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Review

Techno-Economic and Life Cycle Cost Analysis through the Lens of Uncertainty: A Scoping Review

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Abstract: Researchers have long been interested in developing new economic assessment methods to provide credible information and facilitate the sustainable development of new technologies and products. The techno-economic analysis (TEA) and the life cycle cost analysis (LCCA) are the most widely used approaches for modeling and calculating processes' economic impacts. A simulation-based TEA is a cost-benefit analysis that simultaneously considers technical and economic factors. In addition, the method facilitates the development of the entire project and provides a systematic approach for examining the interrelationships between economic and technological aspects. When it comes to economic studies, it is intimately bonded with uncertainty. There are numerous uncertainty sources, classified in various ways. The uncertainty reflects "an inability to determine the precise value of one or more parameters affecting a system." The variability refers to the different values a given parameter may take. This implies that a probability density function (PDF), for instance, can be employed to estimate and quantify the variability of a given parameter. The bias refers to "assumptions that skew an analysis in a certain direction while ignoring other legitimate alternatives, factors, or data." The present study identifies the frequency with which TEA/LCCA studies address uncertainty and gaps within the selected papers through a scoping review. The results indicate that the uncertainty associated with economic factors and model uncertainties were the main sources of uncertainty in TEA and LCCA. Moreover, possibilistic approaches such as the Monte Carlo methodology were the most frequently used tool to cope with the uncertainties associated with LCCA and TEA.

Keywords: techno-economic analysis; uncertainty; life cycle cost; scoping review

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1. Introduction

For many years, designers and contractors have been concerned with minimizing the costs of their projects. Researchers have always sought to develop new economic evaluation methods to give dependable observations and assist in the creation of new products. In this regard, clear and standardized frameworks are required to maximize the effectiveness of these methods [1]. Regarding technological innovation, the techno-economic analysis (TEA) and the life cycle cost analysis (LCCA) are two widespread methodologies. Despite their broad use and acceptance, these instruments lack clear guidelines and comprehensive documentation regarding their features. Both methods suffer from huge ambiguity, and uncertainty analysis is a key element of their process [2,3]. Uncertainty analysis provides valuable and meaningful insights into the consequences of assumptions and the model's underlying structure. As a measure of model quality and robustness, the uncertainty analysis can provide insight into the reliability of the outcome [3].

In contrast to determinism, uncertainty may indicate probability, likelihood, or frequency of occurrence [4]. In one classification, uncertainty can be considered aleatory and epistemic [5]. Aleatory uncertainty is caused by intrinsic variability, whereas epistemic uncertainty results from a lack of knowledge [6]. However, many articles have been published over the years on methods and approaches for evaluating uncertainty (e.g., [7–9]), but there are few literature reviews on this topic. In addition, new and advanced uncertainty techniques are not yet utilized by techno-economics and life cycle cost analysts. It may partly be due to unawareness of the different uncertainty analysis alternatives and their pros and cons. Therefore, a review on this topic might increase awareness of this subject.

PRISMA, which stands for the "preferred reporting items for systematic reviews and meta-analyses" [10–13], is a well-established method for reporting scoping reviews [14]. This process involves illustrating the screening results at each stage in order to report existing studies. In addition to systematic reviews and meta-analyses, PRISMA can also be used to report reviews of other types of research [15]. Following PRISMA guidelines, the scoping review methodology comprehensively reviews TEA and LCCA in an uncertain environment. Three research questions are addressed in the present study:

1. What are the main sources of uncertainty in TEA and LCCA?
2. Which methods/tools were used to cope with these uncertainties?
3. Which probability distribution functions were used to define the uncertainties?

The remainder of the article is outlined as follows: Section 2 describes the background of TEA and LCCA and the potential sources of uncertainty. The study's methodology is described in Section 3, a discussion of the research results is presented in Section 4, and the review is concluded in Section 5.

2. Background

In recent years, both the TEA and LCCA have gained increasing acceptance as appraisal methods for technological projects. This perspective indicates that both TEA and LCCA can serve as practical tools to ensure that resources are allocated appropriately and efficiently based on the technological assessment scopes. The US Department of Defense developed a primary framework of LCCA in the 1960s to systematically assess projects characterized by significant operative expenditures other than capital investments [16]. The following will introduce and discuss the basics of both concepts. Although there have been some techno-economic analyses over the past few decades, a systematic discussion of its methodological approach was only initiated recently [1]. Inevitably, the results of any evaluation based on assumptions and estimates will be uncertain. For decision-makers to make informed decisions, it is necessary to conduct an uncertainty analysis to determine both the reliability of positive results and which technical and economic parameters will most influence the profitability of a project [17]. Therefore, the present section provides the basics and definitions of TEA, LCCA, and their uncertainties.

2.1. Techno-Economic Analysis

Generally, a TEA compares costs and benefits by examining technological and economic aspects [1]. TEA combines engineering design and process modeling with economic evaluation, providing a means of assessing the economic viability of a process. From another perspective, TEA is a method of estimating a plant's performance, emissions, and cost in advance of its construction. A variety of definitions of evaluation methods are presented in the literature, most of which differ in terms of the evaluation scope and level of detail. TEA was offered not only as a tool in which investment and performance analysis converge but also as an appropriate approach for integrating engineering design and process modeling with the economic aspects [1,18].

Despite the significant increase in the use of TEA, in the absence of an agreed upon definition, it is difficult to determine what constitutes a TEA [19]. However, researchers have attempted to define the methodology of TEA. Kuppens et al. [17] discussed that three key questions need to be answered by a TEA: What is the mechanism of the technology? Does the technology have profit potential? How desirable is the technology? Nevertheless, they defined TEA as a combination of economic and technical evaluations. There are still some methodological guidelines that need to be clarified despite the effectiveness of the provided definition. In addition, the NABC (National Advanced Biofuels Consortium) provided a detailed description of the purpose of TEA in order to determine the financial viability of a conversion strategy. As part of TEA, engineering design, process modeling, and economic evaluation are integrated. Appendix A provides some definitions and statements of TEA.

Before delving into existing uncertainty analysis methodologies, offering a general overview of techno-economic models is useful since different investigations may necessitate different uncertainty analysis techniques. Van der Spek et al. [3] summarized the types of uncertain parameters based on the model complexity (simple, moderate, and complex). For simple models, uncertain parameters include financial parameters such as lifetime, discount rate, fuel and consumables costs, and scaling exponents. In moderate systems, uncertain parameters include simple model parameters, equipment sizes, equipment costs, and escalation factors. In addition, uncertain parameters include scaling factors, detailed capital costs, operational costs, and simple and moderate parameters in complex models. Giacomella [1] reported that the TEA's methodological steps could be categorized into the following six steps: (1) defining technology readiness levels (TRL), (2) system elements and boundaries identification, (3) Analyzing market conditions, costs, and feasibility, (4) profitability analysis, (5) analysis of risk and uncertainty using sensitivity and scenario forecasting, and (6) recommendations.

2.2. Life Cycle Cost Analysis

Life cycle cost analysis (LCCA) is a technique used to evaluate all relevant expenses of a project, product, or measure over its time. LCCA takes into account all costs, including initial costs (such as capital investment, purchase, and installation), future costs (such as energy, operating, maintenance, capital replacement, and financing costs), and any resale, salvage, or disposal costs, over the lifetime of the project or product [20–23]. Compared to TEA, LCCA relies on a broader regulatory foundation. The LCCA may depend on a broader set of legal regulations, standards, and guidelines than the TEA, whose primary sources are individual guidelines and intellectual debate [1]. The European Union recognizes LCCA through its directives (2014/24/EU [24], 2014/25/EU [25]), and several product-specific standards have been developed for the oil and gas and construction industries. (ISO 15663:2000 and 15686:2017, respectively).

In the literature, LCCA is also described in several different ways, but it appears to have a higher degree of coherence than TEA. As obtained from definitions in Appendix A, LCCA facilitates the proper decision-making process by aggregating and estimating costs into easy-to-read figures, as well as revealing and counting the influence of different factors, such as the time value of money and other uncertain economic factors, on decisions. The cost generally includes all costs related to production, operation, maintenance, and retiring/disposing of a product from the cradle to the grave.

Uncertainty in parameters, such as cash flows and their timing, interest rates, and duration analysis, are the most commonly reported uncertainty sources in LCCA. The uncertainty of cash flow is called cash flow unpredictability [26]. The uncertainty of interest rates results from fluctuating economic conditions and markets, and the change of interest rates over time puts uncertainty into any study [27,28]. The literature addresses uncertainty in describing the cash flows' timing using the same reasoning that applies to interest rates and cash flows.

According to the literature [1,29,30], the TEA's methodological steps can be categorized into the following five steps: (1) problem definition and objectives, (2) cost analysis, (3) discounting future cash flows and economic evaluation, (4) considering risks and uncertainties, and (5) comparing the alternatives and possibilities.

2.3. Uncertainty

According to Finnveden et al. [31], uncertainty is defined as the deviation between a quantity measured or calculated and its true value and discussed many reasons to make the uncertainty happen. Different variables influence how decision-makers interpret uncertain outcomes, including their preferences, timing, and scenario framing [32]. In the literature, sources of uncertainty, such as data, choices, and relations, are distinguished from types of uncertainty. As examples of uncertainty types, data variability, inconsistency between alternative products, and an incorrect relationship between pollutant emissions and their environmental impact can be cited. [33]. From the literature, an overview of different types of uncertainty and their definitions is given in Table 1. As seen, 26 different types of uncertainty were listed and defined. The most significant types of uncertainty in TEA and LCCA are model, parameter, and scenario uncertainties, as well as variability (see Section 4). Over time, different methods have been developed to deal with different types of uncertainty. Uncertainty modeling can be used to reduce, evaluate, and demonstrate uncertainty. These methods can be classified into four groups: deterministic, probabilistic, possibilistic, and other methods [34]. In another classification, these methods were categorized into quantitative and qualitative techniques [35]. Barahmand et al. [36] reported another classification which consists of possibilistic, probabilistic, hybrid possibilistic-probabilistic, interval-based analysis, robust optimization, and information gap decision theory. A diagram illustrating well-known methods of dealing with various types of uncertainty is shown in Figure 1 (based on [34,37]).

Table 1. Overview of different types and sources of uncertainty.

Type	Source	Ref.
Variability	An unpredictable result of changes in systems (involving time, space, or other variables)	[38]
Systematic errors	Bias in sampling procedures or measuring equipment	[38]
Measurement error	Errors that appear random due to imperfections in the measurement equipment and observational methods	[38]
Random errors	A measurement error caused by varying factors between measurements	Oxford definition
Parameter uncertainty	Measurement errors, sampling errors, variability, and surrogate data contribute to incomplete knowledge of parameters	[39]
Model uncertainty	Our limitations in representing physical systems may result in uncertainty when we approximate a model in order to solve a problem.	[38]
Scenario uncertainty	A level of uncertainty associated with specifying an exposure scenario that is consistent with the purpose and scope of the exposure assessment	[40]
Exposure factor Uncertainty	Contributes to the specification of numerical values for human exposure	[40]
Uncertainty due to choices	Different choices of partitioning methods, etc.	[41]
Spatial variability	The phenomenon occurs when the value of a quantity is different at different spatial locations. A descriptive spatial statistic such as the range can be used to assess spatial variability.	[42]
Temporal variability	A measure of the frequency and magnitude of fluctuations in ecosystem structure such as standing stocks of resources and species abundance	[43]

Table 1. *Cont.*

Type	Source	Ref.
Data uncertainty	This type of data contains noise that causes it to deviate from the correct or original values.	[44]
Completeness uncertainty	Like modeling uncertainties, completeness uncertainties occur at the beginning of the probabilistic risk analysis process. In probabilistic risk analysis, there is uncertainty as to whether all significant phenomena and significant relationships have been considered.	[45]
Aleatory uncertainty	Samples and parameters are intrinsically random	[38]
Epistemic uncertainty	An insufficient understanding of fundamental phenomena	[38]
Ambiguity	Being open to multiple interpretations	Oxford definition
Volitional uncertainty	Whether or not an individual will follow through on an individual's commitment	[46]
Statistical variation	A measure of how widely distributed a group of data is	[47,48]
Subjective judgment	A lack of certainty in the interpretation of data or the estimations of experts	[38]
Linguistic imprecision	Depends on the utterance alternatives available to the speaker in the context	[49]
Inherent randomness	Resulting from the irreducibility of a system to a deterministic system	[38]
Disagreement	Lack of consensus or approval, inconsistency or correspondence	Oxford definition
Approximation	Nearly accurate but not exactly correct value or quantity	Oxford definition
Semantic uncertainty	Occurs when humans give names to things, especially when those things are mapped as geographic data	[50]
Interpretational uncertainty	Occurs when interpreters use inconsistent decoding methodologies to extract information from data or models.	Helmholtz dictionary

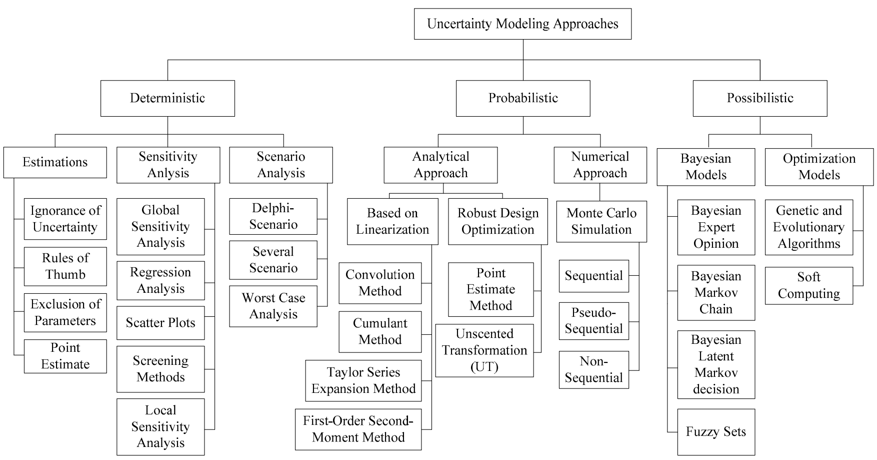

Figure 1. Classification of different methods to cope with system uncertainties.

3. Methodology

The present study uses a scoping review methodology to summarize and analyze the history and status of uncertainty considerations in techno-economic and life cycle cost assessments, as well as indicate related challenges and limitations. The choice of this type of review was based on the fact that it involves multiple structured searches and a rigorous search methodology [51]. As part of the process, PRISMA flow diagrams are used to report on the papers found at each stage [10]. Flow diagrams based on the PRISMA methodology have been well established as a methodology for scoping reviews [52]. The objective of this method is not to conduct a mapping or a systematic review since the identified literature will not be critically evaluated. Instead, thematic data analysis is presented descriptively and qualitatively [53].

Furthermore, promising areas for improvement and knowledge gaps were identified. The purpose of a scoping review is to describe the key concepts underpinning a research area, as well as the available sources and types of evidence. It may be performed as a standalone project, particularly when the subject matter is complex or has not been thoroughly investigated [54]. Scoping studies are conducted for at least four reasons [55]:

1. Analyzing the scope, range, and nature of the study,
2. An assessment of the feasibility of conducting a comprehensive systematic review,
3. Sharing and summarizing findings, and
4. Knowledge gaps identification

3.1. Searching Procedure

As seen in Figure 2, scoping review protocol consists of five main stages: identifying research questions and relevant studies, selecting studies, charting the data, and summarizing and reporting the results [53]. To conduct this study, the following steps were performed.

1. Three main research questions were defined (stage 1).
2. A preliminary search was conducted in two scientific databases, Scopus and ScienceDirect (stage 2), using the following search strings. These search strings are: For Scopus: TITLE-ABS-KEY ((techno-economic OR (life AND cycle AND cost*)) AND(uncertainty)) For ScienceDirect: (techno-economic OR life cycle cost) AND uncertainty The initial search was not limited at this level. Titles, abstracts, and keywords were searched across the selected databases. Thus, 3635 and 680 documents (in all categories) were indexed in Scopus and ScienceDirect, respectively.
3. The main interest was to study the most recent studies. Therefore, the studies conducted in the last 5 years were chosen (2017–April 2022). As a result of applying this limit, the number of documents decreased to 1777 for Scopus and 470 for ScienceDirect, respectively (stage 2).

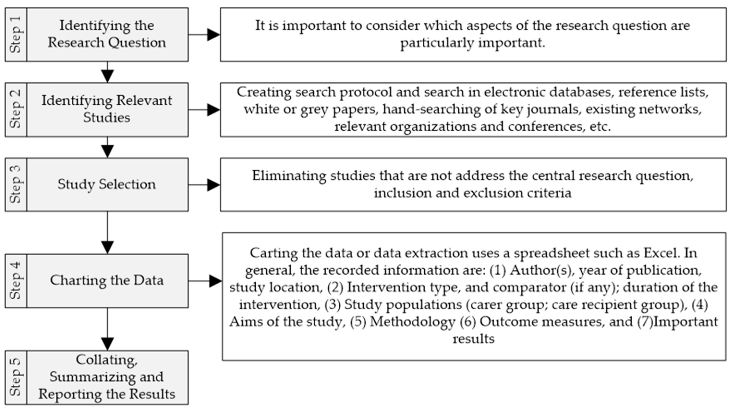

Figure 2. Overall research process scheme based on PRISMA adapted from [14].

4. In the next step, the language of the studies was also limited to English. Consequently, only a few documents were removed from Scopus. The remaining studies were indexed in Scopus and ScienceDirect as 1741 and 470, respectively (stage 2 continued).
5. Limiting the search strings only to the title (stage 2 continued), the number of articles dropped significantly (63 and 35 for Scopus and ScienceDirect).
6. All the documents obtained from ScienceDirect were repeated in the Scopus list. Therefore, in this step, by trimming the list and removing duplicates, 63 documents remained (stage 3). The remaining articles were listed in Excel to perform the necessary investigation.
7. A full-text screening was conducted to determine the eligibility of the studies. Accordingly, three studies were deemed non-relevant and were eliminated from the list (stage 3 continued). The list contained 60 publications at this stage.
8. To obtain more credible results, the results were limited to only journal papers, and book chapters and conference papers were eliminated. All in all, the final list included 47 studies.
9. The Bolographic information was extracted and reported (stages 4 and 5), including the title, country of origin, year of publication, the study's aim and scope, methodology, barriers and challenges, and other observations.

The PRISMA flow diagram of the study is illustrated in Figure 3. PRISMA methodology, a well-established reporting template, illustrates the screening process results to report the remaining studies at each stage of the screening process.

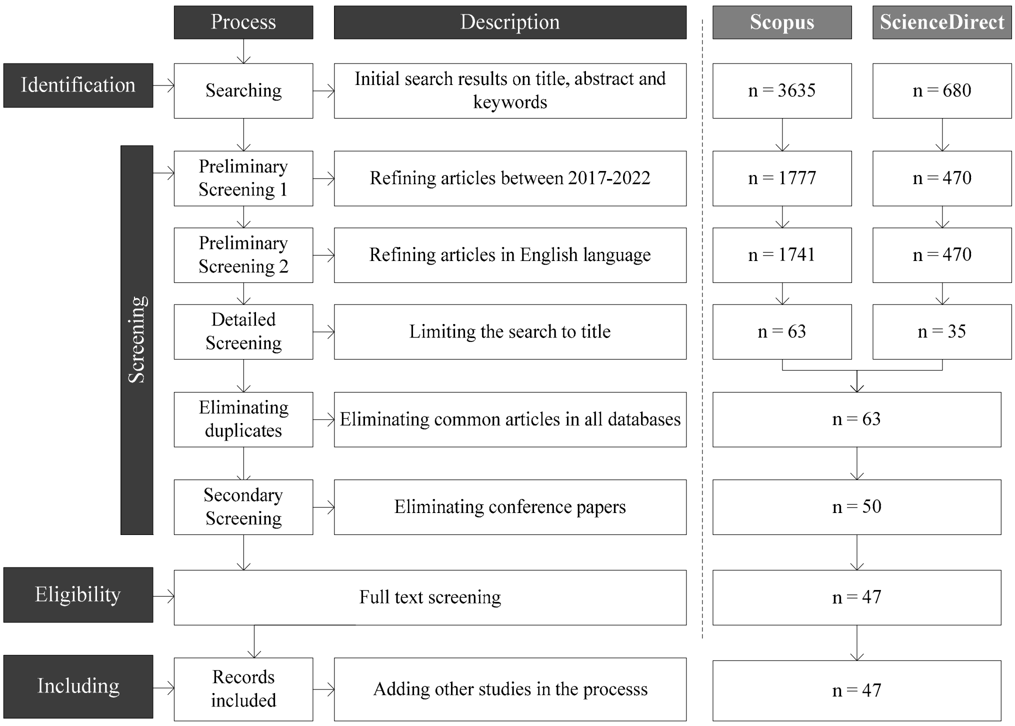

Figure 3. PRISMA flow diagram.

3.2. Limitation

The present study was limited to English language studies published after 2017. Furthermore, conference papers, proceedings, and grey literature, such as publicly accessible records and technical reports, have not been studied.

4. Results and Discussion

An overview of the latest studies on applying uncertainty analysis to TEA and LCCA (47 selected studies from the scoping review) is provided in this section.

4.1. Descriptive Analysis

4.1.1. Number of Publications

The year-wise analysis provides an overall perspective of the research progress over the study period. Based on data from 2017 to April 2022, Figure 4 shows how many studies were published. The early studies from the Scopus database were also presented to provide a better understanding of the trend over time. As a whole, TEA and LCCA are becoming increasingly popular for investigating uncertainty. With 15 publications, 2021 has made the greatest contribution. So far, there has been only one publication in the first quarter of 2022; however, it is expected to have fewer publications than in 2021. Since 2017, interests in the topic have increased significantly.

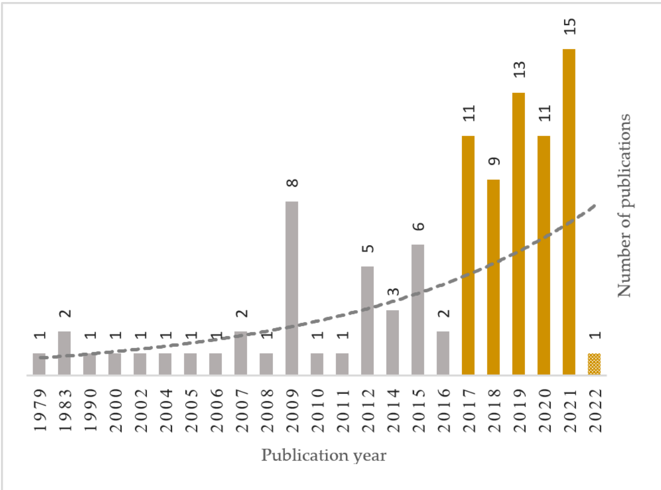

Figure 4. Number of selected studies over the years and overall trend.

4.1.2. The Origin of Studies

Based on country-wise analysis of the selected publications, 27 countries contributed to 47 publications. Figure 5 illustrates that the United States has contributed the most publications, with 14 studies, followed by the United Kingdom with 7 publications. China and the Netherlands have five publications each.

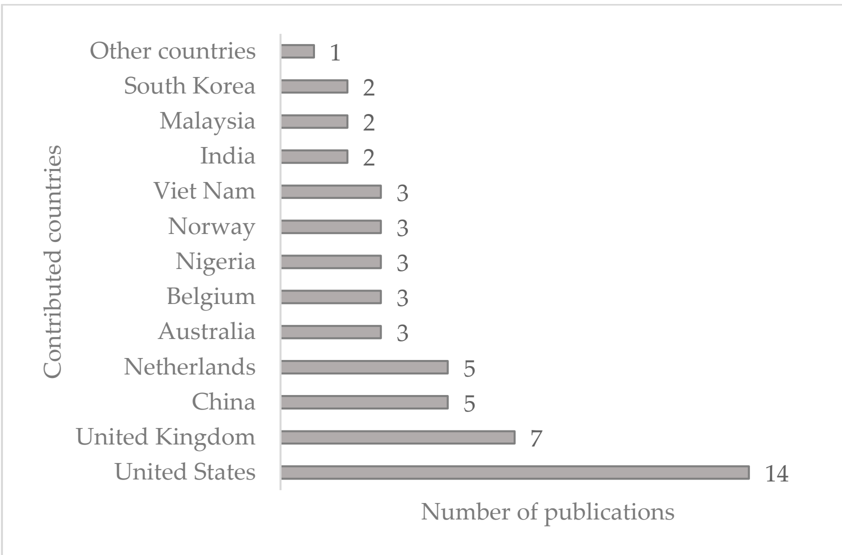

Figure 5. Country's contribution to publications.

4.1.3. Publications by Document Type

Although conference papers have been eliminated from this review, to have a meaningful comparison of types of published studies on the topic, conference papers were added to 47 selected studies. Most selected documents were articles, followed by conference papers, which accounted for 20 percent of the selected documents. Figure 6 illustrates the significance of the study based on only three review articles. Van der Spek et al. [3] critically reviewed the uncertain aspects of TEA in CO_2 capture and storage technologies. On the other hand, Sun and Carmichael [27] reviewed the uncertainties related to economic and financial variables within infrastructure LCCA. Ilg et al. [34] defined 33 different uncertainty sources and 24 methods to handle the uncertainties associated with LCCA decisions for infrastructure projects.

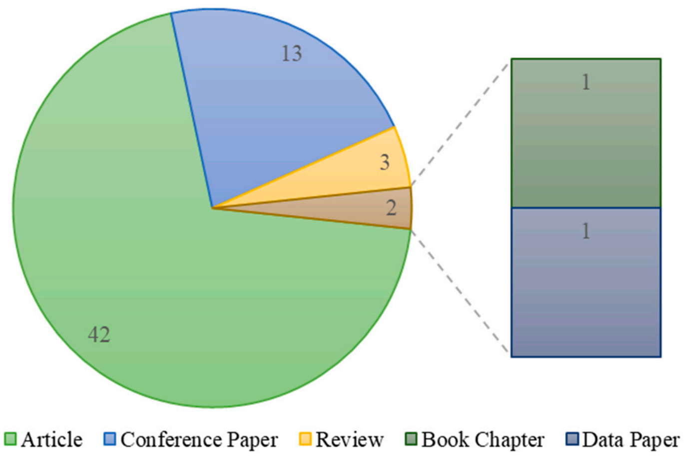

Figure 6. Categorization based on document types before eliminating conference papers.

4.1.4. Publications by Subject Area

As shown in Table 2, the selected studies can be classified into 17 areas based on the extracted information from the Scopus database. Engineering, energy, and environmental sciences were the leading sectors on this topic by 27, 22, and 19 percent, respectively.

Table 2. Subject areas in the selected publications.

Engineering	27%
Energy	22%
Environmental Science	19%
Chemical Engineering	7%
Chemistry	5%
Earth and Planetary Sciences	4%
Agricultural and Biological Sciences	3%
Materials Science	2%
Physics and Astronomy	2%
Biochemistry, Genetics, and Molecular Biology	2%
Business, Management, and Accounting	2%
Computer Science	2%
Social Sciences	1%
Decision Sciences, Economics and Finance, Mathematics	1%

4.2. Content-Based Analysis

To answer the research questions, this section provides a comprehensive content-based analysis. The purpose of this section is to provide an overview of recent research conducted in the last 5 years. Except for review articles by der Spek et al. [3] and Sun and Carmichael [27], other studies focused on TEA and LCCA of the specific case study. As seen in Table 3, these studies were categorized into three different classes.

Table 3. Categorization of the studies.

Techno-economic analysis (TEA)	33
Life cycle cost analysis (LCCA)	13
Techno-economic-environmental analysis (TEEA)	1

The interest in studying TEA under uncertainty was the highest at almost 70 percent. For example, a techno-economic study was conducted by Coppitters et al. [56], taking technical, economic, and environmental uncertainties into account. In order to maximize the carbon intensity and Levelized cost of driving, they performed robust design optimization on a solar- and wind-powered hydrogen refueling system and hydrogen- and diesel-powered bus fleet. The carbon intensity is the carbon emissions per unit of energy consumed (CO_2 emissions/energy) [57–59]. The Levelized cost of driving calculates how much it costs to drive a vehicle per kilometer over its life cycle [60]. For all uncertainties, uniform distribution can be expressed as lower and upper bounds because there were very few data points for these parameters. Thus, it is challenging to determine their distributions. Their uncertain parameters were divided into two categories: aleatory (grid electricity price and GHG emissions, energy consumption, annual solar irradiance, average ambient temperature, diesel price and the inflation rate) and epistemic (30 the economic and environmental parameters) uncertainty. They employed a sparse polynomial chaos expansion (SPCE) approach in order to perform uncertainty quantification on a system with a high degree of stochasticity [61], which is computationally efficient. Zhenzhen and Kai [9] developed a techno-economic analysis of producing cross-laminated timber (CLT) panels, an emerging and green alternative to steel and concrete, in the Southern United States. The authors considered the uncertainty and variations in feedstock, plant capacity, manufacturing parameters, as well as capital and operating costs in order to fill the knowledge gap. The Monte Carlo simulation was used to assess the effects of these variations on minimum selling prices (MSPs) for CLT panels. The MSP is a crucial indicator for determining the economic viability of a product since it represents the minimal selling price required to reach the cash flow breakeven point [62]. Lo et al. [63] performed a TEA and feasibility analysis on a biomass gasification process, considering five supply chain uncertainties: syngas and transportation fuel prices, biomass quality, supply, and pricing via Monte Carlo simulation (MCS). McNulty et al. [64] developed a techno-economic analysis model including process variability and related uncertainties in field-grown plant-based manufacturing. They employed the MCS to quantify the effect of variation and uncertainties in profitability-related indicators such as internal rate of return, cost of goods, and process performance forecast variables such as product purity and annual throughput [65]. The predictive modeling, uncertainty analysis, optimization, and TEA of bio-catalyzed biodiesel production from Azidirica Indica oil were accomplished by Oke et al. [66]. The predictive model and optimizations were developed in Design Expert® software. The model uncertainty analysis was performed using the Monte Carlo simulation in Oracle Crystal Ball® software on input variables of biodiesel production. The process simulation and economic analysis were conducted in ASPEN Batch Process Developer® V10. Moreover, a sensitivity analysis was performed to assess the process's profitability, assessing the economic efficiency and feasibility of the proposed production process. Net present value (NPV), payback Time (PBT), and return on investment (ROI) were used to investigate the profitability of this process. Amini and Noble [7] developed a techno-economic optimization method to identify the ideal size and quantity of flotation cells for a specific circuit configuration, taking into account the possibility of variability in various input parameters, including feed grade, kinetic coefficients, and metal price. In the first step, a sensitivity analysis was undertaken to identify the uncertain parameters. After simplifying the optimization issue, the sample average approximation (SAA) methodology was used to identify the equipment configuration (i.e., cell size and number) that optimizes the plant's net present value while accounting for the range of probable input values resulting from parameter uncertainty. SAA is a method for solving stochastic optimization problems based on the Monte Carlo simulation [67]. Alfonso-Cardero et al. [68] conducted a process simulation and a TEA for the anaerobic digestion of Cuban sugarcane vinasses under uncertainty. For the application of biogas, the following three scenarios were considered: electricity production, biomethane as vehicle fuel, and biomethane for gas grid injection. Accordingly, sensitivity analyses were conducted on each scenario to determine the parameters that have the greatest impact on the investment's economic viability such as electricity selling price and cost of $Ca(OH)_2$. Compared to the baseline, input parameters were varied by 25%, 50%, and 75%. Moreover, a stochastic modeling using the MCS was performed to find the probability distribution of the NPV as the main output.

Only one article used techno-economic-environmental analysis (TEEA). Hosseini et al. [69] proposed a framework for evaluating the techno-economic-environmental effects of various levels of network integration and storage devices on the performance of integrated gas and electricity networks. They employed MCS to sample their sources of uncertainty, such as loads, renewable energy sources, and economic and environmental key factors.

A full list of uncertainty sources associated with selected TEA studies is provided in Appendix B. Moreover, Table 4 summarizes different approaches and tools used to cope with the system uncertainties, PDFs of uncertain data, and the application of the studies associated with TEA.

Table 4. Uncertainty methods, probability distribution functions, and applications in TEA.

	Model/Tool	Trials	PDF	Application
1	UQ by SPCE	N/A	Uniform	Heavy-duty transport (Bus)
2	SA By MCS	1000	Mostly Uniform and a Triangular	Economic feasibility of cross-laminated timber
3	MCS		Probability distributions	Biomass gasification
4	MCS	20,000 and 60,000	Normal, Triangular, Logistic, Scaled beta	Field-grown bioproducts manufacturing
5	MCS, SA	100,000	Normal	Bio-catalyzed biodiesel production
6	SAA by MCS SA		uniform, normal, and lognormal	Cell-Based Flotation Circuits
7	SA, UA by MCS	10,000	Normal	Anaerobic digestion of Cuban sugarcane vinasses
8	MCS, SA	10,000	Triangular	Cooking oil to jet fuel production
9	ScA	N/A	Weibull distribution	Wind energy potential in selected sites
10	MCS	10,000	Normal, Triangular, Logistic, Lognormal,	Wet waste hydrothermal liquefaction (HTL)
11	MCS, SA	30,000	Normal	Biodiesel production from palm kernel oil
12	MCS	100,000	Normal	Technologies for the extraction of crude anthocyanin powder
13	GABCAO	N/A	N/A	Distribution network
14	MCS	50,000	Two-half-Lognormal	An off-grid stand-alone photovoltaic system for hydrogen electrolysis

Table 4. *Cont.*

	Model/Tool	Trials	PDF	Application
15	Review	N/A		CO_2 Capture and Storage (CCS) technologies
16	MCS, SA			Biorefineries
17	GSA, MCS, RO by (MCS + GA)		Uniform, Weibull, Beta	Design of remote micro-grid
18	MCS, SIM	10,000	Normal,	Performances of a CO_2 Absorber
19	MMO	N/A		Enhanced Geothermal System (EGS)
20	MOM	N/A		Hybrid harmonic filter planning
21	SUA	N/A		Ship power and propulsion concepts
22	ScA, SA	N/A		Fuel cell vehicles
23	GSA by MCS + SIM	100,000	Normal	Directly coupled photovoltaic-electrolyzer system
24	MCS	10,000	Normal, Pareto, Lognormal, Triangular, Maximum extreme	Algal-derived bio-crude via hydrothermal liquefaction
25	ANN + MCS		Uniform, Normal	Power to gaseoxy-fuel boiler hybrid system
26	MCS	10,000	Triangular, Boot-strapped, Uniform, Linear	Incorporating microbial oil production into the concept of a biorefinery
27	MCS, SA, PA		Triangular	A distributed hydrogen refueling station using glycerol steam reforming
28	NIPCE	N/A		Directly coupled photovoltaic-electrolyzer system
29	GBM, ARIMA, and MRJD	N/A	Normal,	Profitability assessment of offshore wind energy
30	MCS, SA	1,000,000	Normal	Biomass-to-liquid systems for the production of transportation fuels
31	NLOA, SA	N/A	Interval Uncertainties	Biodiesel Production
32	NIPCE, MCS		Normal	CO_2 capture from enclosed environments
33	SA	N/A	Normal, Uniform, Lognormal, Triangular	Butanol production from corn stover
34	SA	N/A	N/A	Very early stage CO_2 capture technologies

Table 4. *Cont.*

35	SA, PM, MCS	3000	Normal, Lognormal	Producing high-value propylene glycol from low-value biodiesel glycerol
36	MCS, SA		Uniform	biodiesel production
37	PM, SA	N/A		Very early stage CO_2 capture technologies
38	MCS	1000	Normal	Gas and electricity network integration and storage

On the other hand, 27 percent of the studies addressed LCCA. For example, to maintain the safety and welfare of communities, asset management systems (AMSs) [70] should keep infrastructure assists in acceptable condition. By including probabilistic and complex uncertain models in AMSs, it has been argued that project-level AMSs can maximize maintenance activities over the assets' life cycle [71]. Asghari et al. [71] developed a deep neural network (DNN) model for replacing the time-consuming simulation modules of optimization algorithms. In order to make complex AMSs computationally applicable to all network assets, they estimated the LCCA results using a trained machine-learning model. Machine learning algorithms such as DNN mimic the brain's information processing [72]. In this model, deterioration (modeled by first-order Markov chain), hazards and the hazard responses of assets (modeled by the Poisson process), and costs volatility (modeled by the Wiener process) were the main sources of uncertainty. Despite this method's relatively high computing costs, trained DNN models may provide comparable outcomes hundreds of times faster than Monte Carlo simulations. Table 5 lists the sources of uncertainty in the studies related to LCCA. Moreover, Table 6 summarizes different approaches and tools used to cope with the system uncertainties, PDFs of uncertain data, and the application of the studies associated with LCCA. In Tables 4 and 6, "N/A" in the "Trials" column indicates the uncertainty method does not belong to the probabilistic approach and does not utilize trials. In addition, the empty "Trials" section indicates that although the method requires trials, the authors did not provide any additional information.

Table 5. Sources of uncertainty in life cycle cost studies.

	Reference	Sources of Uncertainty
1	[71]	Deterioration, hazards and the hazard responses of assets, costs volatility
4	[73]	Electricity prices, renewable energy sources, and load uncertainties
5	[74]	Model parameter and scenario uncertainties
6	[75]	Measurement sensors which provide the state information; activated dampers, which produce reactive forces and provide additional damping; and controllers, which control actuator outputs based on state measurements.
9	[76]	Energy price and electrical demand, wind speed
12	[77]	Capital and operating costs
13	[2]	
14	[78]	Uncertainties in the cost calculation
17	[79]	Energy price and electrical demand
19	[34]	Review
22	[80]	Uncertainty in the input data

Table 6. Uncertainty methods, probability distribution functions, and applications in LCCA.

	Model/Tool	Trials	Probability Distribution Function	Application
1	DNN	N/A	Different PDFs	Infrastructure asset management
2	SPA by MCS	100,000	Uniform	The service life of a viaduct (a bridge)
3	MCS			Slab track mono-block sleeper system for Indonesian urban metro railway
4	MSO	N/A	Normal, Weibull, Beta	Optimal reinforcement framework for distribution system
5	MCS, NPB	1000	Uniform	HDPE pipe alternatives
6	MCS		binomial, Uniform	High-performance control systems
7	SFA, HOM by MCS			Four-story modern ductile reinforced concrete building in Los Angeles
8	ScA	N/A		Railway turnouts
9	MSO	N/A	Normal, Beta, Weibull	Distribution system planning
10	MCS		Normal, Uniform, Lognormal, Triangular, Weibull	Uncertainty in LCCA
11	FOTSE	N/A	Normal, Uniform, Lognormal	Highway bridge structures
12	ScA	N/A		Lignocellulose biomass solvent liquefaction and sugar fermentation to ethanol
13	Review	N/A		Financial variables within the infrastructure
14	LIDRA by MCS		Triangular	Green infrastructure
15	ScA	N/A		Deep extra heavy oil green field
16	MOO with RA	N/A	Normal	Maintenance for bridges
17	MOO	N/A	Normal	Distribution systems reinforcement
18	MCS		Normal, Triangular	Buildings' energy efficiency measures
19	Review	N/A		Long-range infrastructure
20	MCS	1000	Uniform, Lognormal	Pavement industry
21	SA by MLFD + n-way ANOVA	N/A		Bridge
22	PN + MCS		Weibull, Exponential, Lognormal, Normal	Real-time condition monitoring in railways

In general, Monte Carlo simulation methodology and probabilistic approaches are the most frequently used tools and approaches in TEA and LCCA studies. Different PDFs were defined for the uncertain parameters such as normal, Uniform, lognormal, triangular, Weibull, beta, etc. Furthermore, key economic factors and model parameters were the main sources of uncertainty in LCCA and TEA.

5. Conclusions

Two commonly used methods of evaluating a project's economic feasibility are TEA and LCCA. Both methods are subject to great ambiguity, and uncertainty analysis forms a key component of their methodologies. The current study fills a gap left by the absence of comprehensive reviews on LCCA and TEA in an uncertain environment. The results indicate that there has been a greater interest in studying uncertain aspects of TEA than LCCA, possibly because TEA considers both economic and technical aspects of the problem. In both LCCA and TEA, key economic factors and model parameters were the main sources of uncertainty. Moreover, recent studies have also demonstrated an interest in adopting the probabilistic approach, particularly the Monte Carlo simulation. To address the uncertainty associated with parameter values, probabilistic methods must utilize probability distribution functions. The normal distribution functions, followed by lognormal and uniform PFDs, were the most frequently used PDF associated with the uncertain parameters in LCCA and TEA. This implies that choosing an appropriate PDF plays a crucial role in probabilistic approaches. According to the results, sensitivity analysis and Monte Carlo simulation were used in more than half of the studies to analyze uncertainty, confirming their complementary nature. Whereas LCCA and TEA studies suffer from significant uncertainties, it is suggested that uncertainty analysis should be considered in all future studies. The authors also suggest that possibilistic approaches such as fuzzy set theory be tested and compared to possibilistic approaches.

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Nomenclature

ANN	Artificial Neural Network	NPB	Non-Parametric Bootstrapping
ANOVA	Analysis of Variance	PM	Pedigree Matrix
ARIMA	Auto-Regressive Integrated Moving Average	PN	Petri Net
DNN	Deep Neural Networks	PDF	Probability Distribution Function
FOATSE	First Order Analysis Taylor Series Expansion	PA	Profitability Analysis
GA	Genetic Algorithm	RO	Robust Optimization
GBM	Geometric Brownian Motion	SAA	Sample Average Approximation
GABCAO	Global Artificial Bee Colony Algorithm Optimization	ScA	Scenario Analysis
GSA	Global Sensitivity Analysis	SFA	Seismic Fragility Assessment
LIDRA	Low Impact Development Rapid Assessment	SPA	Semi-Probabilistic Approach
MRJD	Mean -Reversion and Jump-Diffusion	SA	Sensitivity Analysis
MCS	Monte Carlo Simulation	SIM	Sobol's Indices Methodology
MLFD	Multi-Level Factorial Design	SPCE	Sparse Polynomial Chaos Expansion
MOO	Multi-Objective Optimization	SRA	System Reliability Analysis
MMO	Multiple Model Optimization	SUA	System Uncertainty Analysis
MSO	Multi-Scenario Optimization	UA	Uncertainty Analysis
N/A	Not applicable	HOM	Hazard Occurrence Model
NIPCE	Non-Intrusive Polynomial Chaos Expansion		

Appendix A

Table A1. Definitions of techno-economic analysis (TEA) in the literature based on Giacomella [1] and Smur et al. [81].

Definition	Reference
"The evaluation of the technic performance or potential and the economic feasibility of a new technology that aims to improve the social or environmental impact of a technology currently in practice, and which helps decision-makers in directing research and development or investments."	[17]
"The techno-economic evaluation incorporates results from both investment and performance analysis to select the most cost-efficient solution for a certain scenario and performance requirements."	[18]
"Iterative process illustrating the valorization of potential technologies. It adopts design techniques to estimate costs and revenues aimed at identifying profitability. Next, risk analysis is performed in support of risk reduction strategies."	[19]
"Techno-economic modelling methods are typically used to evaluate the economic feasibility of new technologies and services. Techno-economic modelling combines forecasting network design and investment analysis methods, typically utilizing the spreadsheet-based tool."	[81]
"TEA is a methodology framework to analyse the technical and economic performance of a process, product or service and includes studies on the economic impact of research, development, demonstration, and deployment of technologies, quantifying the cost of manufacturing and market opportunities."	[82]
"The TEA model is an integrated model, with direct linkages between the economic and technological parts. The dynamic character of TEA, where a change in one parameter directly affects all output indicators, is key to identifying the most influencing parameters for a feasible technology."	[83]
"The techno-economic analysis (TEA) involves evaluating a process/technology through a process simulation approach."	[84]

Table A2. Definitions of LCCA in the literature.

Definition	Reference
In an LCCA, all the significant net expenditures arising during the ownership of an asset are identified and quantified in order to optimize the total cost of asset ownership.	[85]
The life cycle cost of a product (LCCA) involves the total cost throughout its entire lifespan.	[86]
As a result of LCCA analysis, an estimate of the total incremental costs associated with developing, producing, using, and retiring a particular product can be determined	[87]
A conventional life cycle cost analysis assesses all costs associated with the life cycle of a product that are directly borne by the main producer or user	[88]
The LCCA is a type of investment calculus that incorporates a life-cycle perspective beyond that offered by traditional investment calculus. As well as considering investment costs, it also considers operating costs over the product's expected lifetime.	[89]
The LCCA methodology enables comparisons of costs over a given period, taking into account relevant integral economic factors	[90]
In LCCA, all present and future costs essential to a system are summed together in present value during a given life cycle.	[91]
A life cycle cost assessment is a method of evaluating life-cycle costs in a systematic manner. It can examine a project's entire life cycle, a selected period of time, or a selected stage in its life cycle	[92]

Appendix B

Table A3. Sources of uncertainty in techno-economic studies.

	Reference	Sources of Uncertainty
1	[56]	The grid electricity and diesel price, grid electricity's greenhouse gas emissions, energy consumption, annual solar irradiance, average ambient temperature, inflation rate, economic and environmental parameters
2	[9]	Variations in the feedstock, plant capacities, manufacturing parameters, and capital and operating costs
3	[63]	Syngas and transportation fuel prices, biomass quality, supply and pricing
4	[64]	Main indicators of profitability such as internal rate of return, cost of goods, and performance forecast variables, such as product purity and annual throughput)
5	[66]	Input variables of biodiesel production, profitability indicators
6	[7]	Different input parameters, including feed grade, kinetic coefficients, and metal price
7	[68]	Input parameters such as electricity selling price and cost of $Ca(OH)_2$
8	[93]	Economic parameters
9	[94]	A historical time series of wind directions and speeds in the years between 2000–2019, mean wind speeds, power density, most probable wind speeds, maximum energy carrying speeds, and predominant wind directions in wind passes are presented in this section
10	[95]	Feedstock composition, HTL yield model, aqueous-phase product treatment, utility consumption, and equipment sizing and costing
11	[96]	Biodiesel production input variables and profitability indicators
12	[97]	Process parameters such as materials and energy demands, production costs, and unit production costs
13	[98]	Various distributed energy resources (DERs) data, wind, solar and electric vehicles (EVs)
14	[99]	Wide range of system parameters (Electrolyzer, PV, and economic parameters)
15	[3]	Review
16	[100]	Coefficients of cost correlation and parameters of scenarios
17	[101]	System parameters including electrolyzer, PV, H_2 tank, battery bank, fuel cell) and economic parameters
18	[102]	Solvent property uncertainties on a rate-based absorb model (density, viscosity, solubility, surface tension, equilibrium between vapor and liquid, chemical reaction kinetics, heat of reaction, specific heat capacity)
19	[103]	Several geological and structural parameters are uncertain, including the stress field, the location and orientation of natural fractures and faults, the temperature distribution, and the pressure distribution within the reservoir
20	[104]	Model parameters
21	[105]	Technical and financial parameters
22	[106]	The price of energy, technological uncertainty regarding internal combustion, hybrid, plug-in hybrid, battery, and fuel cell electric under various progress scenarios for 2035 and 2050
23	[107]	Parameters of the PV-electrolyzer system from a technical and economic perspective
24	[108]	The uncertainty of bio-crude yields, quality, utility consumption, and efficiency, as well as key economic indicators
25	[109]	Process and economic variables
26	[110]	Process and economic variables
27	[111]	Economic key factors

Table A3. *Cont.*

	Reference	Sources of Uncertainty
30	[112]	Economic key factors
31	[113]	Economic key factors
32	[114]	Number of people inside the room
33	[115]	Estimate feedstock requirements, costs, life-cycle energy usage, greenhouse gas emissions for grower payments and field operations, and major parameters associated with the transportation of corn stover feedstock
34	[116]	Technical and economic parameters
35	[117]	Technical parameters and environmental uncertainties
36	[118]	Price of biodiesel and feedstock, the efficiency of biodiesel conversion, and operating costs
37	[119]	Post-combustion CO_2 capture techno-economic parameters
38	[69]	Technical, economic, and environmental parameters (electricity and heat loads, wind and PV generation, EE unit factors for EE evaluation)

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