Renewable Energy Focus 49 (2024) 100581

Contents lists available at ScienceDirect

Renewable Energy Focus

journal homepage: www.elsevier.com/locate/ref

Research Review

Integrated life cycle sustainability assessment with future energy mix: A review of methodologies for evaluating the sustainability of multiple power generation technologies development

Mohammad Hemmati *, Navid Bayati, Thomas Ebel

Center for Industrial Electronics, University of Southern Denmark, Sønderborg, Denmark

ARTICLE INFO

Keywords:
Impact assessment
Life Cycle
Energy mix
Multi-criteria analysis
Dynamic analysis
Machine learning

ABSTRACT

One key driver of sustainable goal development is the transition to sustainable electricity resources. The sustainability impact assessment of power production evaluates all potential impacts on society, the environment, and the economy, as well as finds a reasonable solution to shift towards renewable. Given the multitude of quantitative and qualitative methodologies for sustainability analysis, alongside the absence of a unified procedure, selecting an appropriate method poses a significant challenge in conducting this task. Therefore, this paper conducts an extensive review of the methodologies employed for assessing the sustainability of power generation within the future energy mix, as reflected in scientific publications over the past decade (2013–2024). The main objective of this paper is to compare the methodologies and assess their efficiency as suitable tools for analyzing the sustainability of technologies in different geographical regions. The research methodology, following the screening process, selects 102 papers within the study's scope to undergo a critical examination based on sustainability evaluation approaches. It also provides an overview of novel dynamic methods and the application of artificial intelligence in sustainability assessment. The primary findings indicate a deficiency in a standardized approach for sustainability evaluation within electrical technology. In addressing uncertainties in impact assessment due to various parameters, dynamic methods with multiple temporal accuracies are recommended over a static life cycle. The paper includes a case study comparing methods—multi-criteria decision-making, and ranking, scoring—in the Indonesian context. Considering 15 environmental, social, and economic indicators to evaluate the sustainability in Lombok, results indicate that hydropower, gas, and solar technologies exhibit the highest sustainability scores, respectively.

1. Introduction

The world's energy consumption has about doubled over the last 30 years [1], and due to the absence of any changes to energy policies, it is anticipated that the growth in worldwide energy demand will accelerate in the upcoming years. The overall primary energy supply reached 28,660 TWh in 2022 [2]. Despite the growing contribution of renewable energy sources, fossil fuels continue to be the dominant source of energy supply, accounting for 61% of the total energy supply, worldwide. Globally, coal is the primary source of power production by 37%, with gas coming in second by 23%. Nuclear and hydropower provide most of the low-carbon energy production by 9, and 14%, respectively, and wind and solar power production units are responsible for producing 12% of global energy.

In this context, the social-economic-environmental effects of various energy technologies are becoming a more important consideration to support policy choices; in this regard, carbon footprint, and LCSA are frequently utilized. Carbon footprint evaluation approaches with a single indicator results in oversimplification. Hence, in the case of power production technologies, focusing only on one indicator, e.g. greenhouse gas emissions may lead to incorrect conclusions regarding their eco-social-environmental consequence. Thus, to assess the sustainability of power-producing technologies, a wide range of impact categories need to be taken into account. LCSA is a comprehensive method that considers many indicators from all social, economic, and environmental aspects to support policy decisions on power capacity development.

Examining energy systems through the lens of sustainable development serves as a crucial tool in shaping energy policies and technological development agendas. Achieving this goal necessitates a clear

* Corresponding author.
E-mail address: hemmati@sdu.dk (M. Hemmati).

https://doi.org/10.1016/j.ref.2024.100581
Received 8 May 2024; Received in revised form 13 May 2024; Accepted 16 May 2024
Available online 21 May 2024

Nomenclature

Abbreviation

Index	Description
Al	Artificial intelligent
AP	Acidification potential
CML	Centrum voor Milieukunde Leide
EP	Eutrophication Potential (mol N-eq/ kWh)
ETP	Eco-Toxicity Potential (CTUe/ kWh)
EV	Electric vehicle
DAR	Depletion of Abiotic Resources (kg Sb-eq/ kWh)
GWP	Global warming potential (kg CO2/kWh)
HTP	Human Toxicity Potential (CTUh/ kWh)
MCDM	Multi-criteria decision making
MCA	Multi-criteria analysis
ML	Machine learning
LCA	Life cycle assessment
LCC	Life cycle costing
LCIA	Life cycle impact assessment
LCOE	Levelized cost ($/kWh)
LCSA	Life cycle sustainability assessment
ODP	Ozone depletion Potential (kg CFC-11-eq/ kWh)
POFP	Photochemical Ozone Formation Potential (kg NMVOC-eq/ kWh)
s-LCA	Social life cycle assessment
SDG	Sustainable development goal
TRACI	Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts
WtE	Waste to electricity

Parameter and variable

a	Index for technology
$V(a)$	Total sustainability score
w_i	Weight of importance for decision aspect
$V_i(a)$	The score shows the performance of technology a in aspect i
I	Total number of decision aspects (in this study equals 3)

delineation of relevant indicators essential for informed decision-making strategies and processes. While the literature review indicates that various methodologies for sustainability assessment, including LCA, MCDM, optimization-based methods, dynamic analysis, etc. have been employed across different studies without adhering to a unified standard, a comprehensive comparative analysis of these methodologies, delineating their strengths and weaknesses, and identifying future research directions, is lacking. In addition, considering that a wide range of technologies, structures, and applications take part in electricity production, classification, and comparison of life cycle analysis methods from the perspective of methodology and impact categories should be developed to ensure the correct implementation of LCSA.

To mitigate the considerable challenge related to selecting the right method for sustainability analysis of electricity production technologies in shaping the future energy mix, due to the variety of quantitative and qualitative approaches, as well as the lack of a standardized procedure, this paper offers a critical and comparative examination of the prevalent methodologies utilized by scientific researchers during the past 10 years (2013-2024). By undertaking this comprehensive review, the paper aims to shed light on the strengths and weaknesses of different sustainability assessment methodologies, providing valuable insights for researchers, policymakers, and stakeholders involved in energy transition efforts. The set of economic, social, and environmental indicators that are conducted for LCSA are evaluated for multiple power generation facilities considering the geographical coverage of the literature. This paper undertakes a comprehensive examination of integration techniques essential for a holistic LCSA. Delving into the realm of sustainability evaluation for energy systems, it meticulously reviews the MCDM methodologies, dynamic approaches, and emerging trends of AI. By elucidating these critical aspects, the paper sheds light on the evolving landscape of sustainable energy systems, offering valuable insights into the interplay between power generation technologies, impact assessment, and decision-making processes.

In the second part, this paper conducts a comparative LCSA study focusing on a real-world scenario in Lombok Island, Indonesia. The aim is to ascertain the most sustainable power generation technology for informing future energy mix strategies under two different methods, including ranking & scoring, and MCDM. Both renewable and non-renewable power production facilities are considered in this study, including wind, solar, hydropower, biomass, waste-to-electricity incineration, coal, natural gas, and diesel. For this purpose, 8 environmental, 4 economic, and 3 social indicators are implemented to conduct LCSA on 1 kWh electricity generation as a function unit.

2. Research methodology

The research methodology has been carried out in 5 steps as shown in Fig. 1.

2.1. Database search to conduct the literature

A thorough examination of the literature has been conducted employing principles from set theory to define the search domain. The search domain is defined by all the studies that dive into the sustainability assessment in the energy mix. The set of keywords for searching is shown in Fig. 1. The prevalence of the search led to the formation of a database comparing 247 valid publications specifically examining the life cycle of energy production.

2.2. Screening process

Based on the screening criteria, including publications year (between 2013-2024), sustainability of the energy mix, and studies examining at least two types of technologies, the research population is formed, including 102 papers.

2.3. Data extraction and categorization

In this stage, all information from a database, including the type of technologies, considered indicators and methods, as well as sustainability evaluation methodologies (e.g. LCC, LCA, dynamic approach, etc.) are extracted and categorized.

2.4. Quality assessment criteria

All reviewed papers are evaluated based on the data availability, reliability of the results, integration of sustainability aspects, and appropriateness of methods and interpretation.

2.5. Synthesis and analysis

In the last step, the strengths, weaknesses, advantages, and gaps of all reviewed papers based on critical reflection have been discussed. Also, new trends, future research directions, and main challenges are highlighted.

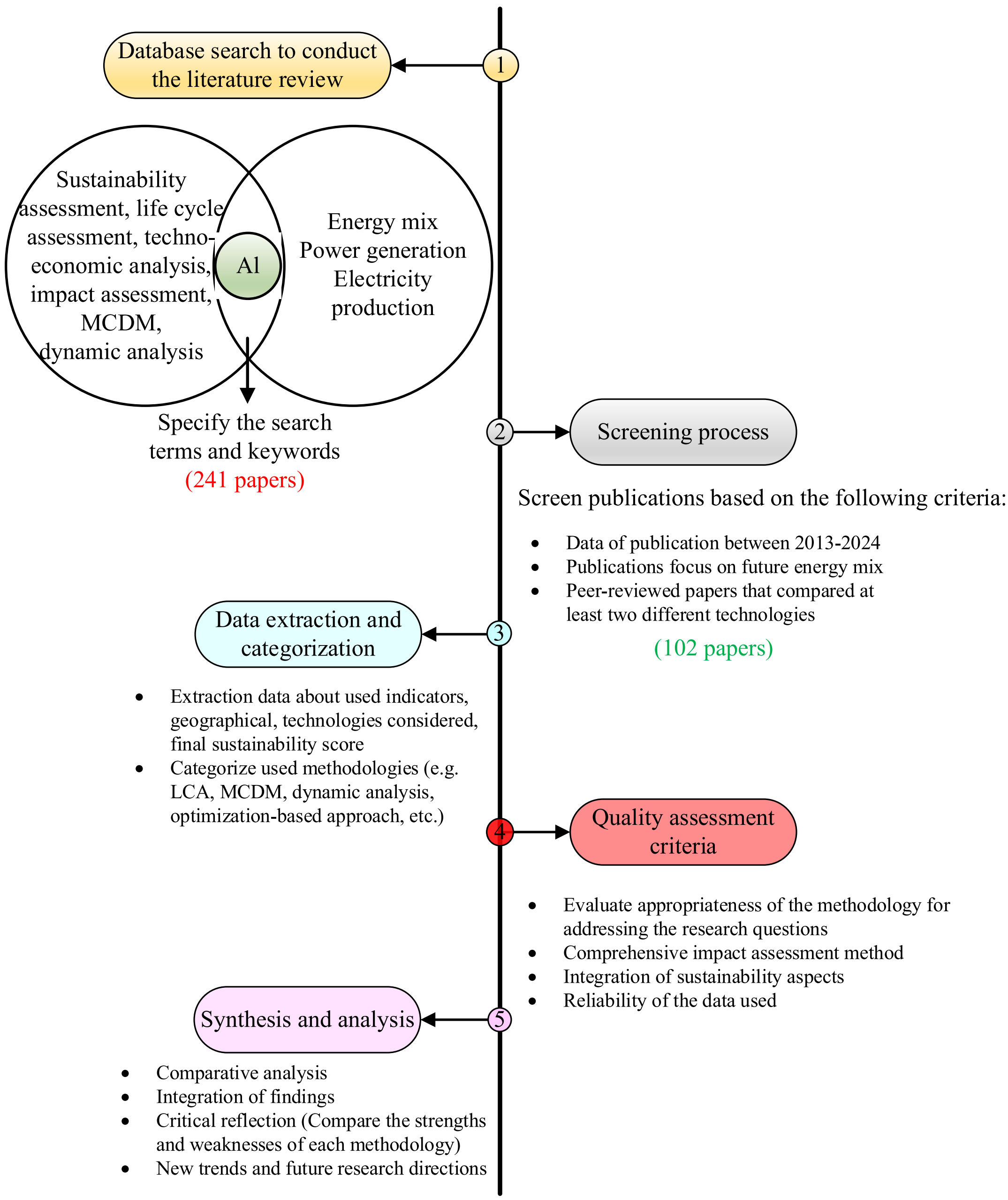

Fig. 1. Overview of the proposed research methodology and screening process to conduct the database

3. Review, qualitative, and quantitative classification of sustainability assessment methods

The ISO 14040/14044 standards provide the foundation for the LCSA process, considering environmental, economic, and social aspects, as depicted in Fig. 2 [3].

The four mandatory steps consist of goal and scope specification, inventory assessment, impact assessment, and interpretation. All calculations and evaluations are based on the function unit, which in the case of electricity production, 1 kWh of electricity [4]. The scope of the life cycle includes different stages, including contraction, material in raw, usage, maintenance, replacement, and end of life. This paper selected publications that assess the sustainability considering stages defined in the EN 15804 document.

LCA methods

LCA is a systematic methodology for evaluating the environmental impacts associated with the entire life cycle of a product or process, including raw material extraction, manufacturing, use, and end-of-life disposal. The most effective survey and systematic review on LCA for electricity production technologies are given by [5–14]. In the LCA, after determining the goal, the impact list is determined for all subsystems so that the input and output and all potential pollution (to air, to the soil, and to water) in the life chain are calculated based on the function unit. After determining the environmental impact indicators- the most well-known of which is global warming- the inventory of the previous step is first characterized and then classified in the LCIA phase. There are multiple LCIA methods in the literature. The difference between these methods is the number of characterization factors included, the number of indicators, and the normalization factors. For example, the land use indicator is evaluated under the CML baseline method, while the TRACI

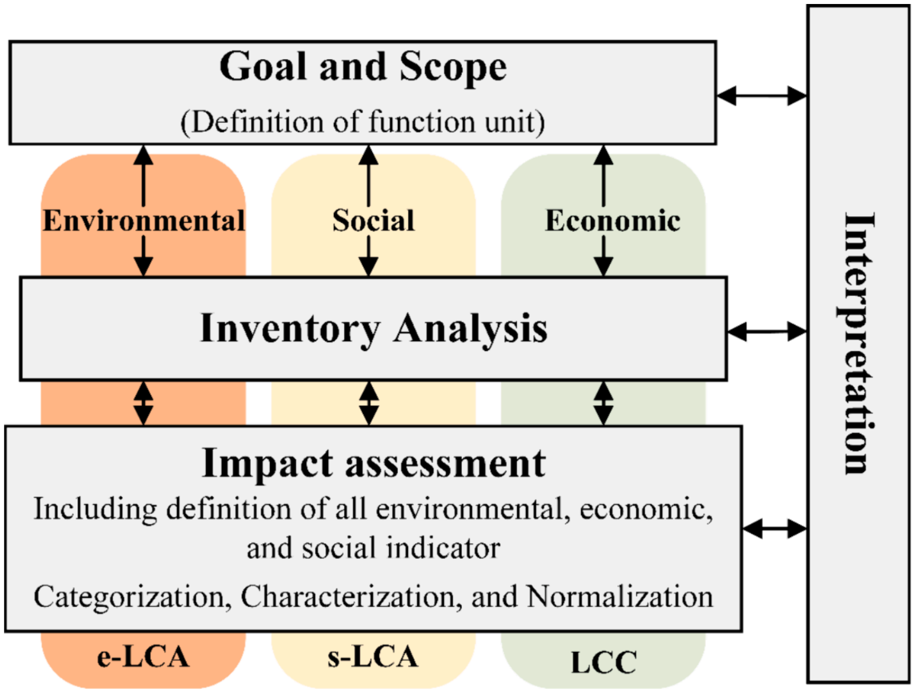

Fig. 2. Concept of LCSA-based ISO 14040/14044

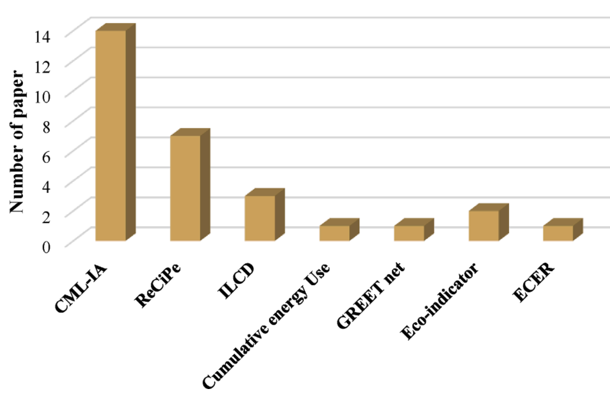

Fig. 3. Quantitative comparison of impact assessment methods by 29 papers

can't address it in LCIA. CML baseline and non-baseline are the most useful methods due to their user-friendly, the availability of normalization coefficients, and the consideration of more than 60,000 factors, which can cover a wide range of environmental impact assessments [15]. A quantitative comparison of 29 reviewed papers based on methods in Fig. 3 shows that the CML-IA was used in 14 cases.

Life cycle costing

LCC is a methodology for assessing the economic costs and benefits associated with the entire life cycle of a product or process. In the context of power generation technology, LCC can be used to compare the total costs of different energy sources and technologies, including capital investment, operational expenses, maintenance costs, and externalities.

LCC analysis is developed for electricity generation units as a useful tool in several studies. Prospective LCC of power production from solid waste in Nigeria was developed by [16]. Overall results of all scenarios showed that the incineration technology is the most economical option based on its positive LCC, lowest payback, and LCOE, as well as the highest internal rate of return. Ref. [17] aims to assess the electricity sources for EVs using an LCC framework, considering wind, solar, hydropower, coal, and diesel. Results of LCC showed that PV power generation was the most expensive solution by 0.2107 USD/kWh, while natural gas is the cheapest one by 0.0661 USD/kWh for initial fuel of electricity generation in the case of EVs. The LCC analysis on the long-term investment cost optimization of coal, gas, and liquid fuel power generation in India was studied by [18]. This study also implemented a real options analysis theory (ROAT) method that help to create flexibility in the model. Findings indicated that a thermal energy project can be delayed by its time of expiration, and its cost is twice the construction of a gas plant.

s-LCA methods

The s-LCA is a methodology for evaluating the social impacts associated with the entire life cycle of a product or process, including labor conditions, human rights, community health, and social equity. In the context of power generation technology, SLCA can be used to assess the social implications of energy projects, such as job creation, displacement of communities, and access to energy services.

A methodology for s-LCA on electricity production in Spain has been suggested in [19], including PV, wind, nuclear, gas, biomass, coal, and storage technologies. This work did not introduce a certain option as the most sustainable technology for the Spanish power grid but proves that the s-LCA by analyzing the job creation and human rights can optimize the future electricity. A prospective s-LCA of electricity production from solid waste in Nigeria for multiple technologies, including incineration, gasification, landfill, and anaerobic digestion was studied by [20] by comparing the social benefits of waste-to-electricity technologies with electricity import and diesel power plants. No encompassing and definition of social indicators was reviewed in this paper. The energy justice concept is introduced by [21] as a new index for the level of development in society based on the s-LCA. Multiple indicators for several stakeholders are analyzed and concluded that low-carbon energy technologies provide social benefits, including human rights and job creation. However, the role of stakeholders from a social point of view, besides the proper definition of selected indicators has not been addressed. Ref [22] concluded that the PV sources require 95% longer labor hours per kWh, and are not yet completely friendly to human

Table 1
Quantitative and geographical analysis on LCA, LCC, and s-LCA

	LCA	s-LCA	LCC
Number of studied publications	**30**	**13**	**19**
Geographically wide	Africa [31] Czech Public [32] Iran [33] France [34] Norway [35] Turkey [36] Portugal [37–39] Brazil [40,41] Spain [42] Italy [43–45] USA [46,47] Poland [48,49] Indonesia [50–54] Nigeria [55] Greece [56] Mexico [57] China [58,59] Mauritius [60]	China [61] France [62,63] Belgium [29] Myanmar [26] Nigeria [20] Brazil [25] Spain [19,24,64] Taiwan [28] Portugal [23] Africa [65]	Spain [66] Kenya [67] China [68–71] Brazil [72] USA [73–75] Indonesia [76] Greece [77] South Korea [76] India [17,76,78] Nigeria [16] Croatia [79] Sweden [80]

social life. In [23], the comparative s-LCA on biomass power generation in Portugal was developed. The results indicated that the implementation of fluidized-bed furnace technology reduces by 15–19% the negative social impacts, except for women in the sectoral labor force.

3.3.1. Stakeholder engagement and social acceptance

Because s-LCA is dependent on several variables, including macro policies and a large number of stakeholders, it leads to different results in countries. For example, PV power is selected as a beneficial technology for job creation, with 1.5 humans per kWh in Spain [24]. In Brazil, the coal power technology reduces the child labor indicator up to 0.4 person per kWh [25]. Hydropower cannot provide social benefits, including social welfare and proper job creation in Myanmar [26]. A similar study in a neighborhood country indicates reverse results [27]. The s-LCA in Taiwan concluded that the lack of experienced wind plant construction workers potentially increases while the share of wind power will rise to 25% by 2025 [28]. Job creation indicator for offshore and onshore wind power in Belgium reached 0.15 and 0.23 jobs per MW [29].

In [30], social acceptance of solar panel energy in heritage buildings, including barriers, challenges, and benefits of PV energy for stakeholders are evaluated in the case of Italy. This paper indicated that it's crucial to consider cultural and aesthetic factors alongside the integration of photovoltaic (PV) systems in heritage buildings.

The geographical distribution of reviewed papers in LCA, LCC, and s-LCA methodologies is presented in Table 1.

MCDM methods in sustainability evaluation

MCDM is crucial in sustainability assessment, offering a structured approach to evaluate options based on multiple criteria simultaneously. Decision-makers face complex environmental, social, and economic factors, making traditional methods insufficient. MCDM allows comprehensive consideration of these criteria, weighing trade-offs and synergies. By incorporating stakeholder preferences, MCDM ensures transparent decision-making aligned with sustainability goals. Its systematic approach advances sustainability objectives and fosters resilience in socio-environmental systems.

The future energy mix of Pakistan under an integrated MCDM sustainability approach was studied by [81]. Results reveal hydropower

Table 2
Compared sustainable technology for electricity generation under social-eco-environmental assessment.

Ref	Country	Sustainable Technology from Three Components of LCSA			2022 total installed capacity of selected technology (% in Energy Mix) [2]
		Social	Economic	Environmental	
[81]	Pakistan	Run-of-River	Run-of-River	Run-of-River	687 TWh (29%)
[82]	UK	Wind	Gas	Wind and PV	Wind: 613 TWh (4.6%) PV: 101 TWh (>1%) Gas: 3821 TWh (29%)
[83]	Turkey	Hydropower	Geothermal	Hydropower	Hydropower: 1582 TWh (26%) Geothermal: 71 TWh (1%)
[84]	UK	Coal	Gas	Wind	Wind: 613 TWh (4.6%) Gas: 3821 TWh (29%) Coal: 4628 TWh (35%)
[90]	Portugal	Hydropower	Hydropower	Hydropower	343 TWh (24%)
[85]	Spain	PV	Coal	Wind	PV: 215 TWh (3%) Coal: 1988 TWh (23%) Wind: 876 TWh (10%)
[86]	Greek	PV	Coal	Hydropower	PV: 46 TWh (3%) Coal: 882 TWh (53%) Hydropower: 138 TWh (9%)
[87]	Brazil	Hydropower	Hydropower	Wind	Hydropower: 11828 TWh (78%) Wind: 440 TWh (3%)
[92]	Romania	PV	Hydropower	Hydropower	PV: 16.5 TWh (>1%) Hydropower:523 TWh (27%)
[94]	Iran	Wind	Gas	Wind	Wind: 7.6 TWh (>1%) Gas: 4605 TWh (71%)
[95]	World	PV	PV	PV	6091TWh (>1%)
[89]	Egypt	Hydropower	Gas	Hydropower	Hydropower: 460 TWh (12%) Gas: 2927 TWh (72%)
[96]	Turkey	Gas	Gas	Gas	2149 TWh (35%)
[91]	Mexico	PV	Hydropower	Hydropower	PV: 50TWh (>1%) Hydropower: 1075 TWh (14%)
[97]	Spain	Biomass	Wind	Wind	Biomass: 111 TWh (1.2%) Wind: 876 TWh (10%)
[98]	Niger	PV	PV	PV	0.3 TWh (4%)
[99]	Denmark	Wind	Biogas	Biogas	Biogas: 105 TWh (9%) Wind: 250 TWh (22%)

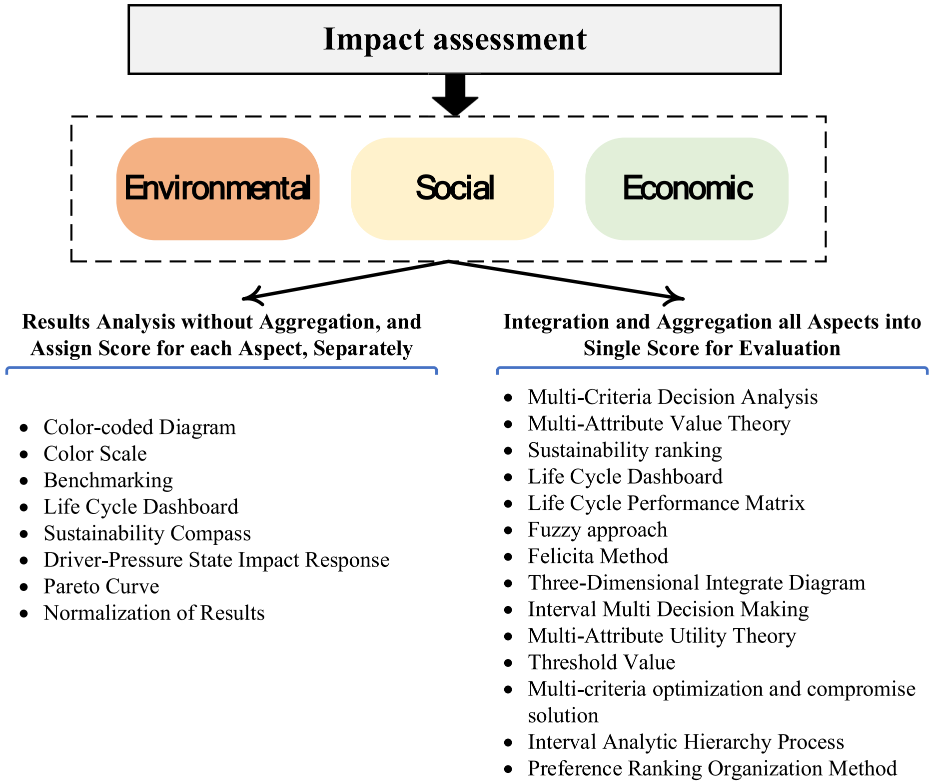

Fig. 4. Overall structure of LCSA analysis methods

power plant is the most sustainable option with the lowest economic and environmental impacts, while oil is found the worst social and economic impacts. A similar study in the case of the future energy mix of the UK has been established [82]. The sustainability impacts of multiple technologies have been analyzed, extending to potential future electrical scenarios. However, without a unified approach to integration, no definitive sustainable outcome has been reached across all potential scenarios. An integrated MCDM sustainability assessment of the energy mix of Turkey was developed by [83]. Hydropower is Turkey's top sustainable energy choice, followed by wind and geothermal options. Hydropower's contribution reduces imported fossil fuel usage by 15 million tons annually. Gas power has low capital costs but high LCOE, ozone depletion, and few direct jobs. The 2070 energy mix scenario of the UK under the MCDM approach was developed by [84]. This research also suffers from the lack of a unified method for the final decision about the most sustainable technology. The 2030 and 2050 energy mix scenarios of Spain under the integrated MCDM were represented by [85]. Aggressive estimates of renewable energy sources offer the greatest benefits in cost savings, employment, and environmental effectiveness, according to findings. However, the social aspect is less explored due to database access uncertainty. A similar study in the case of the Greek power grid engaging the role of the stakeholders in sustainability score was investigated by [86]. Wind electricity generation, followed by hydropower, is the most sustainable technology. However, solar power resources seem to be the most sustainable choice when social impact is given priority. The fragmented MCDM methodology in the Brazilian energy mix was developed by [87,88]. These studies gathered existing data on methodologies and indicators, overlooking innovative assessments of Brazil's capacity development. Furthermore, they lack a unified method for determining the final score. In a similar study and without integration of all sustainability aspects, the MCDM evaluation places natural gas at the highest rank, while nuclear at the lowest ranking for Egypt's energy mix [89]. Also, this method without integration of all aspects in the case of the energy mix of Portugal [90] selects a small hydro as the most sustainable technology in 10 of the 16 indicators used.

In [91], the 2050 energy mix strategies of Mexico under the LCSA are evaluated as a new decision-support approach. This paper does not propose any definitive scenario as a fully sustainable solution and suggests that a trade-off between the available scenarios should be made to provide a better energy mix. In the case of Romania [92], a comprehensive rank and sustainability with equal/ non-equal important weight showed that hydropower is the most sustainable technology. Also, this paper suggested that variations of discount rates and energy efficiency should be engaged in future sustainable development. The energy mix of Nigeria, focusing on solid waste-to-electricity plants under the integrated LCSA was developed by [93]. In this study, four waste-to-electricity technologies, including incineration, landfill, gasification, and anaerobic digestion are evaluated and compared to diesel power generation, and electricity import scenarios.

Further studies were found that address all sustainability dimensions, with key findings and study scopes outlined in Table 2. Notably, the highlighted superior technologies don't necessarily imply superiority or preference; authorities base their final proposals on the constraints and conditions specific to each geographical region.

3.4.1. *Reviewing the integrated sustainability evaluation methods*

The LCSA value is calculated by adding the values of LCA, s-LCA, and LCC, representing the integration of three life cycle approaches. This sum indicates the sustainability of the life cycle perspective. Two LCSA methods are identified: one evaluates life cycle analyses independently to draw sustainability comparisons, while the other combines all three life cycle studies into a single score. The first method tends to be more qualitative, while the second aggregates data quantitatively.

Fig. 4 shows the structure of all existing sustainability analysis methods based on the literature. While some studies use color-coded diagrams and a color scale to classify the environmental, economic, and social impacts according to magnitude, many studies present the LCSA results separately and compare the results [90,100]. By aiding in the effect of graphical representation, this kind of method enhances the

Table 3
Categorization of all common sustainability indicators

No.	Indicator	Description	Unit
Environmental Indicators			
1	Global Warming Potential (GWP)	Indicator of possible global warming brought on by greenhouse gas releases into the atmosphere	kg CO2-eq/ kWh
2	Ozone depletion Potential (ODP)	Indication of air pollution that destroys the ozone layer	kg CFC-11-eq/ kWh
3	Acidification Potential (AP)	Indicator of the possible gas release-induced acidity of soils and water	kg mol H+/ kWh
4	Eutrophication – freshwater	Indicator of the freshwater ecosystem's enrichment	kg PO4-eq/ kWh
5	Eutrophication – marine	Indicator of the marine ecosystem's enrichment	Kg N-eq/ kWh
6	Eutrophication Potential (EP)	Indicator of the terrestrial ecosystem's enrichment	mol N-eq/ kWh
7	Photochemical Ozone Formation Potential (POFP)	Indications of gas emissions that influence the production of photochemical ozone	kg NMVOC-eq/ kWh
8	Depletion of Abiotic Resources (DAR)	Indicator of the depletion of natural non-fossil sources	kg Sb-eq/ kWh
9	Human Toxicity Potential (HTP)	Effects of harmful compounds released into the environment on human.	CTUh/ kWh
10	Eco-Toxicity Potential (ETP)	Effects of harmful compounds released into the environment on freshwater organisms	CTUe/ kWh
11	Water use	A measure of the proportion of water consumed, depending on area water shortage variables	m3 world eq/ kWh
12	Land use	Evaluation of the alterations in soil quality	Dimensionless/ kWh
13	Ionizing radiation	Ecosystem harm and human health are related to radioactive emissions	kBq U-235/ kWh
14	Particulate matter emissions	Indicator of the possible prevalence of diseases caused by particulate matter	Disease incidence/ kWh
Social Indicator			
1	Child labor	Indicator to show the effect of depriving children of their childhood	Person/ kWh
2	Working hour	Indicator to show working hour	Hour/ kWh
3	Forced labor	Indicator to show forced labor during the process	Person/kWh
4	Health and Safety (fatalities, Injuries)	Indicator to show how many fatalities and massive accidents during the process	Number of injuries/ kWh
5	Access to sources	Indicator to show the level of access to resources	NA
6	Number of employment	Indicator to show the total number of people who are employed,	Person-year/ kWh
7	Local employment	Indicator to show how many local people are employed	Person-year/ kWh
Economic Indicators			
1	Capital Cost	Indicator to show all the costs required for construction and installation	$
2	Total Annualize cost (including fuel, operation, O&M, and fixed costs)	Indicator to show the sum of annualized capital costs and annual fixed, variable, fuel cost	$/year
3	LCOE	Indicator to show levelized or unit cost	$/ kWh
4	Disposal Cost	Indicator to show costs associated with disposing of waste materials	$/ kWh
5	Payback Period	Indicator to show number of years required to recover the original cash investment	Years/ kWh
6	Internal rate of return	Indicator to show the profitability of potential investments	%
7	Net present value	Indicator to show how much an investment is worth throughout lifetime	$/ kWh

sustainability analysis. Furthermore, comparative benchmarking analyses are employed in some studies [97]. The life cycle sustainability dashboard technique was also used, but it did not include the aggregation step; instead, it just used color scale charts for analysis [88]. With the use of a graphic representation on a color scale and an analysis tool, each component of sustainability is evaluated independently and assigned a normalized score. Full details of the methods introduced in Fig. 4 are given in [101]. This paper wants to examine the new methods used in the field of sustainability analysis, which are also used in the literature.

Among all the introduced methods, multi-criteria techniques have been used many times to analyze the results and scores of all indicators. These methods typically involve six steps, including (1) problem formulation; (2) requirements identification; (3) goal setting; (4) identification of potential alternatives; (5) development of criteria; and (6) identification and application of decision-making strategy. MCDM, multi-objective decision-making (MODM), Multi-Attribute, Value Theory (MAVA), Multi-Attribute Utility Theory (MAUT), Multi-Criteria Decision Analysis (MCDA), and Simple Multi-Attribute Rating (SMAR) are all among the multi-criteria methods.

According to the Multi-Attribute Value Theory (MAVT), decision-makers weigh the pros and cons of many options by comparing them to indicators that provide a score for each; the option with the highest score is selected.

Based on our study, 57% of investigated papers analyze the sustainability result, separately including the weighting factor [81], color-coded [84,85,90,88,91,96,102] and benchmarking [97]. Meanwhile, 43% of papers use the MCDM methods [61,83,86,87,89,93,95,98]. Also, mixed-integer linear programming optimization-based MCDM [94], and fuzzy-based MCDM [103], are used for sustainability analysis.

3.5. Life Cycle Sustainability Indicators

A sustainability indicator assesses the overall sustainability of a system by analyzing its environmental, social, and economic components. These indicators can cover various concerns such as resources used, emissions, and biodiversity, either quantitatively or qualitatively. Table 3 lists the main sustainability impact categories implemented in power generation studies for all environmental, social, and economic aspects.

The sustainability indicator is a metric that is used to evaluate the overall sustainability of a system by analyzing its environmental, social, and economic components under LCIA. Resources used, emissions, biodiversity, and other concerns can all be covered by quantitative or qualitative sustainability indicators.

Global warming and acidification are the most often utilized environmental indicators in impact assessments; eutrophication and the

Table 4
Comparison of 9 articles with common indicators and technologies in terms of the sustainable selected technology

No.	Indicator	Reference								
		[81]	[83]	[84]	[85]	[86]	[89]	[90]	[91]	[94]
1	GW	Run-of-River	Run-of-River	Wind	Onshore Wind	Hydro	Hydro	Hydro	Hydro	Hydro
2	ODP	Run-of-River	Geothermal	Nuclear	Onshore Wind	Wind	Onshore Wind	Hydro	Nuclear	Hydro
3	AP	Run-of-River	Hydro	Onshore Wind	Onshore Wind	Hydro	Onshore Wind	Hydro	Hydro	Onshore Wind
4	EP	Run-of-River	Hydro	Nuclear	Onshore Wind	Hydro	Hydro	Hydro	Hydro	Hydro
5	POFP	Run-of-River	Hydro	Onshore Wind	Onshore Wind	Hydro	Hydro	Hydro	Hydro	Onshore Wind
6	HTP	Run-of-River	Hydro	Onshore Wind	Onshore Wind	Hydro	Hydro	Hydro	Hydro	Hydro
7	Land use	Hydro	Geothermal	Onshore Wind	Onshore Wind	Offshore Wind	Nuclear	Offshore Wind	Offshore Wind	Biomass
8	Number of employment	Coal	Run-of-River	PV	PV	PV	Coal	PV	PV	PV
9	Number of fatalities and accidents	Run-of-River	PV	PV	PV	Offshore Wind	Hydro	Hydro	Nuclear	Onshore Wind
10	Capital Cost	Hydro	Geothermal	Gas	Coal	Coal	Gas	Gas	Hydro	Gas
11	Total Annualize cost	Wind	Hydro	Gas	Coal	Coal	Gas	Offshore Wind	Gas	Gas
12	LCOE	Hydro	Hydro	Gas	Hydro	Coal	Coal	Offshore Wind	Hydro	Gas
13	Payback Period	Gas	Coal	Gas	Coal	Coal	Coal	Gas	Coal	Gas

production of photochemical ozone are the next most used indicators [94,103]. The most popular indicators are changeable and cover a range of environmental domains, including effects on soil, water, air, ecosystems, and humans [43–45,50–54]. The primary economic indicators include power costs, raw material costs, manufacturing and capital expenses, payback period, LCOE, and operating and maintenance costs. It should be noted that the total annualized cost is used which contains all costs in terms of operation, fuel, and maintenance costs [68,69,74,75,67,70]. The primary social indicators contain employment, community, and worker welfare, fair compensation, discrimination, working hours, workplace accidents, training, child labor, and forced labor [19,24,64,62,63].

9 articles have investigated all three economic, environmental, and social aspects, examining 13 common indicators. Alongside common quantitative indicators used throughout the life cycle to potentially reflect the impacts of a process or a procedure on air, soil, water, etc., numerous qualitative indices can also be utilized in the analysis of sustainability [104]. These indices, defined based on the 17 sustainable development goals (SDGs), can somewhat cover the weaknesses of many indicators, especially from a social perspective. The use of qualitative indicators in sustainability analysis can significantly enhance the attainment of sustainable development goals. These indicators, especially in areas such as social, cultural, and human aspects, can aid in the analysis and evaluation of sustainability. Some qualitative indicators that can be defined based on sustainable development goals include access to infrastructure and services, citizen satisfaction, social empowerment, human rights, transparency and accountability. Table 4 compares the top-ranked technology for each indicator.

3.6. Dynamic sustainability assessment

Traditional (LCA) has long been a cornerstone of sustainability assessment, providing valuable insights into the environmental performance of products and processes. However, static LCA models, which offer a snapshot of environmental impacts at a specific point in time, may not fully capture the dynamic nature of energy systems or adequately address long-term sustainability concerns.

Dynamic LCA emerges as a promising approach to overcome these limitations and provide a more comprehensive understanding of the sustainability implications of energy mix and power generation strategies. Unlike traditional static LCA, dynamic LCA methods consider temporal variability, technological change, and feedback loops within energy systems, allowing for a more accurate assessment of long-term sustainability impacts. By capturing the evolving nature of energy technologies, dynamic LCAs enable decision-makers to anticipate future trends, identify potential environmental hotspots, and design more effective sustainability strategies. In this context, the development of dynamic LCA models is essential for advancing our understanding of sustainability in energy systems and guiding the transition towards more sustainable energy futures. Our research methodology and database have identified 4 papers exploring dynamic LCA within the domain of energy mix strategy [105,94,106,107]. For example, The integrated simulation-optimization framework for LCSA of renewable electricity production in Iran was studied by [94]. This work is one of the main pioneers in the integration of LCSA with optimization-oriented approaches. Dynamic approaches can help solve the integration of sustainability aspects which can be widely considered in future works.

3.6.1. Sustainability assessment via AI

Multiple uncertain parameters influence sustainability indicators. Population growth rate, inflation rate, weather conditions, stakeholder policy changes, pandemics, crisis situations, among others, can affect the accuracy of sustainability assessment. ML and AI methods can be highly effective solutions for managing and processing large volumes of input data and making short-term, medium-term, and long-term predictions, making them invaluable in impact analysis. These approaches offer powerful tools for sustainability assessment due to their ability to process vast amounts of data, identify patterns, and make predictions. The search revealed that only three articles have focused on the application of AI methods in long-term sustainability analysis related to energy production, with most of their emphasis on bioenergy production from agricultural residues [108–110].

3.7. Measurements and uncertainties

All sustainability evaluation methods in the context of power generation for the future energy mix are introduced in previous sections. All methods require the utilization of various assessment approaches,

Table 5
Classification of instruments, uncertainties, and trademarks in sustainability evaluation methods

Ref.	Instrument	Trademark	Origin	Precision	Scope of study	Uncertainty
[81]	SimaPro 8.3.3.0	SimaPro	Netherlands	N/A (Software-based)	Pakistan	Uncertainties in data inputs especially data related to distribution and transmission networks
[83]	Web-HIPRE V 1.22	Web-HIPRE	Finland	0.01 (for social indicator) 1 $ (for economic indicator)	Turkey	Uncertainty in input data and regionally specific data
[84]	Gabi V 4.4	Gabi	Germany	N/A (Software-based)	U.K.	Uncertainty of renewable energy technologies and the cost of immature
[85]	Microsoft Excel	Microsoft	U.S.A	1 $ (for LCOE)	Spain	Uncertainty of electricity price
[86]	GEMIS V 4.9.5	GEMIS	Denmark	N/A (Software-based)	Greece	Uncertainty of efficiency of technology in upcoming year
[89]	Microsoft Excel	Microsoft	U.S.A	0.1 (for social indicator)	Egypt	Uncertainty of input data and electricity price
[90]	SimaPro V8.0	SimaPro	Netherlands	N/A (Software-based)	Portugal	Uncertainty of social data and stakeholders
[91]	GAMS	GAMS	U.S.A	N/A (Software-based)	Mexico	Uncertainty of renewable power generation based on the climate condition
[94]	GAMS/ MATLAB	GAMS	U.S.A	N/A (Software-based)	Iran	Uncertainty of electricity price
[57]	SimaPro V8.0	SimaPro	Netherlands	0.01 (for environmental indicator)	Mexico	N/A
[60]	SimaPro V7.0	SimaPro	Netherlands	N/A (Software-based)	China	Uncertainty of power generated by renewable technologies
[37]	Microsoft Excel	Microsoft	U.S.A	N/A (Software-based)	Portugal	N/A
[38]	Gabi V 6.0	Gabi	Germany	N/A (Software-based)	Portugal	N/A
[39]	Microsoft Excel	Microsoft	U.S.A	N/A (Software-based)	Portugal	uncertainty of electricity price, distribution, and transmission long-term planning
[111]	Gabi V8.7	Gabi	Germany	N/A (Software-based)	Germany	Uncertainty of wind speed
[41]	SimaPro V8.0	SimaPro	Netherland	1 (for environmental indicator)	Brazil	Short/long-term uncertainty of coal mining
[49]	SimaPro V7.3	SimaPro	Netherland	N/A (Software-based)	Poland	Uncertainty of long-term national polities during lifespan
[49]	SimaPro V8.2.3	SimaPro	Netherland	N/A (Software-based)	Czech Republic	N/A
[35]	Microsoft Excel	Microsoft	U.S.A	0.1 (for greenhouse gas production)	Norway	Uncertainty related to the cost of PV panel
[46]	SimaPro V8.0	SimaPro	Netherland	0.1 (for carbon production)	USA	Uncertainty of combustion and cooling technology
[56]	SimaPro V7.0	SimaPro	Netherland	N/A (Software-based)	Greece	N/A
[33]	GAMS	GAMS	U.S.A	1 (time for load prediction)	Iran	Uncertainty of renewable energy production
[32]	Microsoft Excel	Microsoft	U.S.A	N/A (Software-based)	Czech Republic	Uncertainty of PV panel efficiency
[43]	SimaPro V7.0	SimaPro	Netherland	N/A (Software-based)	Italy	N/A
[45]	N/A	N/A	N/A	0.01 (for energy loss)	Italy	Uncertainty of energy recovery conversion efficiency at the upcoming year
[34]	GEMIS V4.9	GEMIS	Denmark	N/A (Software-based)	France	Uncertainty of efficiency for all type of power generation technologies
[50]	SimaPro V9.0	SimaPro	Netherland	N/A (Software-based)	Indonesia	Uncertainty of input data especially combustion technology
[51]	SimaPro V 9.1.0.8	SimaPro	Netherland	0.1 error in environmental data	Indonesia	Uncertainties in data inputs and modeling assumptions
[53]	OpenLCA V1.9	OpenLCA	Germany	N/A (Software-based)	Indonesia	N/A
[52]	OpenLCA V1.9	OpenLCA	Germany	N/A (Software-based)	Indonesia	N/A
[31]	OpenLCA V1.9 SimaPro V7.0	OpenLCA SimaPro	Germany Netherland	N/A (Software-based)	Nigeria	Uncertainties in data inputs and modeling assumptions
[112]	Gabi V4.4	Gabi	Germany	N/A (Software-based)	Denmark	Uncertainty of distribution and transmission networks, as well as cable technology
[58]	Gabi V4.0	Gabi	Germany	0.1 carbon emission	China	Uncertainty in raw material

accompanied by the use of specific instruments and considerations of uncertainties. The aim of this section is to classify the instruments utilized, identify associated uncertainties, and document the trademarks or brands of these instruments across the reviewed literature. Table 5 provides a summary of the classification of instruments, uncertainties, and trademarks for evaluated papers. The classification enables us to gain insights into the common practices and trends in the field of sustainability assessment in power generation, as well as to identify potential gaps and areas for further research.

4. Synthesis and discussion

4.1. Comparative analysis, and critical reflection on LCA

The high number of studies conducted in the field of LCA proves that life cycle analysis has reached perfection. Although new methods can be used to integrate optimization-based methods to improve LCA modeling. Due to the simplicity of the midpoint indicators, this method is quite understandable. However, presenting analytical techniques such as sensitivity analysis, uncertainty analysis, and also examining the land use indicator, which is very important in the construction of a power plant, can be proper parameters for the classification of studies in this field, as shown in Table 6.

In the case of environmental impact analysis, it should be noted that the determination of the LCIA method strongly affects the analyzed indicators. Characterization factors may be derived in two common ways: at the midpoint and endpoint levels. Midpoint indicators concentrate on specific environmental issues, such as acidification or global warming. Endpoint indicators, which include the influence on human health, biodiversity, and resource scarcity, are three higher aggregate levels on which the environmental impact is displayed. The understanding of the LCIA data is made easier by converting midpoints to endpoints. But as the aggregation process goes on, the degree of uncertainty in the outcomes rises. Fig. 5 shows the overview of midpoint and endpoint indicators, besides all the possible advantages and disadvantages of both methods.

Table 6
Comparison of studied works in the field of LCA.

Ref	LCIA method	Advantages/ most important results	Disadvantages/ weaknesses
[57]	CML-IA	✓ Considering both midpoint and endpoint indicators. ✓ Acidification is the highest impact by 1.27×10e-02.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator. × No separation of indicators for each subsystem.
[60]	CML-IA	✓ Global warming of electricity mix is 868 kg CO2 per MWh.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator. × Ignoring energy efficiency of power generation technologies.
[37]	ReCiPe	✓ Considering time frame for evaluation which select best technology in the next 10 years.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator. × Ignoring energy efficiency of power generation technologies.
[38]	CML-IA	✓ 61% of total environmental impact comes from large scale battery construction.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator. × Ignoring energy efficiency of power generation technologies.
[39]	CML-IA	✓ Transmission grids contribute to 5-14% environmental impacts. ✓ Considering energy efficiency in model.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator.
[111]	ILCD	✓ 27% of environmental impact of renewable sources caused by replacement and transportation of input material. ✓ Considering land use indicator in LCA.	× Not providing sensitivity analysis on input data.
[41]	CML-IA	✓ Global warming is about 0.0856 kg CO2. ✓ Considering land use indicator in LCA.	× Not providing sensitivity analysis on input data.
[48]	CML, ReCiPe, ILCD	✓ Develop reliability of data source in LCA for the first time	× Not providing sensitivity analysis on input data. × Ignoring land use indicator
[49]	Eco-indicator	✓ Providing a reliable database for current and future electricity generation in Czech and Poland. ✓ Providing the sensitivity analysis on input data.	× Ignoring land use indicator
[35]	ReCiPe	✓ Material requirements for renewable power generation per kWh, is 11-40 times more than fossil fuel. ✓ Providing the sensitivity analysis on input data. ✓ Considering land use indicator in LCA model.	————————
[46]	ECER	✓ Focusing on endpoint categories which human health is the most contributed impact by pump storage with 7.74e-05 per kWh. ✓ Providing the sensitivity analysis on input data. ✓ Considering land use indicator in LCA model. ✓ Considering the role of power generation model in LCA	× Complexity in analysis due to ignoring the midpoint categories
[47]	ReCiPe	✓ Developing uncertainty analysis on input data. ✓ Providing the sensitivity analysis on input data. ✓ Considering land use indicator in LCA model. ✓ Considering the role of power generation model in LCA.	————————
[56]	Eco-indicator	✓ Separation of the share of transmission grid from power generation which shows transmission has a 70-90% lower impact. ✓ Providing the sensitivity analysis on input data.	× Ignoring the land use indicator
[33]	GREET.net	✓ Urban electricity supply result in 0.603 kg CO2/kWh. ✓ Considering energy efficiency in model.	× Not providing sensitivity analysis on input data. × Ignoring the land use indicator.
[32]	CML-IA	✓ Considering energy efficiency in model. ✓ PV has the highest impact on particular matter by 1.69 m^3/kWh	× Not providing sensitivity analysis on input data. × Ignoring the land use indicator.
[42]	CML-IA	✓ Due to metal requirements for PV panels, abiotic depletion will grow up to 5-time by 2050. ✓ Considering technology efficiency in LCA model.	× Not providing sensitivity analysis on input data. × Ignoring the land use indicator.
[43]	CML-IA	✓ Using PV in low voltage reduces the global warming by up to 83% compared to electricity from the grid.	× Not providing sensitivity analysis on input data. × Ignoring the land use indicator.
[45]	ReCiPe	✓ 55% of environmental impacts are reduced when the energy allocation is developed in LCA model which reveals the importance of land use indicator. ✓ Considering lad use indicator in LCA. ✓ Providing the sensitivity analysis on input data.	————————
[34]	ILCD	✓ 75% of total emission by hydro comes from construction phase.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator.
[50]	CML-IA	✓ Considering co-firing option for coal-power plant and analyzing it in LCA model. ✓ Providing the sensitivity analysis on input data.	× Ignoring land use indicator.
[51]	Cumulative energy use	✓ Coal power plant contributes to 70.52% of total CO2. ✓ Analyzing land use indicator in model ✓ Developing uncertainty modeling based on Monte Carlo on input data.	× Not providing sensitivity analysis on input data.
[53]	CML-IA	✓ Combustion chamber process of gas-fired unit has the highest acidification up to 50.22%.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator.
[52]	CML-IA	✓ Combustion chamber has highest acidification by 80.32% during combined cycle plant operation. ✓ Developing uncertainty based on Monte Carlo on input data. ✓ Providing the sensitivity analysis on input data.	× Ignoring land use indicator.
[31]	CML, ReCiPe	✓ Literature review on LCA model.	× No discussion on land use indicator × Not providing sensitivity analysis on input data.
[112]	ReCiPe	✓ Considering underground and overhead 0.4 and 50 kV line in LCA. ✓ From environmental aspect point of view, underground line has much impact. ✓ Aluminum conductor is better for environment compared to copper cable.	× Not providing sensitivity analysis on input data. × Ignoring land use indicator
[59]	CML-IA	✓ Wind power installation reduces greenhouse by 767 gr CO2 per kWh. ✓ Providing sensitivity analysis for input data	× Ignoring land use

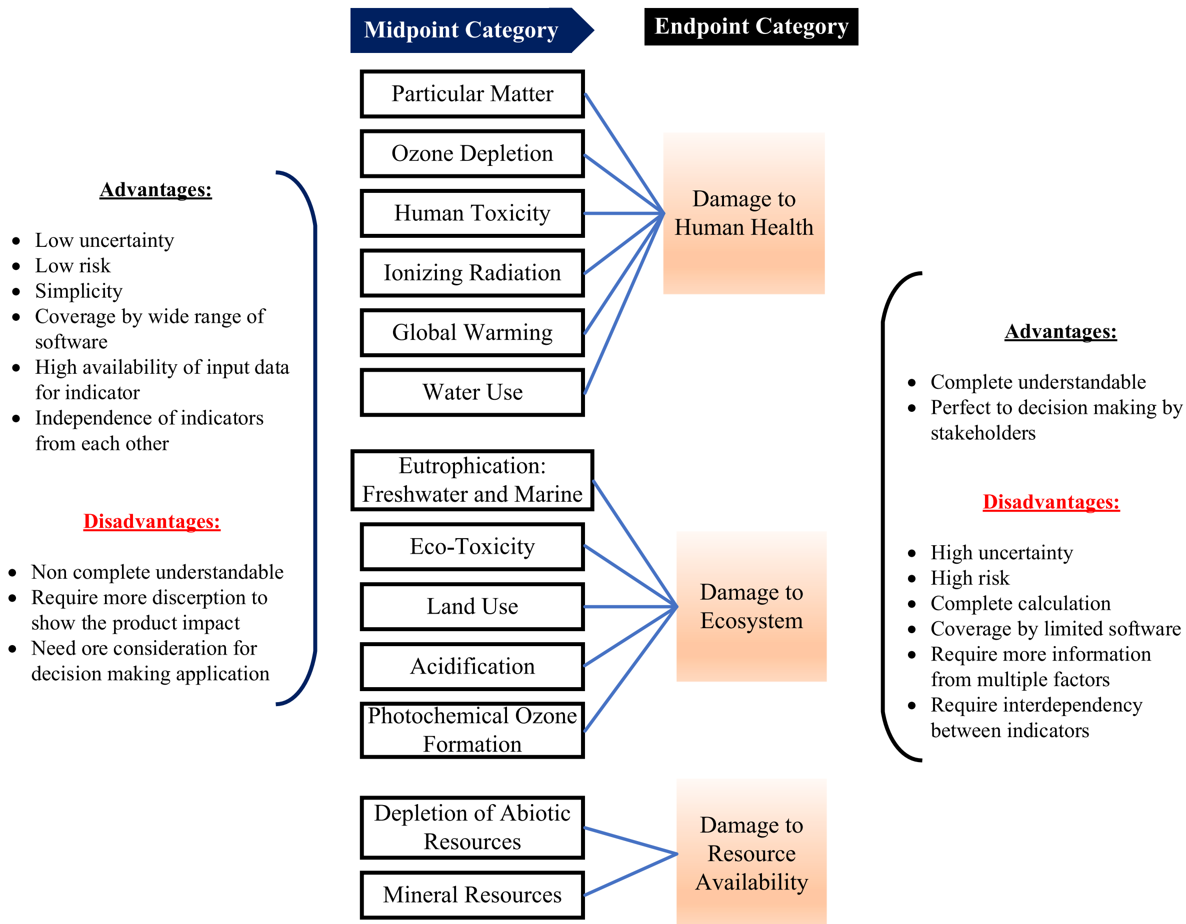

Fig. 5. Overview of midpoint and endpoint categories

4.2. *Comparative analysis and critical reflection on LCC*

The LCC method, while valuable for assessing the economic dimensions of energy technologies, exhibits several limitations when applied to sustainability assessment. Firstly, its primary focus on economic costs overlooks critical sustainability aspects beyond financial considerations, such as environmental impacts, social equity, and resource depletion. Furthermore, the method's reliance on discounting future costs and benefits may undervalue long-term sustainability goals and prioritize short-term economic gains [16,17,18]. Additionally, LCC assumes economic rationality and perfect information, ignoring decision-makers' uncertainties, biases, and incomplete information.

It also tends to neglect non-market values, such as ecosystem services and human well-being, which are essential for comprehensive sustainability assessment. Moreover, the method's lack of integration with other assessment approaches, such as LCA or MCDM, limits its ability to provide a holistic understanding of energy technology sustainability.

This approach should go beyond economic costs and incorporate environmental, social, and ethical considerations into decision-making processes. Furthermore, it should account for uncertainties and risks associated with energy technologies, such as fluctuating fuel prices and policy changes, to ensure robust decision-making under uncertain conditions. All limitations and challenges of LCC are provided in Fig. 6.

4.3. *Comparative analysis and critical reflection on s-LCA*

The social analysis of sustainability, both in terms of method and indicator selection, faces many challenges that strongly affect the results. The dearth of readily available databases is another difficulty for social and economic research. In contrast to environmental data, which already has several updated databases covering different industries, goods, and places, economic and social databases still need to progress in this direction. The challenges are presented in Fig. 7. It should be mentioned that the works studied in the field of electricity production technologies have not proposed a solution for these challenges.

4.4. *Comparative analysis and critical reflection of MCDM methods*

In summary, while MCDM approaches offer valuable tools for the sustainability assessment of energy mix and power generation technologies, they are not without limitations. Addressing issues related to subjectivity, complexity, data quality, weighting, and temporal/spatial considerations is essential to ensure robust and credible decision-making in energy sustainability assessments. Integrating MCDM with complementary methods and engaging stakeholders transparently can help mitigate these limitations and enhance the effectiveness of sustainability decision support processes. The considerable challenges related to MCDM integration with sustainability assessment are mentioned in Fig. 8.

4.5. *Emerging trends and methods, recommendations for future research directions*

Alongside the challenges highlighted in the previous section, the presence of numerous uncertain parameters such as climate change, economic conditions, and political/ social changes, are driving sustainability assessment methods towards active approaches, considering the temporal dimension. However, among these, methods focusing on

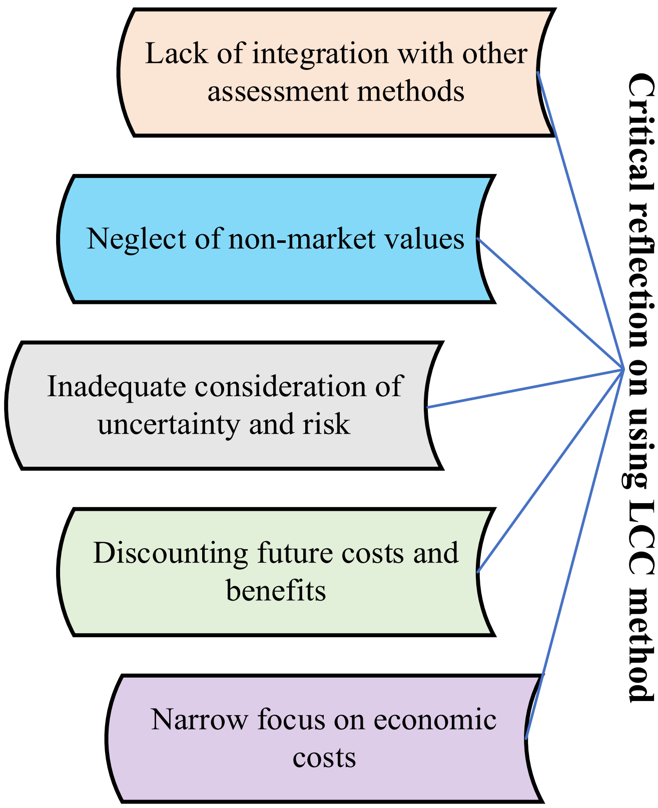

Fig. 6. Considerable challenges of the LCC method

introducing integrated dynamic techniques through more precise and novel indicators have become more prominent. Here are the most prominent trends for future directions:

- Exploration of novel metrics and indicators:

Trends include the development of indicators for circular economy performance, planetary boundaries, social carrying capacity, and regenerative capacity.

- Quantification of uncertainty and sensitivity analysis:

Sustainability assessments acknowledge uncertainties, emphasizing quantification through advanced statistical methods and sensitivity analysis. These techniques evaluate the reliability of results by accounting for uncertainties in data, assumptions, and model parameters, aiding in informed decision-making.

- Data-driven decision making:

AI and ML enable data-driven decision-making in sustainability assessment by analyzing real-time data from various sources, including sensors, satellites, and databases. This allows for more accurate and timely assessments of environmental impact, resource efficiency, and risk factors.

- Optimization and prediction:

AI and ML algorithms can optimize processes and predict outcomes in sustainability assessment and life cycle analysis.

- Open data and transparency:

There's a growing emphasis on open data and transparency in LCSA research and practice. Only 7 references in this paper provided open data on calculation.

5. Sustainability evaluation on Lombok case study

The numerical LCSA study on Lombok Island, Indonesia is discussed. Lombok is one of the southern islands of Indonesia with a total land area of 4,725 km^2, and a population of 3.7 million, which is not connected to the national electricity grid [113]. This causes the price of electricity is double of average tariff in the average price of electricity in Indonesia. By the end of 2022 the total installed capacity on this island, which is mostly based on fossil fuels, reaches 416 megawatts [114]. Fig. 9 shows the overview of this island along with the installed power capacity.

Under this study, a sustainable strategy is investigated for capacity development in this island that provides suitable social-environmental-economic benefits.

Considering the appropriate potential of this island in terms of installing various renewable and non-renewable resources, 8 technologies, including wind, PV, hydro, biomass, WtE, oil, gas, and coal, are analyzed and compared in LCSA.

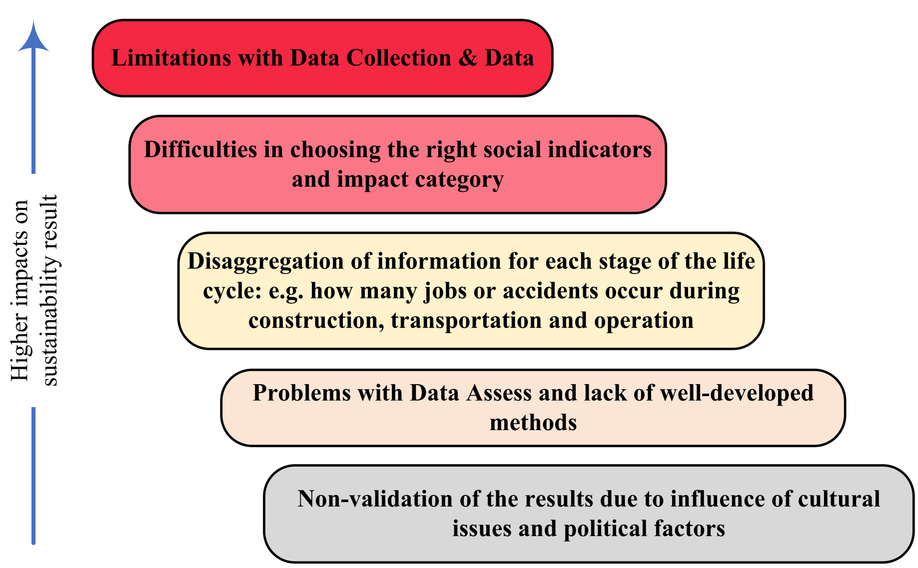

Fig. 7. Limitations and challenges with s-LCA

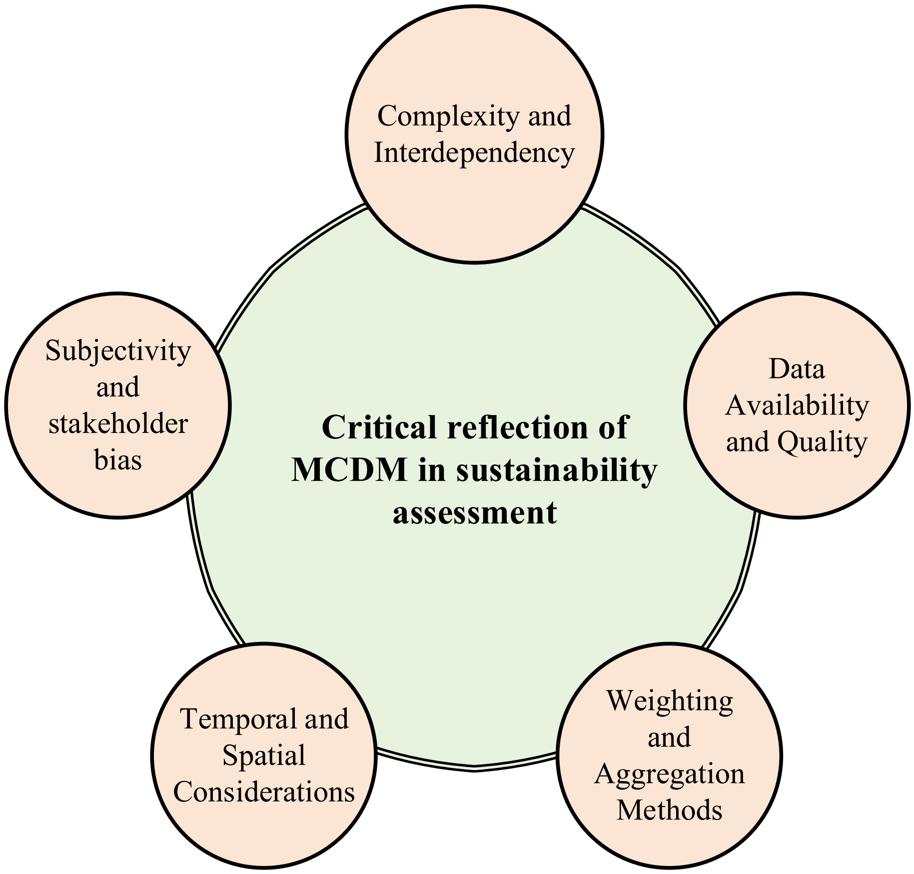

Fig. 8. Considerable challenges of MCDM in sustainability evaluation

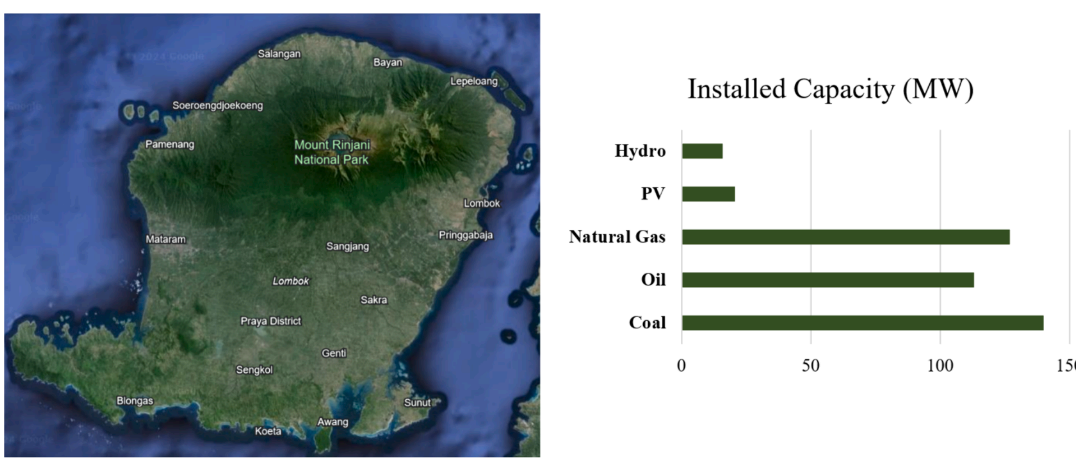

Fig. 9. Lombok Island overview and Installed Capacity by 2022.

5.1. Goal and Scope of LCSA

The goal of the proposed LCSA is to analyze all environmental, social, and economic aspects of power generation from different types of power generation technologies under the 1 kWh electricity generation as a function unit, which the scope is provided in Fig. 10.

5.2. Inventory and impact assessment

The inventory list is conducted based on data collection from literature, technical reports, annual reports, and correspondence with Indonesian partners, including input and output, materials, energy loss, pollution, costs, the number of jobs created, accidents, etc. It should be noted that this information is available upon request.

5.3. Interpretation

In this phase, all analyses on LCA, s-LCA, and LCC based on the considered indicators for all power generation technologies are conducted. Firstly, the aspects are investigated, separately, then the final sustainability score is provided based on two analytic methods, including Ranking & Score, and integrated MCDM.

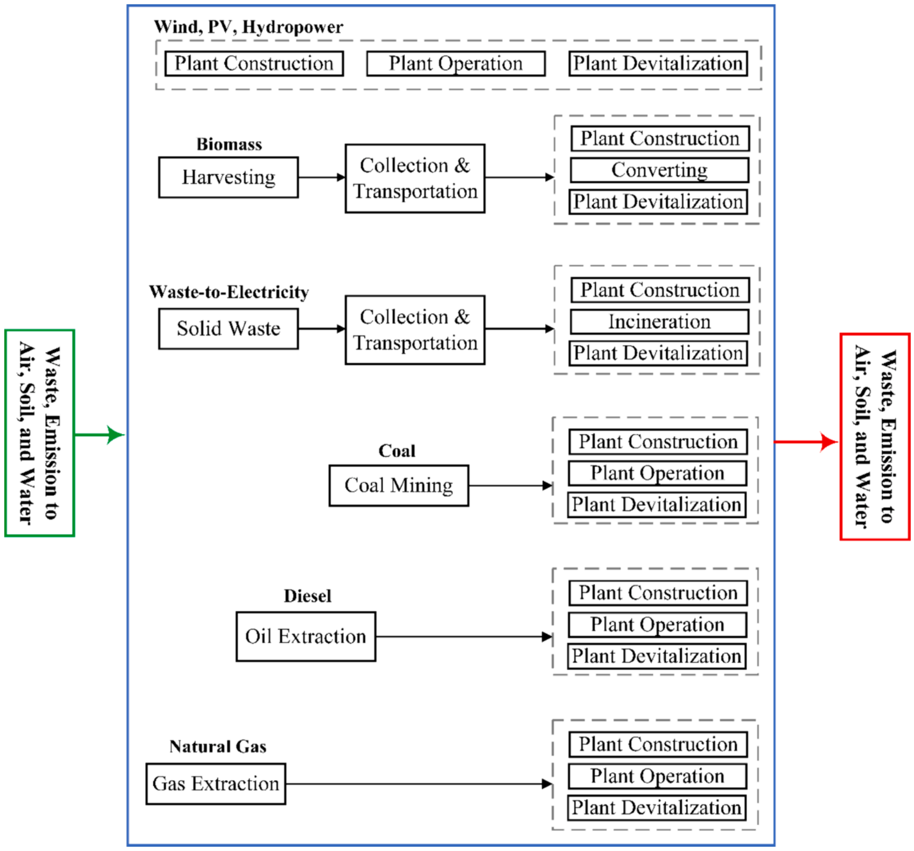

Fig. 10. LCSA scope and options in Lombok Island

5.4. Result and discussion

Firstly, the impact assessment of all power generation options is analyzed for each aspect, individually. Then, the final sustainability score is examined under the aggregation approaches, using score & ranking, and MCDM.

5.4.1. LCA Sustainability Results

This section evaluates the environmental impacts of proposed technologies using GWP, AP, ODP, POFP, EP, HTP, ETP, and DAR indicators. Using the CML-IA non-baseline method, all midpoint indicators are classified and characterized. It should be noted that the details of LCIA based on the CML-IA are available upon request.

Fig. 11 shows the LCA on technologies per functional unit. Accordingly, hydropower in terms of 7 indicators, is the most sustainable technology for Lombok and is only in second place in terms of HTP. As expected, fossil fuels have destructive effects, and considering the promising results of gas, this technology could be a much more sustainable strategy for Lombok's future, which is one of the reasons for the higher electricity price, is to use of diesel leased generators. Wind and solar technologies have the same effects, however, solar is more sustainable in terms of DAR.

5.4.2. s-LCA Sustainability Results

Three indicators, including number of employments, fatalities, and rate of local workforce per function unit are analyzed for s-LCA of power generation in Lombok. Fig. 12 shows the results on s-LCA. From the employments, PV is much more sustainable than other technologies. It should be noted that this number contains all stages (plant construction, operation, and devitalization). Meanwhile, gas creates the least number of jobs. In terms of the number of accidents, gas, and hydro are better for labor safety, while coal has the most accidents. The WtE has the highest local labor rate due to the need for more people to collect and transportation.

5.4.3. LCC Sustainability Results

To analyze the economic aspect, 4 indicators, including capital and annualized cost, LCOE, and payback period are considered for LCC.

Fig. 13 shows that renewables are still not economical and require high capital investment. Meanwhile, gas and diesel are more economical. However, in terms of annual costs, including operation, fuel, and maintenance costs, the scales tip in wind, solar, and then hydro favor. In the form of LCOE, hydro is more sustainable. Also, from a payback perspective, gas is more economical (less than 1 year). Between renewables, WtE has a suitable economic situation from a payback period perspective.

5.5. Integration of Sustainability Aspects for Final Score

As stated, the analysis of sustainability final results is possible in two separate and integrated methods. Basically, the main complication of analyzing sustainability results is that each indicator has a different unit and dimension.

In this part, two methods, Score & Ranking, and MCDM, are used for the final sustainability score of the technologies introduced in the following sub-sections, the results of which will be discussed in the following.

5.5.1. Score & Ranking Method

In this method, by assigning points to each member, their rank is determined from the higher to the lower score in each aspect. In this analysis, 8 power generation technologies have been examined, the best technology is assigned a score of 8, and the worst is assigned a score of 1 for each indicator. In this way, technologies are prioritized. The average

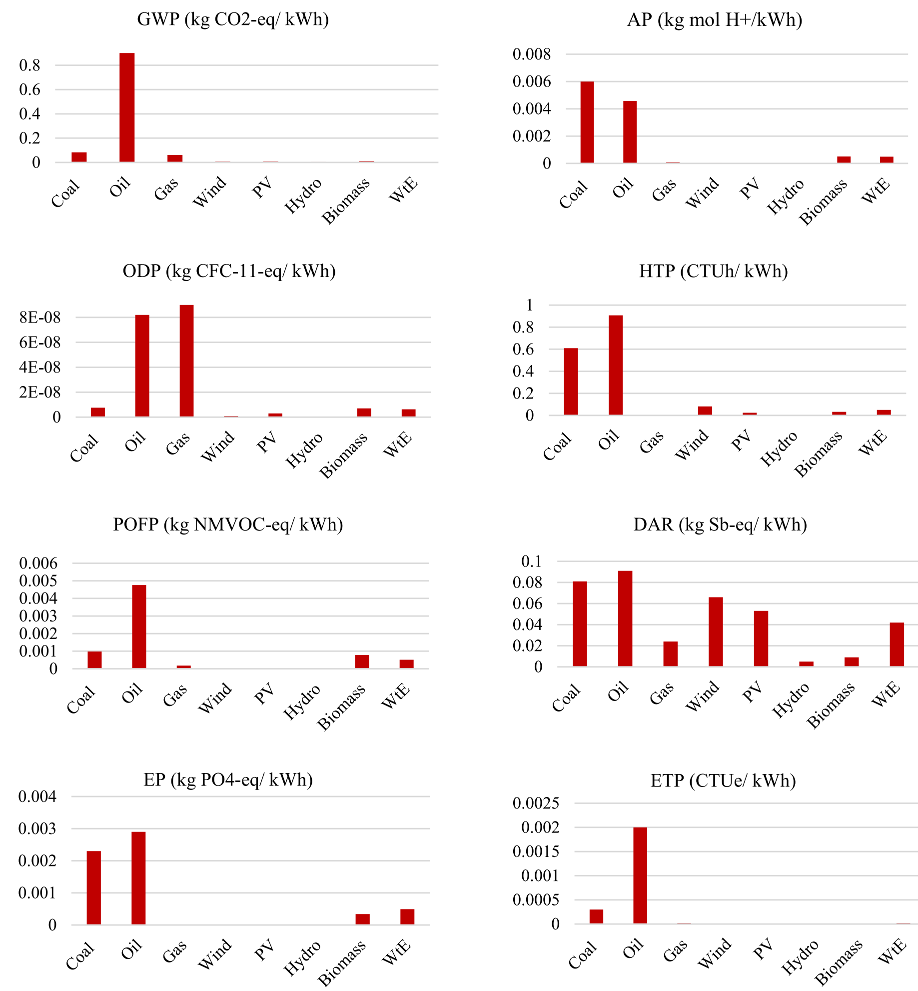

Fig. 11. LCA sustainability on power generation technologies in Lombok Island per 1 kWh electricity production

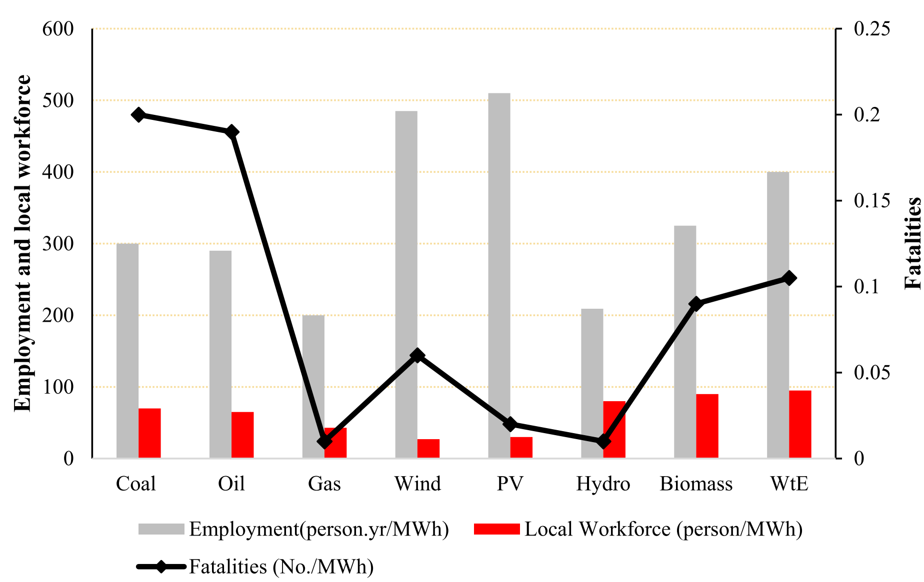

Fig. 12. S-LCA sustainability on power generation technologies in Lombok Island per 1 kWh electricity production

score of each technology in each aspect is selected as its final score. The ranking results of technologies based on this method is provided in Table 7.

For example, hydro's environmental score is 62, and its sustainability score is 7.75 concluding from dividing 62 to 8. Although the results obtained from this method confirm the previous results obtained, however, due to the separate examination of each aspect of sustainability, it cannot create a correct view of scoring and ignores the

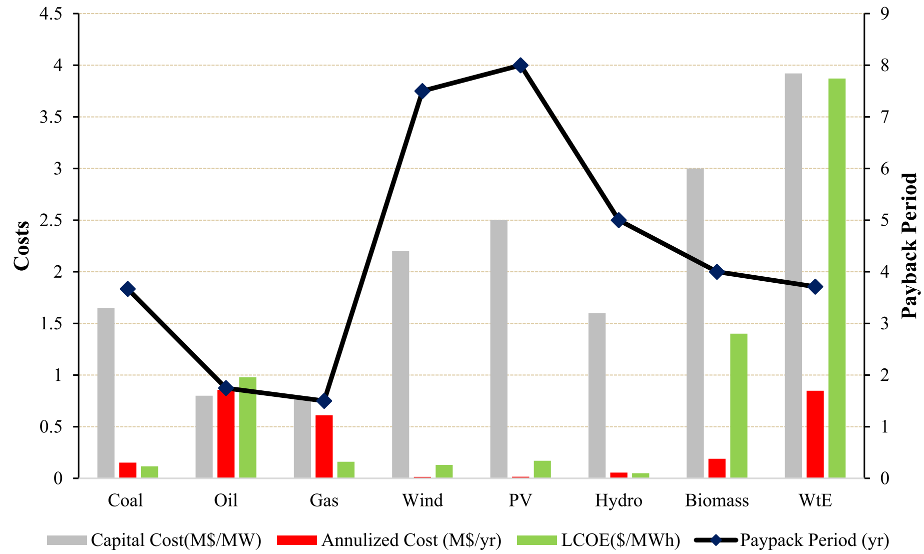

Fig. 13. LCC sustainability on power generation technologies for Lombok Island per 1 kWh electricity production

Table 7
Overall sustainability of power generation technologies in Lombok Island via separate Scoring & Ranking method

	Coal	Oil	Gas	Wind	PV	Hydro	Biomass	WtE
GWP	2	1	3	6	5	7	4	8
AP	1	2	5	6	7	8	3	4
EP	2	1	5	7	6	8	4	3
ODP	3	2	1	7	6	8	4	5
HTP	2	1	8	3	6	7	5	4
POFP	2	1	5	7	6	8	3	4
DAR	2	1	6	3	4	8	7	5
ETP	2	1	4	7	6	8	5	3
Total Score	16	10	37	46	46	62	35	36
Average LCA Score	**2**	**1.25**	**4.62**	**5.75**	**5.75**	**7.75**	**4.375**	**4.5**
Capital Cost	5	7	8	4	3	6	2	1
Annulized Cost	5	1	3	8	7	6	4	2
LCOE	7	3	5	6	4	8	2	1
Paypack Period	6	7	8	2	1	3	4	5
Total Score	23	18	24	20	15	23	12	9
Average LCC Score	**5.75**	**4.5**	**6**	**5**	**3.75**	**5.75**	**3**	**2.25**
Employment	4	3	1	7	8	2	5	6
Fatalities	1	2	8	5	6	7	4	3
Local Workforce	5	4	3	1	2	6	7	8
Total Score	10	9	12	13	16	15	16	17
Average s-LCA Score	**3.33**	**3**	**4**	**4.33**	**5.33**	**5**	**5.33**	**5.67**

* Dark block shows the best technology.

most important challenge, which is the integration of aspects. This method concludes that hydro, coal, and WtE are the most sustainable technologies from environmental, economic, and social aspects, respectively.

5.5.2. MCDM Analysis

As mentioned, multi/criteria analysis can cover the considerable challenge related to sustainability integration. The numerical integrated LCSA based on the MCDM method is examined in this section. This method calculates each option's overall sustainability score as:

$$V(a) = \sum_{i=1}^{I} w_i V_i(a) \tag{1}$$

The MCDM was done in two steps to determine the overall sustainability score for each alternative. First, the values of the corresponding sustainability indicators determined in the sustainability assessment and their weights of relevance were utilized to calculate the scores for each sustainability aspect using (1). The sustainability indicators are then represented by the decision criterion in equation (1). The sustainability elements serve as the choice criteria in the second stage. Using the weights of importance assigned to each aspect and the scores for the sustainability determined in the first stage, equation (1) is applied to estimate the overall sustainability score of technology.

The first step in MCDM is to provide the decision tree, which is available upon request. Equal and different important weights can be considered for aspects to analyze the results. The same weight is considered for each aspect $w_i = 1/3$. The following weights have been applied to the indicators due to the varying numbers of indicators for each sustainability component and to prevent bias:

- 8 environmental indicators: $w_{i=1/8}$,
- 3 social indicators: $w_{i=1/3}$,
- 4 economic indicators: $w_{i=1/4}$,

The final score of sustainability for all aspects is drawn in Fig. 14. As can be seen, these results provide a much better view of the concept of integration of sustainability aspects and can easily determine the best and worst technology both in general and individually as a decision tool.

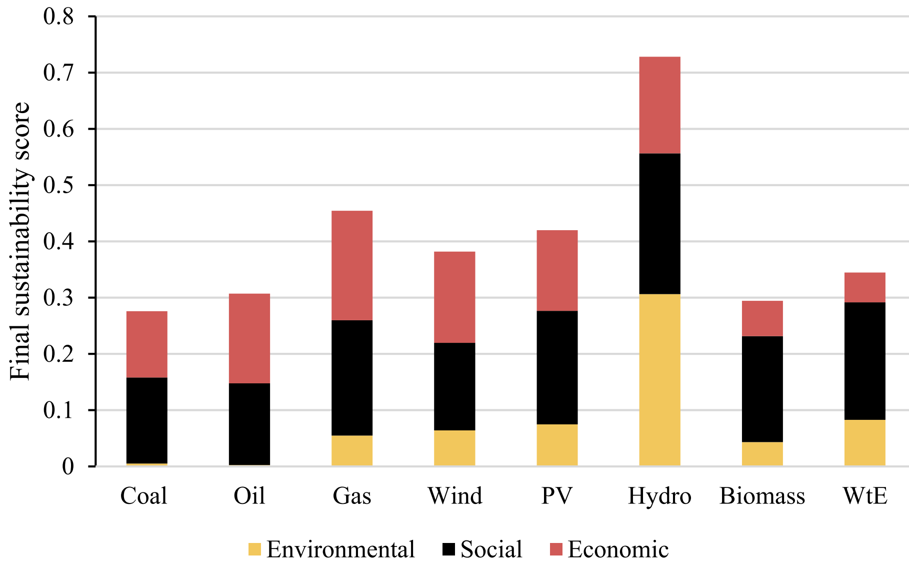

Fig. 14. Final sustainability score of power generation technologies in Lombok Island with equal weights for environmental, social, and economic aspects under MCDM method.

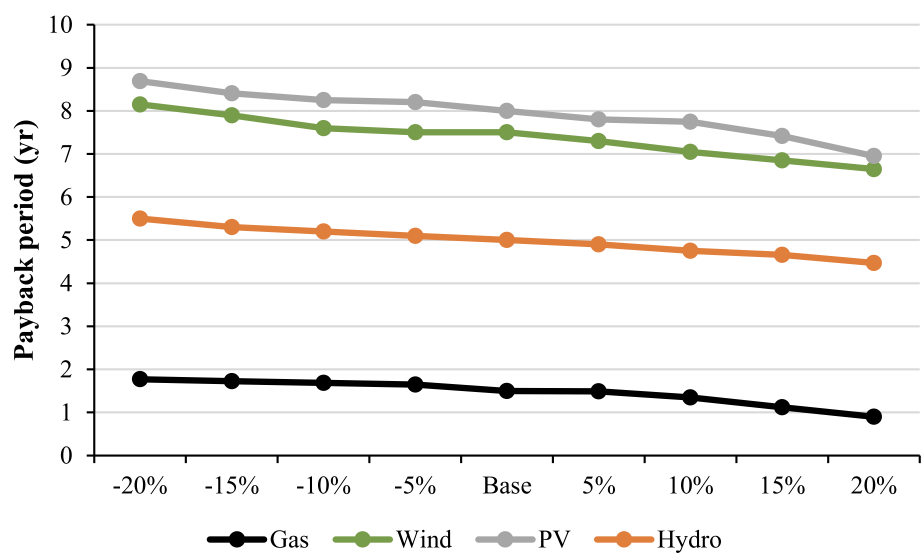

Fig. 15. Sensitivity analysis on electricity price for most sustainable technologies

The results of this method indicate that hydro, gas, and solar are three technologies with high scores in terms of final sustainability. Individually, it can be seen that hydro is completely environmentally friendly. The lack of sufficient social data is quite evident in the results, and the social score of the technologies is not particularly different. Although WtE and solar get the highest score. Economically, gas, diesel, and hydro are much more economical. This analysis was conducted considering the same importance weight for three economic, environmental, and social aspects, while decision-makers and stakeholders can change weights depending on their goals and analyze the results.

5.5.3. Sensitivity and uncertainty analysis

As indicated, the uncertainty of input data can significantly influence the accuracy of results. In this section, a sensitivity analysis of electricity prices and an uncertainty analysis of weighting coefficients on the outcomes from previous sections are presented within the context of Lombok Island. Currently, the electricity price on this island stands at 13.9 ¢/kWh. As indicated, the uncertainty of input data can significantly influence the accuracy of results. In this section, a sensitivity analysis of electricity prices and an uncertainty analysis of weighting coefficients on the outcomes from previous sections are presented within the context of Lombok Island. Currently, the electricity price on this island stands at 13.9 ¢/kWh. The sensitivity analysis is performed by examining the impact of electricity price deviation by ±20% on the payback period for four technologies: gas, hydropower, wind, and solar, as depicted in Fig. 15. An increase in electricity prices has a noteworthy impact on reducing the payback period for solar and gas technologies.

Specifically, with the electricity price reaching 14.6 ¢/kWh in future years, the payback period for gas decreases to below 1 year, and for solar, it diminishes to 6.8 years. This analysis illustrates that adopting supportive policies for electricity generation from renewable sources can serve as an appropriate incentive strategy for cost reduction and, consequently, for reducing the payback period for renewable resources. This sensitivity analysis demonstrates the efficacy of the studied method.

Considering that weighting coefficients can alter the results of sustainability analysis, their variations under uncertainty have been investigated using Monte Carlo simulation. These variations in

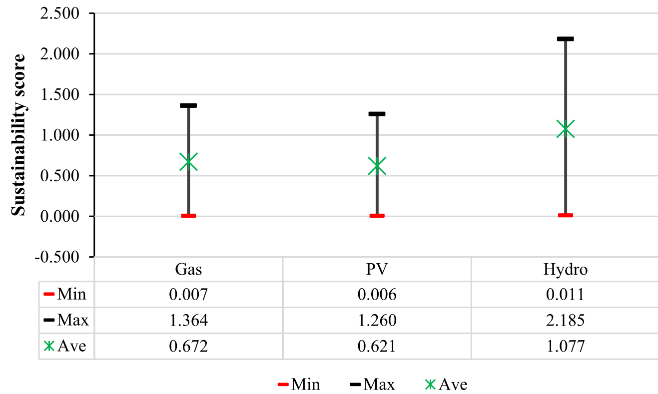

Fig. 16. Min, Max, and Ave scenarios for three high-ranked technologies

weighting coefficients reflect stakeholders' preferences regarding different aspects. To this end, 1000 random variables for weighting coefficients are generated to analyze the final sustainability score for three top technologies: gas, hydro, and solar. Among the 1000 generated scenarios, the minimum, maximum, and average scenarios are depicted in Fig. 16. The uncertainty analysis presented through Monte Carlo simulation demonstrates that under the scenario-based approach, hydro remains the most sustainable technology for Lombok Island.

6. Conclusion

The transition to sustainable electricity resources is identified as a key driver in achieving sustainable development goals, necessitating comprehensive sustainability impact assessments of power production technologies. However, the multitude of quantitative and qualitative methodologies for sustainability analysis, coupled with the absence of a unified procedure, presents a significant challenge in selecting appropriate assessment methods.

To address this challenge, this paper conducted an extensive literature review spanning from 2013 to 2024, analyzing 102 papers to critically examine prevalent methodologies employed for assessing sustainability. The findings reveal a deficiency in standardized approaches for sustainability evaluation within electrical technology, highlighting the need for dynamic methods with multiple temporal accuracies to address uncertainties in impact assessment effectively.

Moreover, the inclusion of a case study focusing on Lombok's future energy mix provided valuable insights into the sustainability of various power generation technologies in the region. By considering 15 environmental, social, and economic indicators, the study found that hydropower, gas, and solar technologies exhibit the highest sustainability scores, respectively. These results underscore the importance of prioritizing the adoption of sustainable technologies to achieve Indonesia's sustainability goals while meeting the energy needs of the region.

Furthermore, the paper highlighted the emerging trend of leveraging artificial intelligence (AI) in sustainability assessment, particularly in dynamic methodologies and data-driven approaches. The application of AI offers promise in addressing the complexities and uncertainties associated with evaluating power generation technologies and facilitating informed decision-making processes. By shedding light on prevailing trends and identifying efficient assessment methods, this research provides valuable insights for policymakers, researchers, and stakeholders involved in shaping the future energy mix.

CRediT authorship contribution statement

Mohammad Hemmati: Writing – original draft, Software, Methodology. **Navid Bayati:** Writing – review & editing, Supervision, Funding acquisition. **Thomas Ebel:** Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

The authors acknowledge the support of the MARGIN project funded by the Danida Fellowship Centre and the Ministry of Foreign Affairs of Denmark to research in growth and transition countries under grant no. 21-M06-AAU.

References

[1] IEA, " World Energy Outlook 2023, IEA, Paris https://www.iea.org/reports/world-energy-outlook-2023, Licence: CC BY 4.0 (report); CC BY NC SA 4.0 (Annex A)," 2023.
[2] H. Ritchie, P. Rosado, Electricity Mix Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/electricity-mix' [Online Resource]," *Our World in Data,* 2020.
[3] L.L.P. de Souza, et al., Life cycle assessment of prospective scenarios maximizing renewable resources in the Brazilian electricity matrix, Renewable Energy Focus 44 (2023) 1–18.
[4] M. Sadiq, P. Kokchang, S. Kittipongvises, Sustainability assessment of renewable power generation systems for scale enactment in off-grid communities, Renewable Energy Focus 46 (2023) 323–337.
[5] M.V. Barros, R. Salvador, C.M. Piekarski, A.C. de Francisco, F.M.C.S. Freire, Life cycle assessment of electricity generation: a review of the characteristics of existing literature, Int. J. Life Cycle Assess. 25 (2020) 36–54.
[6] F. Asdrubali, G. Baldinelli, F. D'Alessandro, F. Scrucca, Life cycle assessment of electricity production from renewable energies: Review and results harmonization, Renew. Sustain. Energy Rev. 42 (2015) 1113–1122.
[7] S.M. Jordaan, C. Combs, E. Guenther, Life cycle assessment of electricity generation: A systematic review of spatiotemporal methods, Advances in Applied Energy 3 (2021) 100058.
[8] R. Turconi, A. Boldrin, T. Astrup, Life cycle assessment (LCA) of electricity generation technologies: Overview, comparability and limitations, Renew. Sustain. Energy Rev. 28 (2013) 555–565.
[9] Y. Wang, Z. Pan, W. Zhang, T.N. Borhani, R. Li, Z. Zhang, Life cycle assessment of combustion-based electricity generation technologies integrated with carbon capture and storage: A review, Environ. Res. 207 (2022) 112219.
[10] S. Verma, G. Dwivedi, P. Verma, Life cycle assessment of electric vehicles in comparison to combustion engine vehicles: a review, Mater. Today:. Proc. 49 (2022) 217–222.
[11] J. G. de Paula do Rosário, R. Salvador, M. V. Barros, C. M. Piekarski, L. M. da Luz, A.C. de Francisco, A review on multi-criteria decision analysis in the life cycle assessment of electricity generation systems, Int. Business, Trade Inst. Sustain., pp. 575-590, 2020.
[12] C. Tomasini-Montenegro, E. Santoyo-Castelazo, H. Gujba, R. Romero, E. Santoyo, Life cycle assessment of geothermal power generation technologies: An updated review, Appl. Therm. Eng. 114 (2017) 1119–1136.
[13] B. Dastjerdi, V. Strezov, M.A. Rajaeifar, R. Kumar, M. Behnia, A systematic review on life cycle assessment of different waste to energy valorization technologies, J. Clean. Prod. 290 (2021) 125747.
[14] M.A. Cusenza, F. Guarino, S. Longo, M. Mistretta, M. Cellura, Environmental assessment of 2030 electricity generation scenarios in Sicily: An integrated approach, Renew. Energy 160 (2020) 1148–1159.
[15] Y.F. Nassar, H.J. El-Khozondar, M. Elnaggar, F.F. El-batta, R.J. El-Khozondar, S. Y. Alsadi, Renewable energy potential in the State of Palestine: Proposals for sustainability, Renew. EnergyFocus (2024) 100576.
[16] O. Nubi, S. Morse, R.J. Murphy, Prospective life cycle costing of electricity generation from municipal solid waste in Nigeria, Sustainability 14 (20) (2022) 13293.
[17] M. Rapa, L. Gobbi, R. Ruggieri, Environmental and economic sustainability of electric vehicles: Life cycle assessment and life cycle costing evaluation of electricity sources, Energies 13 (23) (2020) 6292.
[18] V. Soni, S. Singh, D. Banwet, Sustainable coal consumption and energy production in India using life cycle costing and real options analysis, Sustainable Production and Consumption 6 (2016) 26–37.
[19] T.H. Pérez, J. Rodríguez-Chueca, J.P. Rodríguez, Inclusion of key social indices for a comparative assessment of the sustainability of the life cycle of current and future electricity generation in Spain: A proposed methodology, Sci. Total Environ. 899 (2023) 165541.

[20] O. Nubi, S. Morse, R.J. Murphy, A prospective social life cycle assessment (SLCA) of electricity generation from municipal solid waste in Nigeria, Sustainability 13 (18) (2021) 10177.

[21] M.-O.-P. Fortier, L. Teron, T.G. Reames, D.T. Munardy, B.M. Sullivan, Introduction to evaluating energy justice across the life cycle: A social life cycle assessment approach, Appl. Energy 236 (2019) 211–219.

[22] S. Takeda, A.R. Keeley, S. Sakurai, S. Managi, C.B. Norris, Are renewables as friendly to humans as to the environment?: A social life cycle assessment of renewable electricity, Sustainability 11 (5) (2019) 1370.

[23] M. Martín-Gamboa, P. Quinteiro, A.C. Dias, D. Iribarren, Comparative social life cycle assessment of two biomass-to-electricity systems, Int. J. Environ. Res. Public Health 18 (9) (2021) 4918.

[24] B. Corona, K.P. Bozhilova-Kisheva, S.I. Olsen, G. San Miguel, Social life cycle assessment of a concentrated solar power plant in Spain: a methodological proposal, J. Ind. Ecol. 21 (6) (2017) 1566–1577.

[25] A. Souza, M.D.B. Watanabe, O. Cavalett, C.M.L. Ugaya, A. Bonomi, Social life cycle assessment of first and second-generation ethanol production technologies in Brazil, Int. J. Life Cycle Assess. 23 (2018) 617–628.

[26] T.S. Aung, T.B. Fischer, A.S. Azmi, Social impacts of large-scale hydropower project in Myanmar: a social life cycle assessment of Shweli hydropower dam 1, Int. J. Life Cycle Assess. 26 (2021) 417–433.

[27] E. Rashid, N. Majed, Integrated life cycle sustainability assessment of the electricity generation sector in Bangladesh: Towards sustainable electricity generation, Energy Rep. 10 (2023) 3993–4012.

[28] Y.-C. Tseng, Y.-M. Lee, S.-J. Liao, An integrated assessment framework of offshore wind power projects applying equator principles and social life cycle assessment, Sustainability 9 (10) (2017) 1822.

[29] A. Buchmayr, E. Verhofstadt, L. Van Ootegem, G. Thomassen, S.E. Taelman, J. Dewulf, Exploring the global and local social sustainability of wind energy technologies: An application of a social impact assessment framework, Appl. Energy 312 (2022) 118808.

[30] E. Lucchi, J. Adami, A.E. Stawinoga, Social acceptance of photovoltaic systems in heritage buildings and landscapes: Exploring barriers, benefits, drivers, and challenges for technical stakeholders in northern Italy, Sustainable Energy Technol. Assess. 60 (2023) 103544.

[31] V. Mukoro, A. Gallego-Schmid, M. Sharmina, Life cycle assessment of renewable energy in Africa, Sustain. Prod. Consumpt. 28 (2021) 1314–1332.

[32] M. Šerešová, J. Štefanica, M. Vitvarová, K. Zakuciová, P. Wolf, V. Kočí, Life cycle performance of various energy sources used in the Czech Republic, Energies 13 (21) (2020) 5833.

[33] H. Yousefi, R. Habibifar, A. Farhadi, S.M. Hosseini, Integrated energy, cost, and environmental life cycle analysis of electricity generation and supply in Tehran, Iran, Sustain. Cities Soc. 97 (2023) 104748.

[34] V. Rakotoson, J.P. Praene, A life cycle assessment approach to the electricity generation of French overseas territories, J. Clean. Prod. 168 (2017) 755–763.

[35] E.G. Hertwich, et al., Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies, Proc. Natl. Acad. Sci. 112 (20) (2015) 6277–6282.

[36] Z. Günkaya, A. Özdemir, A. Özkan, M. Banar, Environmental performance of electricity generation based on resources: a life cycle assessment case study in Turkey, Sustainability 8 (11) (2016) 1097.

[37] A.A. Martins, et al., Life cycle assessment tool of electricity generation in Portugal, Environ. Dev. Sustain. 20 (2018) 129–143.

[38] P. Stenzel, A. Schreiber, J. Marx, C. Wulf, M. Schreieder, L. Stephan, Renewable energies for Graciosa Island, Azores–life cycle assessment of electricity generation, Energy Procedia 135 (2017) 62–74.

[39] R. Garcia, P. Marques, F. Freire, Life-cycle assessment of electricity in Portugal, Appl. Energy 134 (2014) 563–572.

[40] D.A.L. Silva, I. Delai, M.L.D. Montes, A.R. Ometto, Life cycle assessment of the sugarcane bagasse electricity generation in Brazil, Renew. Sustain. Energy Rev. 32 (2014) 532–547.

[41] Á. Restrepo, E. Bazzo, R. Miyake, A life cycle assessment of the Brazilian coal used for electric power generation, J. Clean. Prod. 92 (2015) 179–186.

[42] D. García-Gusano, D. Garraín, J. Dufour, Prospective life cycle assessment of the Spanish electricity production, Renew. Sustain. Energy Rev. 75 (2017) 21–34.

[43] S. Longo, M. Cellura, P. Girardi, Life Cycle Assessment of electricity production from refuse derived fuel: A case study in Italy, Sci. Total Environ. 738 (2020) 139719.

[44] M.V. Rocco, A. Di Lucchio, E. Colombo, Exergy life cycle assessment of electricity production from waste-to-energy technology: a hybrid input-output approach, Appl. Energy 194 (2017) 832–844.

[45] L. Lijó, et al., Life Cycle Assessment of electricity production in Italy from anaerobic co-digestion of pig slurry and energy crops, Renew. Energy 68 (2014) 625–635.

[46] M.P. Mahmud, N. Huda, S.H. Farjana, C. Lang, Life-cycle impact assessment of renewable electricity generation systems in the United States, Renew. Energy 151 (2020) 1028–1045.

[47] X. Shen, R.R. Kommalapati, Z. Huque, The comparative life cycle assessment of power generation from lignocellulosic biomass, Sustainability 7 (10) (2015) 12974–12987.

[48] L. Lelek, J. Kulczycka, A. Lewandowska, J. Zarebska, Life cycle assessment of energy generation in Poland, Int. J. Life Cycle Assess. 21 (2016) 1–14.

[49] D. Burchart-Korol, P. Pustejovska, A. Blaut, S. Jursova, J. Korol, Comparative life cycle assessment of current and future electricity generation systems in the Czech Republic and Poland, Int. J. Life Cycle Assess. 23 (2018) 2165–2177.

[50] E.I. Wiloso, et al., Production of sorghum pellets for electricity generation in Indonesia: A life cycle assessment, Biofuel Res. J. 7 (3) (2020) 1178–1194.

[51] R. Nugroho, J. Hanafi, K. Shobatake, Y.-Y. Chun, K. Tahara, W.W. Purwanto, Life cycle inventories and life cycle assessment for an electricity grid network: case study of the Jamali grid, Indonesia, Int. J. Life Cycle Assess. 27 (8) (2022) 1081–1091.

[52] P. D. Sinaga, S. S. Moersidik, U. S. Hamzah, "Life Cycle Assessment of a combined cycle power plant in Indonesia," in *IOP Conference Series: Earth and Environmental Science*, 2021, vol. 716, no. 1: IOP Publishing, p. 012122.

[53] R. Annisa, et al., Life cycle Assessment of natural gas combined cycle steam power generation systems in Indonesia: case Study on Gresik power plant vol. 753, no. 1 (2021) 012039.

[54] R. Sianipar, M.S. Boedoyo, N.A. Sasongko, Application of LCA (Life Cycle Assessment) to Solar Energy Development in Indonesia, International Journal of Innovative Science and Research Technology (2022) 128–132.

[55] T. Ayodele, A. Ogunjuyigbe, M. Alao, Life cycle assessment of waste-to-energy (WtE) technologies for electricity generation using municipal solid waste in Nigeria, Appl. Energy 201 (2017) 200–218.

[56] N. Orfanos, D. Mitzelos, A. Sagani, V. Dedoussis, Life-cycle environmental performance assessment of electricity generation and transmission systems in Greece, Renew. Energy 139 (2019) 1447–1462.

[57] M.M. Parascanu, M. Kaltschmitt, A. Rödl, G. Soreanu, L. Sánchez-Silva, Life cycle assessment of electricity generation from combustion and gasification of biomass in Mexico, Sustainable Production and Consumption 27 (2021) 72–85.

[58] Q. Yue, S. Li, X. Hu, Y. Zhang, M. Xue, H. Wang, Sustainability Analysis of Electricity Generation Technologies Based on Life-Cycle Assessment and Life-Cycle Cost—A Case Study in Liaoning Province, Energ. Technol. 7 (7) (2019) 1900365.

[59] J. Chen, et al., Green development strategy of offshore wind farm in China guided by life cycle assessment, Resour. Conserv. Recycl. 188 (2023) 106652.

[60] R. Brizmohun, T. Ramjeawon, A. Azapagic, Life cycle assessment of electricity generation in Mauritius, J. Clean. Prod. 106 (2015) 565–575.

[61] Y. Wu, Y. Wang, K. Chen, C. Xu, L. Li, Social sustainability assessment of small hydropower with hesitant PROMETHEE method, Sustain. Cities Soc. 35 (2017) 522–537.

[62] J. Lehmann, G. Bouillass, R. Fofack-Garcia, P. Pérez-López, Towards social Life Cycle Assessment of Energy Systems: a case study on offshore wind farms from companies' perspective, in: E3S Web of Conferences, vol. 349, EDP Sciences, 2022, p. 12002.

[63] J. Lehmann, "Integration of Social Life Cycle Assessment as a tool for the evaluation and decision-making in the design phase of offshore wind farm projects in France," Paris Sciences & Lettres, 2023.

[64] B. Corona and G. San Miguel, "Social performance of electricity generation in a solar power plant in Spain—a life cycle perspective," *Social Life Cycle Assessment: Case Studies from the Textile and Energy Sectors,* pp. 1-57, 2019.

[65] A. Saravanan, P.S. Kumar, "Social Life Cycle Assessment of Renewable Bio-Energy Products," Social Life Cycle Assessment: Case Studies from the Textile and Energy Sectors, pp. 99-111, 2019.

[66] B. Corona, E. Cerrajero, D. López, G. San Miguel, Full environmental life cycle cost analysis of concentrating solar power technology: Contribution of externalities to overall energy costs, Sol. Energy 135 (2016) 758–768.

[67] K. Ndwali, J.G. Njiri, E.M. Wanjiru, Multi-objective optimal sizing of grid connected photovoltaic batteryless system minimizing the total life cycle cost and the grid energy, Renew. Energy 148 (2020) 1256–1265.

[68] X. Yuan, et al., Life cycle cost of electricity production: A comparative study of coal-fired, biomass, and wind power in China, Energies 14 (12) (2021) 3463.

[69] C. Li, F. Wang, D. Zhang, X. Ye, Cost management for waste to energy systems using life cycle costing approach: A case study from China, J. Renewable Sustainable Energy 8 (2) (2016) pp.

[70] Q. Li, et al., Life cycle assessment and life cycle cost analysis of a 40 MW wind farm with consideration of the infrastructure, Renew. Sustain. Energy Rev. 138 (2021) 110499.

[71] C. Zhang, J. Yang, Economic benefits assessments of "coal-to-electricity" project in rural residents heating based on life cycle cost, J. Clean. Prod. 213 (2019) 217–224.

[72] B. Zakeri, S. Syri, Electrical energy storage systems: A comparative life cycle cost analysis, Renew. Sustain. Energy Rev. 42 (2015) 569–596.

[73] C.-T. Li, H. Peng, J. Sun, Life cycle cost analysis of wind power considering stochastic uncertainties, Energy 75 (2014) 411–418.

[74] A.K. Abu-Rumman, I. Muslih, M. Barghash, Life cycle costing of PV generation system, Journal of applied research on industrial engineering 4 (4) (2017) 252–258.

[75] A.K. Abu-Rumman, I. Muslih, M. Barghash, Life cycle costing of wind generation system, J. Appl. Res. Industr. Eng. 4 (3) (2017) 185–191.

[76] S.S. Aji, Y.S. Kim, K.Y. Ahn, Y.D. Lee, Life-cycle cost minimization of gas turbine power cycles for distributed power generation using sequential quadratic programming method, Energies 11 (12) (2018) 3511.

[77] A. Rentizelas, D. Georgakellos, Incorporating life cycle external cost in optimization of the electricity generation mix, Energy Policy 65 (2014) 134–149.

[78] N. Ranganath, D. Sarkar, Life cycle costing analysis of solar photo voltaic generation system in Indian scenario, Int. J. Sustain. Eng. 14 (6) (2021) 1698–1713.

[79] M. Perčić, I. Ančić, N. Vladimir, Life-cycle cost assessments of different power system configurations to reduce the carbon footprint in the Croatian short-sea shipping sector, Renew. Sustain. Energy Rev. 131 (2020) 110028.

[80] M.S. Gustafsson, J.A. Myhren, E. Dotzauer, M. Gustafsson, Life cycle cost of building energy renovation measures, considering future energy production scenarios, Energies 12 (14) (2019) 2719.
[81] M.Z. Akber, M.J. Thaheem, H. Arshad, Life cycle sustainability assessment of electricity generation in Pakistan: Policy regime for a sustainable energy mix, Energy Policy 111 (2017) 111–126.
[82] L.J. Stamford, Life cycle sustainability assessment of electricity generation: a methodology and an application in the UK context. The University of Manchester (United Kingdom), 2012.
[83] B. Atilgan, A. Azapagic, An integrated life cycle sustainability assessment of electricity generation in Turkey, Energy Policy 93 (2016) 168–186.
[84] L. Stamford, A. Azapagic, Life cycle sustainability assessment of UK electricity scenarios to 2070, Energy Sustain. Dev. 23 (2014) 194–211.
[85] G. San Miguel, M. Cerrato, Life cycle sustainability assessment of the Spanish electricity: Past, present and future projections, Energies 13 (8) (2020) 1896.
[86] A. Roinioti, C. Koroneos, Integrated life cycle sustainability assessment of the Greek interconnected electricity system, Sustain. Energy Technol. Assess. 32 (2019) 29–46.
[87] J.G. Lassio, A. Magrini, D.C. Branco, Life cycle-based sustainability indicators for electricity generation: A systematic review and a proposal for assessments in Brazil, J. Clean. Prod. 311 (2021) 127568.
[88] R.B. Zortea, V.G. Maciel, A. Passuello, Sustainability assessment of soybean production in Southern Brazil: A life cycle approach, Sustain. Prod. Consump. 13 (2018) 102–112.
[89] M. Shaaban, J. Scheffran, J. Böhner, M.S. Elsobki, Sustainability assessment of electricity generation technologies in Egypt using multi-criteria decision analysis, Energies 11 (5) (2018) 1117.
[90] J. Kabayo, P. Marques, R. Garcia, F. Freire, Life-cycle sustainability assessment of key electricity generation systems in Portugal, Energy 176 (2019) 131–142.
[91] E.R.S. García, A. Morales-Acevedo, Optimizing the energy portfolio of the Mexican electricity sector by 2050 considering CO2eq emissions and life cycle assessment, Energy Procedia 57 (2014) 850–859.
[92] A. Maxim, Sustainability assessment of electricity generation technologies using weighted multi-criteria decision analysis, Energy Policy 65 (2014) 284–297.
[93] O. Nubi, S. Morse, R.J. Murphy, Life cycle sustainability assessment of electricity generation from municipal solid waste in Nigeria: a prospective study, Energies 15 (23) (2022) 9173.
[94] M.S. Atabaki, M. Mohammadi, V. Aryanpur, An integrated simulation-optimization modelling approach for sustainability assessment of electricity generation system, Sustainable Energy Technol. Assess. 52 (2022) 102010.
[95] V. Campos-Guzmán, M.S. García-Cáscales, N. Espinosa, A. Urbina, Life Cycle Analysis with Multi-Criteria Decision Making: A review of approaches for the sustainability evaluation of renewable energy technologies, Renew. Sustain. Energy Rev. 104 (2019) 343–366.
[96] A. Pınar, L. Aydın, Economic input-output life cycle sustainability assessment of electricity generation in Turkey between 1995 and 2009, Turkish Journal of Energy Policy 3 (7) (2018) 50–69.
[97] A. Valente, D. Iribarren, J. Dufour, Comparative life cycle sustainability assessment of renewable and conventional hydrogen, Sci. Total Environ. 756 (2021) 144132.
[98] R. Bhandari, B.E. Arce, V. Sessa, R. Adamou, Sustainability assessment of electricity generation in Niger using a weighted multi-criteria decision approach, Sustainability 13 (1) (2021) 385.
[99] R. Turconi, D. Tonini, C.F. Nielsen, C.G. Simonsen, T. Astrup, Environmental impacts of future low-carbon electricity systems: detailed life cycle assessment of a Danish case study, Appl. Energy 132 (2014) 66–73.
[100] B. Corona, G. San Miguel, Life cycle sustainability analysis applied to an innovative configuration of concentrated solar power, Int. J. Life Cycle Assess. 24 (2019) 1444–1460.
[101] C. Visentin, A.W. da Silva Trentin, A.B. Braun, A. Thomé, Life cycle sustainability assessment: A systematic literature review through the application perspective, indicators, and methodologies, J. Clean. Prod. 270 (2020) 122509.
[102] R. Contreras-Lisperguer, E. Batuecas, C. Mayo, R. Díaz, F. Pérez, C. Springer, Sustainability assessment of electricity cogeneration from sugarcane bagasse in Jamaica, J. Clean. Prod. 200 (2018) 390–401.
[103] J. Ren, Multi-criteria decision making for the prioritization of energy systems under uncertainties after life cycle sustainability assessment, Sustainable Production and Consumption 16 (2018) 45–57.
[104] E. Lucchi, F. Turati, B. Colombo, E. Schito, Climate-responsive design practices: a transdisciplinary methodology for achieving sustainable development goals in cultural and natural heritage, J. Clean. Prod. (2024) 142431.
[105] D. Beloin-Saint-Pierre, P. Padey, B. Périsset, V. Medici, Considering the dynamics of electricity demand and production for the environmental benchmark of Swiss residential buildings that exclusively use electricity vol. 323, no. 1 (2019) 012096.
[106] F. Piccinno, R. Hischier, S. Seeger, C. Som, Predicting the environmental impact of a future nanocellulose production at industrial scale: Application of the life cycle assessment scale-up framework, J. Clean. Prod. 174 (2018) 283–295.
[107] J.-M. Rödger, et al., Combining life cycle assessment and manufacturing system simulation: evaluating dynamic impacts from renewable energy supply on product-specific environmental footprints, Int. J. Precis. Eng. Manuf.-Green Technol. 8 (2021) 1007–1026.
[108] A. Nabavi-Pelesaraei, S. Rafiee, S.S. Mohtasebi, H. Hosseinzadeh-Bandbafha, K.-W. Chau, Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production, Sci. Total Environ. 631 (2018) 1279–1294.
[109] A. Kaab, M. Sharifi, H. Mobli, A. Nabavi-Pelesaraei, K.-W. Chau, Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production, Sci. Total Environ. 664 (2019) 1005–1019.
[110] A. Nabavi-Pelesaraei, R. Bayat, H. Hosseinzadeh-Bandbafha, H. Afrasyabi, K.-W. Chau, Modeling of energy consumption and environmental life cycle assessment for incineration and landfill systems of municipal solid waste management-A case study in Tehran Metropolis of Iran, J. Clean. Prod. 148 (2017) 427–440.
[111] A. Schreiber, J. Marx, P. Zapp, Comparative life cycle assessment of electricity generation by different wind turbine types, J. Clean. Prod. 233 (2019) 561–572.
[112] R. Turconi, C.G. Simonsen, I.P. Byriel, T. Astrup, Life cycle assessment of the Danish electricity distribution network, Int. J. Life Cycle Assess. 19 (2014) 100–108.
[113] KPMG, “Investing in Lombok - Prefeasibility studies on renewable energy solutions in Lombok,” 2019.
[114] D.E. Nasional, Technology Data for the Indonesian Power Sector: Catalogue for Generation and Storage of Electricity, Dewan Energi Nasional, Kemetrian Energi dan Sumber Daya Mineral, 2017.