
R3 Biog	0.2989	0.6711	0.4212	0.0661	0.4023	0.3263	0.5428	0.2987	0.7116	0.4262	0.0912	0.3011	0.3069	0.5839
R4 Biom	0.2147	0.7357	0.3949	0.0777	0.3708	0.2741	0.5265	0.2130	0.7968	0.3618	0.0991	0.2965	0.2344	0.5514
R5 Hydr	0.9568	0.9965	0.9821	0.0094	0.9941	0.9646	0.9944	0.9545	0.9965	0.9751	0.0113	0.9936	0.9582	0.9933

[a] C1: Hard coal, C2: Lignite, C3: Coal gases, C4: Heavy fuel oil, C5: Natural gas, C6: Nuclear, R1: Wind, R2: Photovoltaic, R3: Biogas, R4: Biomass, R5: Hydro.
[b] Standard deviation.
[c] 5th percentile.
[d] 95th percentile.

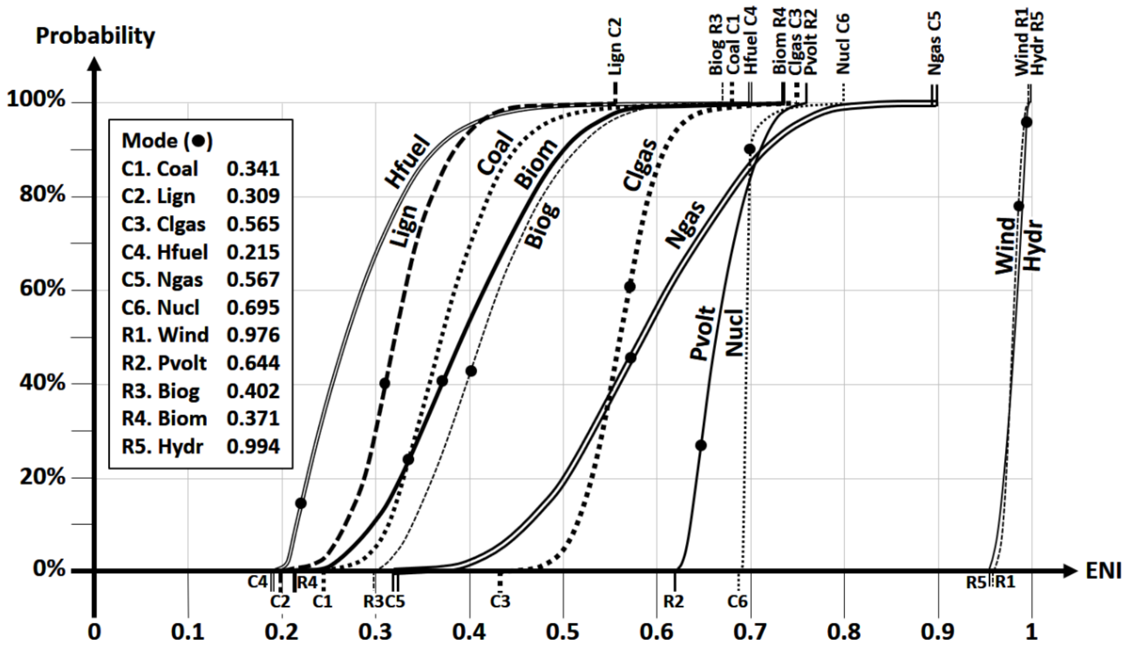

Fig. 3. Cumulative probability curves for the ENIs of the 11 types of power plants in Case

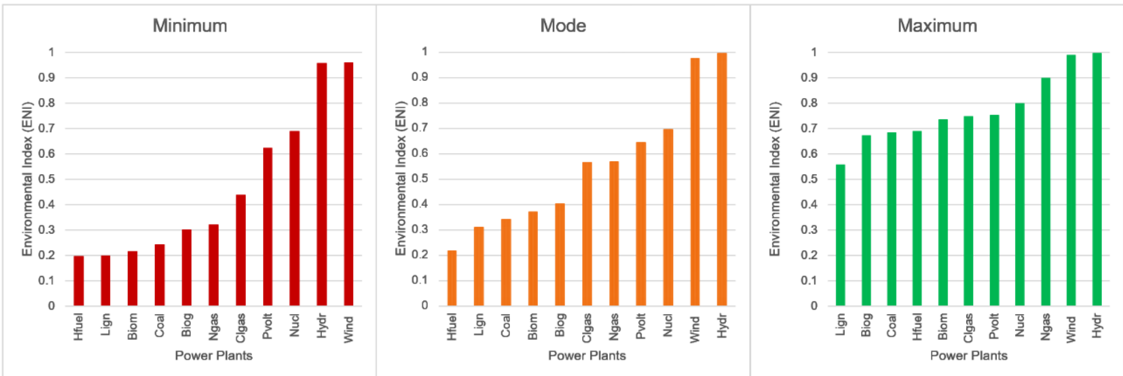

Fig. 4. Minimum, modal and maximum ENI values for the different renewable and non-renewable power plants in Case 1

5.1. Results: comparison between triangular and uniform distributions (Cases 1 and 2)

Beyond the numerical values, it is interesting to compare the rankings obtained in both cases. The main conclusion is that there are no striking differences between the results obtained employing triangular and uniform distributions. Nevertheless, the authors consider that the results from Case 1 (triangular) are more representative, since modal values were taken into account in their calculation process. Therefore, only the results of Case 1 will be discussed in the following section. Section 3 of Appendix A provides further information.

5.2. General results discussion

Making comparisons across different studies is not always simple, or even possible. One reason for this is that the results could have been obtained under different circumstances. Another factor is that potential differences may exist from a methodological point of view. Moreover, the results for the majority of existing studies are similar to the input values used here to feed the

MIVES model. In other words, the literature almost always provides the contribution of power plants to environmental impacts in the corresponding units (for instance, kg of $CO_{2\text{-eq}}$ for global warming potential) without going further. Very few works integrate the different environmental impacts into a unique result. The deterministic study performed by IDAE [40] is one of the few cases in point. Cartelle Barros et al. [66] subsequently extended this analysis, including additional indicators. On the other hand, the original contributions presented in Sections 1 and 2 reinforce the idea that it is difficult to compare this study with ones that already exist. It is therefore not possible to directly compare and contrast the figures of this and other studies. Nevertheless, key findings can be made even if a qualitative comparison is performed, based, for example, on the position that the different alternatives occupy in an environmental ranking.

R5 (hydro) has always obtained the best results, subject to one exception: the highest minimum value that was achieved by R1 (wind). In fact, the hydro minimum value (0.9568) is very near to the best possible result. Yet it should not be forgotten that the decommissioning of the hydro civil engineering works was not included in this study, since they are likely not to be removed. If the opposite occurs, their corresponding environmental indices (*ENIs*) can undergo a reduction, in particular for large hydro power plants. This could result in a small change in the ranking, R1 (wind) being the new best alternative, with indices always above 0.95. Major changes are not likely to occur. The outcomes achieved by hydro and wind options in the present study are in line with those presented in Ref. [40], where mini-hydro and wind power plants occupy the first and second positions, respectively. The decommissioning stage is not included in the IDAE study. As indicated in Section 1, the study performed by Turconi et al. [42] is one of the few in which different types of power plants are analysed, covering several regions throughout the world. Its main limitation is that only GHG, SO_2 and NO_x emissions were taken into account. These pollutants are of paramount importance to the study of global warming potential (GHG), acidification potential (SO_2 and NO_x) and eutrophication potential (NO_x). These environmental impacts were also considered in the present study. Despite the differences in scope between this paper and the one by Turconi et al. [42], the conclusions concerning R5 (hydro) and R1 (wind) are the same, since they also resulted in being the less-polluting options.

At a certain distance, one finds the results for C6 (nuclear) and R2 (photovoltaic) options ranging from 0.6881 to 0.7981 and from 0.6228 to 0.7519, respectively. Both alternatives appear to be high-performing options. Nuclear power plants (R6) are mainly penalised by ionising radiation emissions and the consumption of water. On the other side of the coin, these alternatives hardly contribute to global warming, among other impacts. Other advantages are unrelated to environmental issues, like their independence from atmospheric phenomena. On the other hand, nuclear facilities have noteworthy disadvantages unrelated to the environmental pillar, such as the high risk of cost overruns and construction delays, as well as the potential consequences of accidents. R2 (photovoltaic) is a similar case to R5 (hydro) in that the end-of-life stage was not included, because of feasibility problems. In other words, R2 real alternatives are likely to obtain slightly worse results than the ones presented here. The C6 and R2 results are similar to the ones for IDAE [40], where the photovoltaic and nuclear alternatives performed better than the options with the weakest performance. The results from Turconi et al. [42] are in line with the ones presented here. In other words, C6 (nuclear) and (R2) photovoltaic also presented high-performing results, far from the most contaminating alternatives. In fact, according to the results from Turconi et al. [42], C6 (nuclear) is close to the two best technologies. This is due to the absence of indicators such as ionising radiation, among others, which makes C6 (nuclear) slightly closer to R5 (hydro) and R1 (wind).

The following two alternatives are C5 (natural gas) and C3 (coal gases) power plants. They obtained what can be considered middling results. In fact, they are the last two alternatives of the descending ranking list with mean and modal values over 0.5. C5 appears to be an alternative capable of the best (0.8981) and worst (0.3185). The way in which the fuel is fired seems to play a key role here. Once again, Turconi et al. [42] also found that C5 (natural gas) is a "middling" alternative, capable of best and worst depending on the contaminant emissions studied. It is therefore positioned between the four best options and the worst ones.

Finally, systems fired by biogas (R3), biomass (R4), hard coal (C1), lignite (C2) and fuel oil (C4) take up the last five positions. The non-renewable alternatives (C1, C2 and C4) obtained the expected results, since they are usually considered, by far, the most contaminating ones. This is also the case in IDAE [40] and in Turconi et al. [42]. Their environmental indices (*ENIs*) are likely to be near 0.3, which is far from the *ENIs* obtained by the previous options. Despite the fact that all of them present low-performing results, C1 (coal) appears to be moderately better than C2 (lignite). Atilgan and Azapagic [36] also reached the same conclusion for Turkey. In fact, those authors claim that natural gas power plants present lower impacts than the coal fired ones and these, in turn, present lower impacts than the lignite-fired options. The same conclusion was reached in the present study. While it is generally accepted that renewables are environmentally better than their conventional counterparts, the results for R3 (biogas) and R4 (biomass) can be surprising. Nevertheless, the life cycles of biogas and biomass power plants are similar to those of non-renewable thermal power plants. Moreover, many of the so-called traditional uses of biomass involve the open combustion of wood regardless of emissions or reforestation. However, in general, R3 (biogas) and R4 (biomass) achieved higher *ENIs* than hard coal (C1), lignite (C2) and heavy fuel oil power plants (C4). Similarly, Cartelle Barros et al. [66] affirmed that biomass power plants have lower impacts, but within a similar range, than those attributed to the previously mentioned thermal power plants. A similar conclusion can be extracted from Ref. [42]. On the other hand, it is important to reiterate that the novel aspects of this study make it impossible to compare its results with the ones presented in the papers mentioned in Sections 1 and 2, apart from the comparisons already made.

In Section 4 of Appendix A, the reader can find the discussion on the sensitivity analysis. The main finding is that the classifications may undergo minor changes. Nonetheless, the model appeared to be robust and, thus, the main comments of this section are still applicable.

5.3. Case studies: validation of the model

It is important to validate the results presented in Table 4 and Figs. 3 and 4. There are different alternatives for this purpose. One of these is to make comparisons across studies, as was done in the previous section, with the limitations alluded to before. Another option is to apply the model to, at least, one case study. In this sense, the model was used to evaluate the environmental performance of a natural gas power plant and two biomass power plants (fluidised bed and grate furnace technologies), all of them previously investigated in the literature by Usapein and Chavalparit [32], and by da Costa et al. [23], respectively. In both studies, the dismantling stage is not included. Nevertheless, as discussed below, this will not be an obstacle to testing the accuracy of the model. In this way, its applicability to both non-renewable and renewable real or fictitious case studies will be demonstrated.

First, it is necessary to clarify that no study was found including all the ILCD indicators analysed in this paper. Therefore, the model input values taken from existing studies and shown in Table 5 were not sufficient to feed the complete model. Consequently, the modal values presented in Table 3 were employed for the missing environmental impacts. Moreover, the case studies alluded to did not include the decommissioning stage, covered by the model here presented.

Table 5
Input values from two case studies previously analysed in the literature.

Environmental indicators	Case studies		
	Natural gas [32]	Biomass [23] [a]	Biomass [23] [b]
Acidification (AC)	3.17E-4	3.16E-3	4.14E-3
Climate change (CC)	4.25E-1	9.83E-2	1.62E-1
Ecotoxicity, freshwater (EF)	1.28E-2	-	-
Eutrophication, freshwater (EuF)	1.59E-8	1.39E-5	1.79E-5
Eutrophication, marine (EuM)	9.03E-5	1.47E-3	1.81E-3
Eutrophication, terrestrial (EuT)	9.88E-4	-	-
Human toxicity, cancer effects (HTC)	1.22E-11	-	-
Human toxicity, non-cancer effects (HTNC)	5.89E-10	-	-
Ionising radiation (IR)	2.95E-5	-	-
Ozone depletion (OD)	1.04E-10	-	-
Particulate matter (PM)	2.23E-5	4.37E-4	8.05E-4
Photochemical ozone formation (POF)	2.45E-4	3.17E-3	4.14E-3
Resource depletion, water (RDW)	-	-	-
Resource depletion (RD)	1.10E-8	7.16E-7	8.76E-7
Land Use Indicator Value Calculation (LANCA)	-	-	-

[a] Fluidised bed furnace technology
[b] Grate furnace technology

The environmental indices (*ENIs*) are presented in Table 6. As can be seen, the natural gas power plant obtained a result of 0.7740. This value falls within the minimum and maximum indices presented in Table 4 (Case 1) for this technology (0.3185-0.8981, respectively). There is a considerable difference between 0.7740 and the minimum value. In fact, in this case, achieving the minimum is equivalent to reducing the environmental index (*ENI*) by a percentage close to 59%. In other words, the natural gas power plant must experience an increase in its global environmental impact of more than 59%. It is reasonable to think that the decommissioning stage, under no circumstances, will generate such an impact. Therefore, it can be concluded that, even if the environmental impacts derived from the dismantling operations are added, the index will still be within the range shown in Table 4 and Fig. 3.

On the other hand, the two biomass alternatives obtained a result of 0.3819 and 0.3594, respectively. Once again, these values are within the limits defined in Table 4 and Fig. 3 (Case 1) for this type of power plant (0.2147-0.7357, respectively). A decrease in the global environmental performance close to 40% should be necessary, so that both cases achieve an index below the minimum. Again, it does not seem reasonable to think that the decommissioning activities can produce such a result.

It is therefore possible to conclude that the model can be successfully applied to assess the environmental behaviour of case studies, even if the data used to feed it do not include one of the life cycle stages. It is important to remark that, if some phases are missing, the environmental index (*ENI*) obtained with the model will be higher than the real one, since some impacts are not taken into account. For these particular cases, the model must be used with caution in order to avoid misleading conclusions.

Table 6
Environmental indices (*ENIs*) obtained for the two case studies previously analysed in the literature.

Case studies		
Natural gas [32]	Biomass [23] [a]	Biomass [23] [b]
0.7740	0.3819	0.3594

[a] Fluidised bed furnace technology
[b] Grate furnace technology

6. Conclusions, limitations, policy implications and future developments

A probabilistic environmental impact assessment of six non-renewable and five renewable power plants was carried out in this paper. A MIVES-Monte Carlo model fed with LCA results (midpoint impact methods recommended by the ILCD Handbook) collected by the authors, was used for this purpose. Uncertainty and variability were considered.

This is the first time a probabilistic and worldwide approach has been adopted in terms of environmental behaviour in the electricity generation sector. Therefore, the results can be considered representative for most of the possible real cases. The model can also be used to assess the environmental performance of real case studies. In fact, it was validated by its application to natural gas and biomass power plants, previously analysed in the existing literature.

On the other hand, one of the main limitations of the model presented here is that it should be regularly updated to take into account factors like changes in the maturity level or the emergence of new technologies. In the same line, at the time of using the model for assessing real case studies, the user must collect information to feed it. In other words, data associated with 15 environmental indicators is needed. This is another limitation, since it is not easy to obtain data for certain environmental impact categories that are rarely studied in scientific literature. However, this drawback is linked to a significant advantage: the higher the number of indicators, the greater the relevance and applicability of the results obtained. This shortcoming can be managed in different ways. One option is to use the figures included in Table 3 for the indicators in which the information is missing (as was done in Section 5.3). In fact, it is possible to compare the input values of a real case study with the minimum, mode, and maximum numbers of Table 3 and, on the basis of this comparison, the user can establish the values for the remaining indicators by maintaining the proportion among the two sets (the real one and Table 3). By acting in this way, important errors are not expected. Another alternative is to use a reduced version of the model with the indicators for which information could be found. A normalisation process is required for the weights included in the requirement tree (Table 1). This procedure will provide a simplified environmental index. If it is used with caution, it can give an idea about the environmental performance of the alternative studied. Nevertheless, this simplified approach can lead to wrong conclusions, in particular, if the user does not have an in-depth knowledge of the energy sector, or if the model contains a much smaller number of indicators. Extracting conclusions and making decisions on the basis of only a few environmental impacts is not recommendable.

As for the global results, R5 (hydro) and R1 (wind) appeared to be the best options with environmental indices (*ENIs*) always closely approximating the best possible index. The worst alternatives on the ranking are hard coal (C1), lignite (C2), and heavy fuel oil (C4) fuel powered plants, whose *ENIs* are, in the majority of cases, very far from the best alternatives. Between these two groups, the remaining alternatives are found, with different levels of satisfaction.

Despite the fact that the two best-performing alternatives are renewables, this study demonstrates that not all renewables are consistently “eco-friendly”. For instance, R3 (biogas) and R4 (biomass) power plants are closer to the worst options than to the best renewables. In the same vein, not all the non-renewable options are at the bottom of the list. Some alternatives, such as C6 (nuclear) or C5 (natural gas) can achieve more than acceptable performances. Another interesting finding is that, although there are certain renewables that do not produce pollutants during the operation phase, their impacts can be of considerable magnitude. For instance, R2 (photovoltaic) power plants can have a lower performance than some non-renewable options. In fact, without taking into account the two best options, it can be concluded that the best option is not always the same for all real possible situations. In other words, some of the alternatives that usually have a low performance (for instance, C1: coal) can achieve higher *ENIs* than other options that usually have a better one (for example, R2: photovoltaic). Consequently, some non-renewables can be, in some circumstances, environmentally competitive.

In terms of the model applicability to real case studies, a natural gas and two types of biomass (fluidised bed and grate furnace) power plants were considered. Both the non-renewable and renewable alternatives obtained environmental indices (*ENIs*) within the expected intervals. Therefore, it can be concluded that the model measures the real impact of power plants.

In the authors’ opinion, energy planning authorities at regional, national, or supranational levels should take into account the results of this and other similar studies at the time of making decisions. When possible, it is necessary to boost the less polluting alternatives (mainly hydro and wind) and to equip older power plants fuelled by hard coal, lignite or oil, with technological advances that mitigate their current environmental impacts. Specific modern, non-renewable plants (nuclear; natural gas), adequately located (nuclear: proper soils, absence of terrestrial and sea seismic problems, etc.) and equipped with the most advanced technology, could be employed as a bridge until a complete development of renewable energy could be reached. This is only related to environmental aspects (social issues can affect this statement), and is in line with deLlano et al. [14] who claim that nuclear energy is likely to play an important role in Europe's energy future.

It is important to note that policy interventions can serve to foster the development and mass production of certain energy technologies [84]. This has already led to a decrease in the cost of some renewables that are environmentally friendly, such as wind. Therefore, some technologies that were not economically attractive are now profitable [84].

As for future developments, similar models can be constructed but, this time, using different LCA techniques, such as CML, ReCiPe or TRACI, among others. The results obtained with the new models must be compared with the ones presented here. Another possible development for the future consists of increasing the number of renewable and non-renewable alternatives, including geothermal, solar thermal, tidal stream, tidal barrage or wave energy options. Other lines of work can be focused on dividing the model into sub-models, each one of them studying the impacts associated with only one stage of the life cycle. This could be of great help to identify the most polluting activities and to adopt effective measures to prevent their impacts. The last two possibilities are associated with current limitations of this study.

Finally, it is worth noting that environmental behaviour is probably the most crucial parameter to consider in almost every decision-making problem. However, it is not the only one. Another task for the future would be to construct a complete probabilistic model for assessing the global sustainability of power plants. This model would comprise a set of indicators that make it possible to assess all the sustainability dimensions in detail. The Environmental Index (*ENI*) obtained in this study should be one of those indicators: the most important one.

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Appendix A. Supplementary data: calculation process

Supplementary data related to the calculation process and its results can be found at https://doi.org/10.1016/j.apenergy.2019.114344.

References

[1] de Almeida CF, Maciel VG, Tsambe M, de Abreu Cybis LF. Environmental assessment of a bi-fuel thermal power plant in an isolated power system in the Brazilian Amazon region. J Clean Prod 2017;154:41–50. doi:10.1016/j.jclepro.2017.03.209.

[2] Petrescu L, Bonalumi D, Valenti G, Cormos AM, Cormos CC. Life Cycle Assessment for supercritical pulverized coal power plants with post-combustion carbon capture and storage. J Clean Prod 2017;157:10–21. doi:10.1016/j.jclepro.2017.03.225.

[3] Nanaki EA, Koroneos CJ, Xydis GA. Environmental impact assessment of electricity production from lignite. Environ Prog Sustain Energy 2016;35:1868–75. doi:10.1002/ep.12427.

[4] Falkner R. Global environmental politics and energy: Mapping the research agenda. Energy Res Soc Sci 2014;1:188–97. doi:10.1016/j.erss.2014.03.008.

[5] Galeotti M, Rubashkina Y, Salini S, Verdolini E. Environmental policy performance and its determinants: Application of a three-level random intercept model. Energy Policy 2018;114:134–44. doi:10.1016/j.enpol.2017.11.053.

[6] Diniz Oliveira T, Costa Gurgel A, Tonry S. International market mechanisms under the Paris Agreement: A cooperation between Brazil and Europe. Energy Policy 2019;129:397–409. doi:10.1016/j.enpol.2019.01.056.

[7] Hallegatte S, Rogelj J, Allen M, Clarke L, Edenhofer O, Field CB, Friedlingstein P, van Kesteren L, Knutti R, Mach KJ, Mastrandrea M, Michel A, Minx J, Oppenheimer M, Plattner GK, Riahi K, Schaeffer M, Stocker CF, van Vuuren DP. Mapping the climate change challenge. Nat Clim Chang 2016;6:663–8. doi:10.1038/nclimate3057.

[8] Urpelainen J, Van de Graaf T. United States non-cooperation and the Paris agreement. Clim Policy 2018;18:839–51. doi:10.1080/14693062.2017.1406843.

[9] Cooper M. Governing the global climate commons: The political economy of state and local action, after the U.S. flip-flop on the Paris Agreement. Energy Policy 2018;118:440–54. doi:10.1016/j.enpol.2018.03.037.

[10] Selin H, Vandeveer SD. Broader , Deeper and Greener : European Union Environmental Politics , Policies , and Outcomes. Annu Rev Environ Resour 2015;40:309–35. doi:10.1146/annurev-environ-102014-021210.

[11] De-Llano Paz F, Antelo SI, Calvo Silvosa A, Soares I. The technological and environmental efficiency of the EU-27 power mix: An evaluation based on MPT. Energy 2014;69:67–81. doi:10.1016/j.energy.2014.02.036.

[12] deLlano-Paz F, Martínez Fernandez P, Soares I. Addressing 2030 EU policy framework for energy and climate: Cost, risk and energy security issues. Energy 2016;115:1347–60. doi:10.1016/j.energy.2016.01.068.

[13] van der Ploeg F, Withageny C. Global warming and the green paradox: A review of adverse effects of climate policies. Rev Environ Econ Policy 2015;9:285–303. doi:10.1093/reep/rev008.
[14] deLlano-Paz F, Calvo-Silvosa A, Antelo SI, Soares I. Power generation and pollutant emissions in the European Union: A mean-variance model. J Clean Prod 2018;181:123–35. doi:10.1016/j.jclepro.2018.01.108.
[15] Korre A, Nie Z, Durucan S. Life cycle modelling of fossil fuel power generation with post-combustion CO2 capture. Int J Greenh Gas Control 2010;4:289–300. doi:10.1016/j.ijggc.2009.08.005.
[16] Liu H, Polenske KR, Xi Y, Guo J. Comprehensive evaluation of effects of straw-based electricity generation: A Chinese case. Energy Policy 2010;38:6153–60. doi:10.1016/j.enpol.2010.06.001.
[17] Briones Hidrovo A, Uche J, Martínez-Gracia A. Accounting for GHG net reservoir emissions of hydropower in Ecuador. Renew Energy 2017;112:209–21. doi:10.1016/j.renene.2017.05.047.
[18] Desideri U, Proietti S, Zepparelli F, Sdringola P, Bini S. Life Cycle Assessment of a ground-mounted 1778kWp photovoltaic plant and comparison with traditional energy production systems. Appl Energy 2012;97:930–43. doi:10.1016/j.apenergy.2012.01.055.
[19] Uddin MS, Kumar S. Energy, emissions and environmental impact analysis of wind turbine using life cycle assessment technique. J Clean Prod 2014;69:153–64. doi:10.1016/j.jclepro.2014.01.073.
[20] Hanbury O, Vasquez VR. Life cycle analysis of geothermal energy for power and transportation: A stochastic approach. Renew Energy 2018;115:371–81. doi:10.1016/j.renene.2017.08.053.
[21] Tremeac B, Meunier F. Life cycle analysis of 4.5 MW and 250 W wind turbines. Renew Sustain Energy Rev 2009;13:2104–10. doi:10.1016/j.rser.2009.01.001.
[22] Butnar I, Rodrigo J, Gasol CM, Castells F. Life-cycle assessment of electricity from biomass: Case studies of two biocrops in Spain. Biomass and Bioenergy 2010;34:1780–8. doi:10.1016/j.biombioe.2010.07.013.
[23] da Costa TP, Quinteiro P, Tarelho LA da C, Arroja L, Dias AC. Environmental impacts of forest biomass-to-energy conversion technologies: Grate furnace vs. fluidised bed furnace. J Clean Prod 2018;171:153–62. doi:10.1016/j.jclepro.2017.09.287.
[24] Demir N, Taşkın A. Life cycle assessment of wind turbines in Pınarbaşı-Kayseri. J Clean Prod 2013;54:253–63. doi:10.1016/j.jclepro.2013.04.016.
[25] Huang YF, Gan XJ, Chiueh P Te. Life cycle assessment and net energy analysis of offshore wind power systems. Renew Energy 2017;102:98–106. doi:10.1016/j.renene.2016.10.050.
[26] Fantin V, Giuliano A, Manfredi M, Ottaviano G, Stefanova M, Masoni P. Environmental assessment of electricity generation from an Italian anaerobic digestion plant. Biomass and Bioenergy 2015;83:422–35. doi:10.1016/j.biombioe.2015.10.015.
[27] dos Santos MA, Damázio JM, Rogério JP, Amorim MA, Medeiros AM, Abreu JLS, Maceira ME, Melo AC, Rosa LZ. Estimates of GHG emissions by hydroelectric reservoirs: The Brazilian case. Energy 2017;133:99–107. doi:10.1016/j.energy.2017.05.082.
[28] Mahmud MAP, Huda N, Farjana SH, Lang C. A strategic impact assessment of hydropower plants in alpine and non-alpine areas of Europe. Appl Energy 2019;250:198–214. doi:10.1016/j.apenergy.2019.05.007.
[29] Castelo Branco DA, Moura MCP, Szklo A, Schaeffer R. Emissions reduction potential from CO2 capture: A life-cycle assessment of a Brazilian coal-fired power plant. Energy Policy 2013;61:1221–35. doi:10.1016/j.enpol.2013.06.043.
[30] Restrepo Á, Bazzo E, Miyake R. A life cycle assessment of the Brazilian coal used for electric power generation. J Clean Prod 2015;92:179–86. doi:10.1016/j.jclepro.2014.12.065.
[31] Martín-Gamboa M, Iribarren D, Dufour J. Environmental impact efficiency of natural gas combined cycle power plants: A combined life cycle assessment and dynamic data envelopment analysis approach. Sci Total Environ 2018;615:29–37. doi:10.1016/j.scitotenv.2017.09.243.
[32] Usapein P, Chavalparit O. Life Cycle Assessment of Producing Electricity in Thailand: A Case Study of Natural Gas Power Plant. MATEC Web Conf., vol. 103, 2017, p. 5009. doi:10.1051/matecconf/201710305009.
[33] Şengül H, Bayrak F, Aydinalp Köksal M, Ünver B. A cradle to gate life cycle assessment of Turkish lignite used for electricity generation with site-specific data. J Clean Prod 2016;129:478–90. doi:10.1016/j.jclepro.2016.04.025.
[34] Carless TS, Griffin WM, Fischbeck PS. The environmental competitiveness of small modular reactors: A life cycle study. Energy 2016;114:84–99. doi:10.1016/j.energy.2016.07.111.
[35] Bonou A, Laurent A, Olsen SI. Life cycle assessment of onshore and offshore wind energy-from theory to application. Appl Energy 2016;180:327–37. doi:10.1016/j.apenergy.2016.07.058.
[36] Atilgan B, Azapagic A. Life cycle environmental impacts of electricity from fossil fuels in Turkey. J Clean Prod 2015;106:555–64. doi:10.1016/j.jclepro.2014.07.046.
[37] Atilgan B, Azapagic A. Renewable electricity in Turkey: Life cycle environmental impacts. Renew Energy 2016;89:649–57. doi:10.1016/j.renene.2015.11.082.
[38] Liang X, Wang Z, Zhou Z, Huang Z, Zhou J, Cen K. Up-to-date life cycle assessment and comparison study of clean coal power generation technologies in China. J Clean Prod 2013;39:24–31. doi:10.1016/j.jclepro.2012.08.003.
[39] Weldu YW, Assefa G, Jolliet O. Life cycle human health and ecotoxicological impacts assessment of electricity production from wood biomass compared to coal fuel. Appl Energy 2017;187:564–74. doi:10.1016/j.apenergy.2016.11.101.
[40] IDAE: Instituto para la Diversificación y Ahorro de la Energía (Institute for Energy Diversification and Saving). Impactos ambientales de la producción eléctrica. Análisis de ciclo de vida de ocho tecnologías de

generación eléctrica. 2000.
[41] Wang L, Wang Y, Du H, Zuo J, Yi Man Li R, Zhou Z, Bi F, Garvlehn MP. A comparative life-cycle assessment of hydro-, nuclear and wind power: A China study. Appl Energy 2019;249:37–45. doi:10.1016/j.apenergy.2019.04.099.
[42] Turconi R, Boldrin A, Astrup T. Life cycle assessment (LCA) of electricity generation technologies: Overview, comparability and limitations. Renew Sustain Energy Rev 2013;28:555–65. doi:10.1016/j.rser.2013.08.013.
[43] European Commission. International Reference Life Cycle Data System Handbook - Recommendations for Life Cycle Impact Assessment in the European context. Italy: 2011. doi:10.2788/33030.
[44] Thinkstep. Energy database 2018. GaBi database 2018 LCI documentation. 2018.
[45] Thinkstep. Professional database 2018. GaBi database 2018 LCI documentation. 2018.
[46] Restrepo Á, Miyake R, Kleveston F, Bazzo E. Exergetic and environmental analysis of a pulverized coal power plant. Energy 2012;45:195–202. doi:10.1016/j.energy.2012.01.080.
[47] Wang Y, Sun T. Life cycle assessment of CO2 emissions from wind power plants: Methodology and case studies. Renew Energy 2012;43:30–6. doi:10.1016/j.renene.2011.12.017.
[48] Nguyen TLT, Hermansen JE, Nielsen RG. Environmental assessment of gasification technology for biomass conversion to energy in comparison with other alternatives: The case of wheat straw. J Clean Prod 2013;53:138–48. doi:10.1016/j.jclepro.2013.04.004.
[49] Agrawal KK, Jain S, Jain AK, Dahiya S. Assessment of greenhouse gas emissions from coal and natural gas thermal power plants using life cycle approach. Int J Environ Sci Technol 2014;11:1157–64. doi:10.1007/s13762-013-0420-z.
[50] Kourkoumpas DS, Benekos G, Nikolopoulos N, Karellas S, Grammelis P, Kakaras E. A review of key environmental and energy performance indicators for the case of renewable energy systems when integrated with storage solutions. Appl Energy 2018;231:380–98. doi:10.1016/j.apenergy.2018.09.043.
[51] Yang B, Wei YM, Hou Y, Li H, Wang P. Life cycle environmental impact assessment of fuel mix-based biomass co-firing plants with CO2 capture and storage. Appl Energy 2019;252:113483. doi:10.1016/j.apenergy.2019.113483.
[52] Zhao X, Cai Q, Zhang S, Luo K. The substitution of wind power for coal-fired power to realize China's CO2 emissions reduction targets in 2020 and 2030. Energy 2017;120:164–78. doi:10.1016/j.energy.2016.12.109.
[53] Chiu SLH, Lo IMC. Identifying key process parameters for uncertainty propagation in environmental life cycle assessment for sewage sludge and food waste treatment. J Clean Prod 2018;174:966–76. doi:10.1016/j.jclepro.2017.10.164.
[54] Hauck M, Steinmann ZJN, Laurenzi IJ, Karuppiah R, Huijbregts MAJ. How to quantify uncertainty and variability in life cycle assessment: the case of greenhouse gas emissions of gas power generation in the US. Environ Res Lett 2014;9:74005. doi:10.1088/1748-9326/9/7/074005.
[55] Huijbregts MAJ, Norris G, Bretz R, Ciroth A, Maurice B, Von Bahr B, Weidema B, de Beaufort ASH. Framework for modelling data uncertainty in life cycle inventories. Int J Life Cycle Assess 2001;6:127–32. doi:10.1007/BF02978728.
[56] Sastre CM, González-Arechavala Y, Santos AM. Global warming and energy yield evaluation of Spanish wheat straw electricity generation - A LCA that takes into account parameter uncertainty and variability. Appl Energy 2015;154:900–11. doi:10.1016/j.apenergy.2015.05.108.
[57] Sonnemann GW, Schuhmacher M, Castells F. Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. J Clean Prod 2003;11:279–92. doi:10.1016/S0959-6526(02)00028-8.
[58] Asdrubali F, Baldinelli G, D'Alessandro F, Scrucca F. Life cycle assessment of electricity production from renewable energies: Review and results harmonization. Renew Sustain Energy Rev 2015;42:1113–22. doi:10.1016/j.rser.2014.10.082.
[59] Buonocore E, Vanoli L, Carotenuto A, Ulgiati S. Integrating life cycle assessment and emergy synthesis for the evaluation of a dry steam geothermal power plant in Italy. Energy 2015;86:476–87. doi:10.1016/j.energy.2015.04.048.
[60] Ehtiwesh IAS, Coelho MC, Sousa ACM. Exergetic and environmental life cycle assessment analysis of concentrated solar power plants. Renew Sustain Energy Rev 2016;56:145–55. doi:10.1016/j.rser.2015.11.066.
[61] International Organization for Standardization. Environmental Management-life Cycle Assessment-Principles and Framework. Switzerland: 2006.
[62] International Organization for Standardization. Environmental Management-life Cycle Assessment-Requirements and Guidelines. Switzerland: 2006.
[63] Cartelle Barros JJ, Lara Coira M, de la Cruz López MP, del Caño Gochi A. Comparative analysis of direct employment generated by renewable and non-renewable power plants. Energy 2017;139:542–54. doi:10.1016/j.energy.2017.08.025.
[64] Kupfer T, Baitz Martin, Colodel CM, Kokborg M, Schöll S, Rudolf M, Thellier L, Gonzalez M, Schuller O, Hengstler J, Stoffregen A, Köhler A, Thylmann D. GaBi database and modelling principles 2017. Leinfelden-Echterdingen: 2017.
[65] Vidal-Legaz B, Sala S, Antón A, Maia De Souza D, Nocita M, Putman B, Teixeira RFM. Land-use related environmental indicators for Life Cycle Assessment. Luxembourg: 2016. doi:10.2788/905478.
[66] Cartelle Barros JJ, Lara Coira M, de la Cruz López MP, del Caño Gochi A. Assessing the global sustainability of different electricity generation systems. Energy 2015;89:473–89.

doi:10.1016/j.energy.2015.05.110.
[67] de la Cruz MP, Castro A, del Caño A, Gómez D, Lara M, Cartelle JJ. Comprehensive methods for dealing with uncertainty in assessing sustainability part 1: The MIVES-monte carlo method. In: García-Cascales MS, Sánchez-Lozano JM, Masegosa AD, Cruz-Corona C, editors. Soft Comput. Appl. Renew. Energy Energy Effic., Hershey: IGI Global; 2014, p. 69–106.
[68] Cuadrado J, Zubizarreta M, Pelaz B, Marcos I. Methodology to assess the environmental sustainability of timber structures. Constr Build Mater 2015;86:149–58. doi:10.1016/j.conbuildmat.2015.03.109.
[69] de la Fuente A, Pons O, Josa A, Aguado A. Multi-criteria decision making in the sustainability assessment of sewerage pipe systems. J Clean Prod 2016;112:4762–70. doi:10.1016/j.jclepro.2015.07.002.
[70] de la Fuente A, Armengou J, Pons O, Aguado A. Multi-criteria decision-making model for assessing the sustainability index of wind-turbine support systems: application to a new precast concrete alternative. J Civ Eng Manag 2017;23:194–203. doi:10.3846/13923730.2015.1023347.
[71] del Caño A, Gómez D, de la Cruz MP. Uncertainty analysis in the sustainable design of concrete structures: A probabilistic method. Constr Build Mater 2012;37:865–73. doi:10.1016/j.conbuildmat.2012.04.020.
[72] del Caño A, Pilar de la Cruz M, Gómez D, Pérez M. Fuzzy method for analysing uncertainty in the sustainable design of concrete structures. J Civ Eng Manag 2016;22:924–35. doi:10.3846/13923730.2014.928361.
[73] Gómez D, del Caño A, de la Cruz MP, Josa A. Evaluación de la sostenibilidad en estructuras de hormigón y metálicas. In: Aguado A, editor. Monogr. ACHE Sostenibilidad y construcción, Barcelona: Asociación Científico-Técnica del Hormigón (ACHE); 2012, p. 413–39.
[74] San-José JT, Losada R, Cuadrado J, Garrucho I. Approach to the quantification of the sustainable value in industrial buildings. Build Environ 2007;42:3916–23. doi:10.1016/j.buildenv.2006.11.013.
[75] San-José Lombera J-T, Cuadrado Rojo J. Industrial building design stage based on a system approach to their environmental sustainability. Constr Build Mater 2010;24:438–47. doi:10.1016/j.conbuildmat.2009.10.019.
[76] San-José Lombera J-T, Garrucho Aprea I. A system approach to the environmental analysis of industrial buildings. Build Environ 2010;45:673–83. doi:10.1016/j.buildenv.2009.08.012.
[77] de la Cruz MP, Castro A, del Caño A, Gómez D, Lara M, Gradaille G. Comprehensive Methods for Dealing with Uncertainty in Assessing Sustainability Part 2. In: García-Cascales MS, Sánchez-Lozano JM, Masegosa AD, Cruz-Corona C, editors. Soft Comput. Appl. Renew. energy energy Effic., Hershey: IGI Global; 2014, p. 107–40.
[78] Lindeijer E. Normalization and valuation. In: Udo de Haes H, editor. Towar. a Methodol. life cycle impact Assess., Brussels: SETAC Europe; 1996.
[79] Maurice B, Frischknecht R, Coelho-Schwirtz V, Hungerbühler K. Uncertainty analysis in life cycle inventory. Application to the production of electricity with French coal power plants. J Clean Prod 2000;8:95–108. doi:10.1016/S0959-6526(99)00324-8.
[80] Williams TM. Practical use of distributions in network analysis. J Oper Res Soc 1992;43:265–70. doi:10.1057/jors.1992.35.
[81] Lovie S, Lovie P. Commentary: Charles Spearman and correlation: A commentary on "The proof and measurement of association between two things." Int J Epidemiol 2010;39:1151–3. doi:10.1093/ije/dyq183.
[82] Spearman C. " General Intelligence ," Objectively Determined and Measured. Am J Psychol 1904;15:201–92. doi:10.2307/1412107.
[83] Spearman C. The proof and measurement of association between two things. Int J Epidemiol 2010;39:1137–50. doi:10.1093/ije/dyq191.
[84] Höhne N, Kuramochi T, Warnecke C, Röser F, Fekete H, Hagemann M, Day T, Tewari R, Kurdziel M, Sterl S, Gonzales S. The Paris Agreement: resolving the inconsistency between global goals and national contributions. Clim Policy 2017;17:16–32. doi:10.1080/14693062.2016.1218320.