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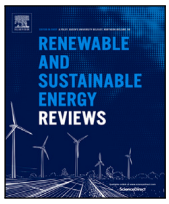

Review article

Multi-criteria decision analysis for evaluating carbon capture technologies in power plants

Nima Sepahi, Adrian Ilinca *, Daniel R. Rousse

Department of Mechanical Engineering, École de Technologie Supérieure, 1100 Notre-Dame Ouest, Montreal, H3C 1K3, Quebec, Canada

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ABSTRACT

Power plants are among the largest contributors to CO_2 emissions, making carbon capture and conversion into valuable products a key strategy to combat climate change and foster a circular economy. However, selecting the optimal CO_2 capture technology is complex due to the wide range of options — such as pre-combustion, post-combustion, and oxy-fuel combustion — and the various technical, economic, environmental, and social factors involved. This study identifies the most promising CO_2 capture technologies for three power plant types: Natural Gas Combined Cycle (NGCC), lignite, and coal. By applying Multi-Criteria Decision Analysis (MCDA), which integrates a systematic literature review with the Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the study ranks existing technologies. For NGCC plants, post-combustion calcium looping emerged as the top choice, with a relative closeness score of 0.790, due to its moderate CO_2 avoidance cost (€33.80/tCO_2), high efficiency (48.31%), and mature Technology Readiness Level (TRL) of 7. In lignite plants, post-combustion chemical absorption with MDEA ranked highest, achieving a relative closeness of 0.865 and a TRL of 9. For coal plants, pre-combustion using the Selexol process combined with Mn-based chemical looping was most promising, with a relative closeness of 0.829, low CO_2 avoidance cost (€19.94/tCO_2), and a net efficiency of 37.13%. These findings underscore the importance of balancing economic performance and technological maturity when selecting CO_2 capture technologies.

Contents

* Corresponding author.
E-mail addresses: nima.sepahi.1@ens.etsmtl.ca (N. Sepahi), adrian.ilinca@etsmtl.ca (A. Ilinca), daniel.rousse@etsmtl.ca (D.R. Rousse).

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Abbreviations

AHP	Analytic Hierarchy Process	IPCC	Intergovernmental Panel on Climate Change
BECCS	Bioenergy with Carbon Capture and Storage		
CAC	Cost of Avoided Carbon	LCOE	Levelized Cost of Electricity
CCE	Carbon Capture Efficiency	MCDA	Multi-Criteria Decision Analysis
CCS	Carbon Capture and Storage	NGCC	Natural Gas Combined Cycle
CCUS	Carbon Capture, Utilization, and Storage	OTM	Oxygen Transport Membrane
CR	Consistency Ratio	ppm	Parts Per Million
CRL	Commercial Readiness Level	SE_{CO_2}	Specific CO_2 Emissions
DAC	Direct Air Capture		
DTAC	Dodecyl Trimethyl Ammonium Chloride	SLR	Systematic Literature Review
GWP	Global Warming Potential	SPECCA	Specific Primary Energy Consumption for CO_2 Avoided
IGCC	Integrated Gasification Combined Cycle	SRL	Social Readiness Level
η_{net}	Net Power Plant Efficiency	TBAB	Tetra-n-butyl Ammonium Bromide
TEA	Techno-Economic Analyses	TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TRL	Technology Readiness Level	WGSMR	Water–Gas-Shift-Membrane-Reactor

1. Introduction

The world is witnessing an alarming increase in the frequency and intensity of climate-related records breaking [1]. On 12 December 2015, world leaders in the historic Paris Agreement committed to significantly reduce global greenhouse gas emissions, aiming to limit the global temperature increase in the current century to 2 degrees Celsius above preindustrial levels, while also striving to restrict the increase to 1.5 degrees [2]. Despite these commitments, according to the sixth report of the Intergovernmental Panel on Climate Change (IPCC), published 8 years later, the average global temperature during 2011–2020 has risen to 1.1 ° C above the baseline of 1850-1900 [3]. Carbon dioxide (CO_2), which accounts for around 66% of the radiative forcing from long-lived greenhouse gases, remains the dominant anthropogenic contributor to atmospheric warming, as reported by the World Meteorological Organization [4].

By April 2024, atmospheric CO_2 concentrations reached a record high of 427 parts per million (ppm), surpassing the global average annual concentration of 421 ppm in 2023 [5]. If this trend continues, global CO_2 concentrations could reach 550 ppm by 2050 [6]. Decarbonization has been highlighted since the 1970s as a key strategy to mitigate climate change [7]. Various strategies exist for reducing carbon dioxide emissions, including improving energy efficiency, expanding renewable energy use, implementing carbon pricing, protecting forests, and capturing CO_2 from industrial sources and power plants [8]. Among these, carbon capture and storage has gained significant attention, particularly following the Paris Agreement [9], due to its potential to significantly reduce emissions from fossil fuel-based industries while supporting climate targets [10]. From an industrial point of view, the captured CO_2 can be stored underground or used to produce fuels, construction materials, or enhance oil recovery, among other applications [11]. Moreover, CCS provides economic benefits by reducing industry carbon taxes and addressing environmental and economic concerns [12].

Meanwhile, the electricity sector, responsible for 40% of global carbon dioxide emissions, is under increasing pressure to adopt cleaner solutions [13]. Carbon capture is commonly implemented through three strategies: pre-combustion, oxyfuel combustion, and post-combustion, each strategy compatible with different CO_2 capture systems, including absorption, adsorption, membrane separation, and chemical looping. Key factors, such as fuel type, gas stream pressure, and CO_2 emission conditions, dictate the appropriate capture approach [14]. A thorough understanding of the advantages and limitations of each technique is critical to making informed decisions about technology adoption [15].

Selecting the optimal CO_2 capture technology involves complex decision making that requires balancing technical, economic, environmental, and social considerations to ensure efficiency and sustainability. Numerous studies have been conducted to compare different CCS technologies, most of which focused on techno-economic analyses to evaluate standard CCS processes [16–22]. Some of these studies have also considered environmental impacts [23–26], while social performance, though critical, is often overlooked or not adequately assessed [27–29]. In general, existing research lacks comprehensive assessments that integrate all perspectives and do not address the full range of configurations and types of power plants, including coal, lignite, and NGCC, holistically.

In this multi-possibles context, this paper aims to address these gaps using a systematic literature review to extract relevant industrial indicators and numerical data combined with MCDA techniques, specifically the AHP and TOPSIS. This approach evaluates and ranks CO_2 capture technologies for three categories of power plants: NGCC, coal, and lignite. These methodologies are vital to balance technical, economic, environmental, and social factors that influence the selection of appropriate technologies.

This research contributes to the field by conducting a systematic literature review (SLR) to identify key mechanisms and categorize common methods for various CCS strategies. The SLR was based on articles published between 2015 and 2024 from Compendex, Web of Science,

Table 1
Comparison of various CO_2 mitigation approaches.

Technology	CO_2 Source	Description	Removal Potential ($GtCO_2$/year) by 2025	Cost (USD/tCO_2)	Reference
DAC	Atmosphere	Captures CO_2 directly from ambient air using liquid or solid sorbents; location-independent.	4	100–600	[12,30–32]
Afforestation and Reforestation	Atmosphere	Planting forests on non-forested land (afforestation) or restoring forests (reforestation); enhances natural carbon sinks.	0.5–3.6	5–50	[12,33–35]
Biochar	Biomass	Pyrolysis of biomass into stable carbon-rich char applied to soil for long-term carbon storage.	0.3–2	90–120	[33,34]
Soil Carbon Sequestration	Soil	Land management techniques to enhance organic carbon storage in soil, improving soil fertility and reducing atmospheric CO_2.	2.3–5.3	0–100	[33,34]
BECCS	Biomass Combustion	Combines bioenergy production with carbon capture and storage at biomass plants, achieving net-negative emissions.	Up to 13.7	30–400	[12,33,34]
CCUS	Fossil Fuel Combustion	Captures CO_2 from industrial processes and power plants and stores it underground in geological formations.	4	50–150	[36]
Ocean Fertilization	Ocean	Adding nutrients to ocean surfaces to enhance phytoplankton growth and CO_2 uptake, promoting biological sequestration.	Up to 3.7	30–120	[33,34,37]
Enhanced Weathering	Minerals	Spreading crushed silicate rocks to accelerate natural CO_2 mineralization, forming stable carbonate minerals.	0.5–4	20–1000	[33,34]

and Scopus, extracting and comparing key indicators. We established a dataset of CO_2 capture technologies for power plants from these indicators and classified them based on the input fuel (coal, lignite, NGCC). Recognizing the frequent omission of social indicators, this study incorporates three social criteria alongside technical, economic, and environmental. The AHP method was used to calculate the weights of these criteria, which were integrated into the TOPSIS method to rank the most promising CO_2 capture technologies for each type of power plant.

The main contributions of this research are as follows:

1. The study introduces a set of comprehensive indicators critical for a holistic evaluation of Carbon Capture and Storage (CCS) technologies. This approach stands out from existing literature examining individual aspects in isolation or focusing on a limited set of criteria. By contrast, this research offers a more integrative analysis, addressing multiple dimensions simultaneously.

2. The developed framework enables a robust comparison between current and emerging CCS technologies, helping stakeholders make informed decisions on the optimal solutions for power plants globally.

The study's structure is as follows: Section 2 provides a literature review, Section 3 details the research methodology, Section 4 presents the results, and Section 5 concludes with policy implications and recommendations.

2. Literature review

Reducing CO_2 emissions requires both point-source capture and atmospheric removal technologies. While carbon capture and storage is widely used in industrial and power generation facilities, it does not address emissions from dispersed sources such as transportation and residential sectors. To compensate for this gap, direct removal technologies extract CO_2 from the atmosphere. Key approaches include afforestation/reforestation, bioenergy with carbon capture and storage, and direct air capture with storage. Afforestation and reforestation enhance natural carbon sinks, bioenergy with carbon capture integrates CO_2 storage into bioenergy production, and direct air capture employs engineered systems to extract and permanently store atmospheric CO_2. Table 1 compares various CO_2 mitigation strategies.

The concept of CO_2 capture from power plants has long been discussed among scientists and experts. The CO_2 capture process generally follows two main stages. First, it employs three primary strategies: pre-combustion, post-combustion, and oxy-fuel combustion, as shown in Fig. 1.

Also, these strategies are combined with technologies like absorption, adsorption, chemical looping, and membrane separation. Various articles comparing CO_2 capture technologies are summarized in Table 2.

Advanced studies increasingly emphasize techno-economic analyses (TEA) to evaluate the viability of CO_2 capture technologies. One such study [16] proposed a hybrid hydrate–membrane process for post-combustion CO_2 capture, integrating membrane separation with hydrate-based CO_2 capture (HHMCC). The study explored four cases using different hydrate promoters and found that this integration significantly reduced energy consumption compared to standalone hydrate methods. The best results were achieved by combining tetra-n-butyl ammonium bromide (TBAB) with dodecyl trimethyl ammonium chloride (DTAC), lowering CO_2 capture costs to 41.75 USD per ton and reducing energy consumption to 1.87 MJ/kg CO_2. The study concluded that coupling these techniques improves the feasibility of CO_2 capture, making it more energy-efficient and cost-effective.

Franz et al. [17] conducted an economic evaluation of CO_2 capture in IGCC plants using porous ceramic membranes. Various capture technologies were simulated, identifying the water–gas-shift-membrane-reactor (WGSMR) as the most promising, achieving 90% CO_2 separation with minimal efficiency loss of 5.8%. The optimal WGSMR case was estimated at 57 €/MWh, with assumptions including CO_2 certificate costs of 30 €/tCO_2, membrane costs of 300 €/m^2, and 8000 operating hours per year. The study highlighted WGSMR's economic advantage over traditional scrubbing technologies like Selexol.

Giordano et al. [18] presented a conceptual design and TEA of a pre-combustion CO_2 capture process using H_2-selective polymeric membranes in an IGCC plant, focusing on optimizing the membrane separation process and economic feasibility. The system used a three-stage membrane for CO_2 capture and hydrogen recovery, with an efficiency penalty of about 5%. The CO_2 capture cost was 16.6 €/t CO_2, with sensitivity analysis indicating potential reductions to below 15 €/t CO_2 by enhancing membrane selectivity and permeance. The study demonstrated the cost-effectiveness of membrane-based capture over conventional solvent-based systems like Selexol.

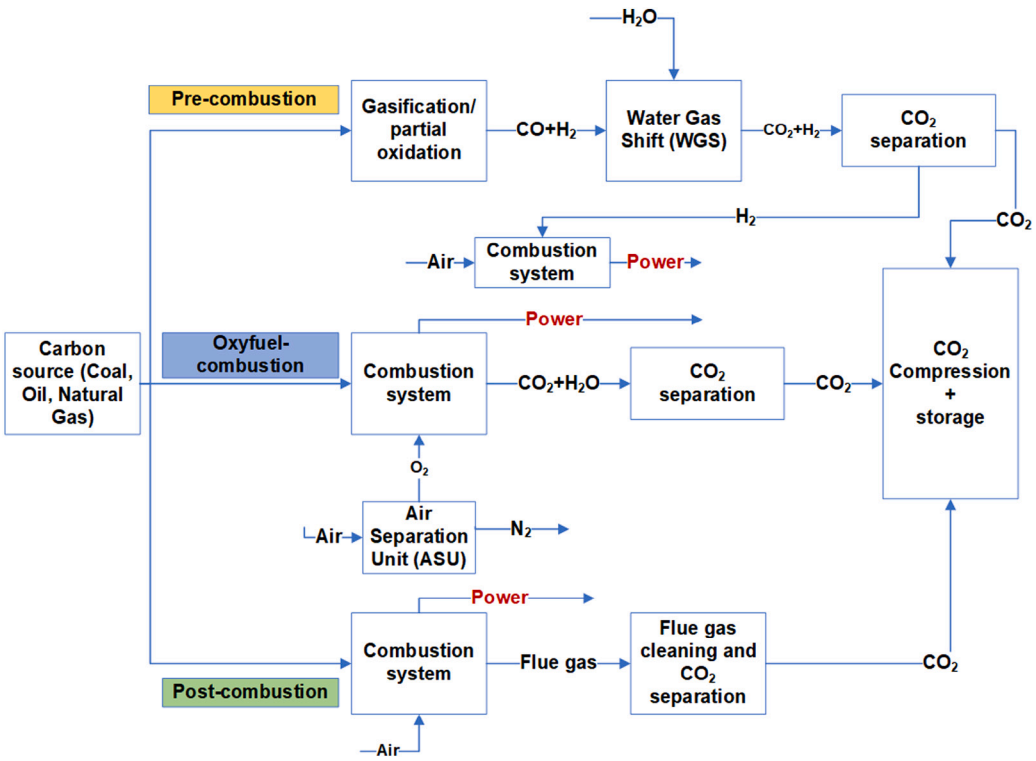

Fig. 1. Schematic flow diagram of various CO2 capture technologies modified from [38–41].

Table 2
Comparison of CO_2 Capture Technologies.

Aspect	Pre-combustion	Oxy-combustion	Post-combustion	Reference
Application in power industry	Integrated Gasification Combined Cycle (IGCC) power plant	Pulverized Coal (PC) power plant, IGCC	PC power plant, NGCC power plant	[42]
CO_2 separation technologies	Absorption by physical solvents, chemical solvents, chemical looping, membrane separation	Adsorption, chemical looping, membrane separation, cryogenic separation	Absorption by chemical solvents, adsorption by solid sorbents, membrane separation, cryogenic separation, swing adsorption, chemical looping	[25,27,43]
Modifications for power plants	Requires significant new infrastructure	Requires major changes to combustion systems	Minimal modifications required	[44]
Development stage	Commercially available, with large-scale projects	Pilot and demonstration, some commercial facilities	Widely used commercially	[30]
Inlet CO_2 concentration	15%–60%	75%–80%	4% for natural gas, 8%–15% for coal	[27,41]
Energy consumption for CO_2 capture (GJ/t CO_2)	3.35	4.05	4.14	[8]
Technology Readiness Level (TRL)	Up to 9	TRL 7 (coal), TRL 4 (gas)	TRL 9 (amine absorption), TRL 7 (sorbent), TRL 6 (calcium looping)	[45]
Limitations	High costs for equipment and support systems	Costly due to cryogenic oxygen and contaminant removal	Low partial pressure makes capture challenging and expensive	[46]

Portillo et al. [19] compared various integration options for an oxygen transport membrane (OTM) unit in a coal oxy-fired circulating fluidized bed power plant, assessing four configurations against cryogenic oxygen-fired and air-fired processes. Results showed OTM configurations reduced efficiency losses by up to 14%, with specific energy consumption at 1.01 kWh/kgCO_2. Investment costs for OTM cases were 39.6–48.2% higher than conventional plants but 10.7% lower than cryogenic oxygen systems. The study concluded that, while OTM technology is not yet commercially mature, it has the potential to improve both economic and energy performance in oxyfuel combustion plants.

Zhai and Rubin [21] conducted a system analysis of physical CO_2 absorption using ionic liquids for pre-combustion capture in IGCC plants. The study modeled 1-hexyl-3-methylimidazolium bis(trifluoro methylsulfonyl)imide ([hmim][Tf2N]) as a physical solvent, revealing that compression and solvent pumping caused the main energy penalties. The cost of CO_2 avoided was estimated at 63 $ per tonne. Comparisons with Selexol showed similar performance, with improvements in CO_2 solubility potentially lowering energy and costs and enhancing viability.

Yun et al. [47] conducted a TEA of CO_2 capture technologies in a coal-fired power plant, systematically comparing absorption and

membrane technologies. Integration of post-combustion CO_2 capture reduced net plant efficiency from 40.7% to 27.0% for MEA absorption and 32.5% for CANSOLV processes. CO_2 capture costs increased the cost of electricity to 180.3 USD/MWh. The study also provided cost diagrams to aid the assessment of low TRL CO_2 capture technologies, supporting early-stage evaluations.

Subraveti et al. [48] presented a TEA of a four-step vacuum swing adsorption (VSA) process for post-combustion CO_2 capture from steam-methane reformer flue gas. The study optimized three adsorbents — Zeolite 13X, UTSA-16, and IISERP MOF2 — to minimize capture costs. IISERP MOF2 achieved the lowest cost at 33.6 €/tonne of CO_2 avoided, while Zeolite 13X and UTSA-16 had higher costs at 90.9 €/tonne and 104.9 €/tonne, respectively. Although MEA absorption performed better at 66.6 €/tonne, the study emphasized VSA technology's potential for future development if adsorbent costs and vacuum pump efficiency improve.

Yagmour Goren et al. [44] reviewed carbon capture technologies, focusing on pre-combustion, post-combustion, and oxy-combustion. The study found that post-combustion capture is the most commercially mature, with amine-based solvents, pressure-vacuum swing adsorption, and gas separation membranes achieving the highest TRL of 9. However, post-combustion processes also showed the highest GWP at 219.53 kg CO_2 eq./MWh. Critical research gaps included the need for stable, cost-effective solvents and improved sorbents with higher adsorption capacities, suggesting future technology directions.

A study by Slavu et al. [26] evaluated the use of ammonia at different concentrations for CO_2 capture in steam power plants, comparing ammonia-based systems with the standard 30% MEA solution. Findings showed that a 7% ammonia solution had the lowest CO_2 capture cost at 59.07 €/tCO_2, with energy penalties ranging from 15% to 35%. The Global Warming Potential (GWP) for ammonia was between 113 to 149 kg CO_2/MWh, while MEA had a GWP of 133 kg CO_2/MWh, indicating that ammonia, especially at higher concentrations, can be a more cost-effective and environmentally friendly option for CO_2 capture.

Cormos et al. [49] conducted a comprehensive techno-economic and environmental assessment of decarbonizing fossil-intensive industrial processes using two CO_2 capture methods: chemical absorption and calcium looping. The study evaluated applications in power generation, iron and steel production, and cement manufacturing, achieving a 90% CO_2 capture rate. Calcium looping offered better overall performance, including energy efficiency, carbon footprint reduction, and cost-effectiveness, particularly in post-combustion capture scenarios. The research highlighted the potential to integrate spent sorbents into production processes, reducing both costs and environmental impacts.

Cormos and Dinca [23] evaluated the techno-economic and environmental impact of decarbonization strategies in Romanian fossil-based power plants. The study examined two post-combustion decarbonization options: a conventional chemical scrubbing process using methyldiethanol-amine (MDEA) and a more innovative calcium looping (CaL) process. The results indicated that decarbonized power plants could achieve efficiencies of 32.5%–36% for coal and lignite and 48%–52% for natural gas, with CO_2 capture rates of 90%. Additionally, the costs of electricity were reduced from 80–120 €/MWh to 55–85 €/MWh. The investment required to modernize Romania's fossil-based power fleet was estimated at 11.2–14.9 billion euros.

Social performance, although crucial, is rarely assessed comprehensively in existing studies. Hekmatmehr et al. [27] conducted a detailed review of carbon capture technologies, emphasizing their Technology Readiness Levels (TRLs). The study examined various CO_2 capture methods, including pre-combustion, post-combustion, oxyfuel combustion, and chemical looping, comparing established and emerging technologies. It highlighted the TRL of each technology, noting that conventional methods like amine-based absorption have high TRLs, indicating maturity and commercial readiness, while newer approaches, such as membrane-based separation and advanced chemical looping, are still at lower TRLs. The review underscores the need for continued development and scale-up of emerging technologies to improve their economic feasibility and integration into existing systems.

Siemenski [28] presented an in-depth analysis of carbon capture, utilization, and storage (CCUS) technologies, focusing on their levels of technological maturity or Technology Readiness Levels (TRLs). The study evaluated various CO_2 capture approaches, such as pre-combustion, post-combustion, and oxy-fuel combustion, comparing their development stages and market readiness. The authors identified that while mature solutions, like amine-based post-combustion capture, have reached high TRLs and are ready for commercial use, emerging technologies, including advanced membranes and chemical looping, are still under development, exhibiting lower TRLs. The review underlined the importance of advancing these emerging technologies through pilot projects and scaling efforts to close the gap to commercialization, highlighting their potential role in achieving carbon reduction targets.

Despite significant advances in carbon capture technologies, existing studies often emphasize techno-economic analyses without comprehensively addressing other crucial factors like social performance and environmental impacts. Many evaluations focus on specific CO_2 capture methods or power plant types, leaving a gap in holistic assessments considering multiple strategies across diverse plant configurations. This study aims to fill this gap by applying a systematic multi-criteria evaluation, incorporating technical, economic, environmental, and social indicators to identify the most promising CO_2 capture solutions for various power plant types.

3. Methodology

This section outlines the key steps to identify the most promising CO_2capture technologies based on the input fuel types used in power plants. The methodology involves selecting appropriate criteria, gathering numeric data through a systematic literature review, calculating the criteria weights using the AHP, and applying the TOPSIS to determine the most promising technology.

As shown in Fig. 2, the flowchart visually outlines the methodology. It begins with conducting a systematic literature review and identifying the criteria needed for evaluating CO2 capture technologies. Using AHP, the criteria are prioritized through pairwise comparisons, and the consistency of the criteria weights is assessed by calculating the consistency ratio (CR). If the CR is below 0.1, the criteria weights are accepted; otherwise, adjustments are made.

In the second part, TOPSIS is applied. This method calculates the positive ideal (best) and negative ideal (worst) solutions. It then measures how close each alternative is to these ideal solutions by calculating the distances. The closeness index is determined for each alternative, leading to the identification of the most promising CO2 capture technology for power plants.

3.1. Definition of criteria and data collection

A systematic literature review was conducted to identify the appropriate indicators and technologies used for CO_2 capture in power plants. Scopus and Web of Science databases were selected due to the customized search option [50] and wide coverage of various scientific fields [51].

Before searching articles in the databases, we developed a list of keywords related to CO_2 capture technologies. The selected keywords were: "CO_2 capture", "pre-combustion", "post-combustion", "oxy-combustion", "chemical looping", "fossil fuel", "techno-economic assessment", and "carbon capture". We combined these keywords using Boolean operators "AND" and "OR" to broaden the search and ensure the inclusion of relevant articles. The search was conducted within the selected databases' titles, abstracts, and keywords.

Several criteria were applied to refine the search. These criteria included limiting the publication years from 2018 to 2025, selecting only

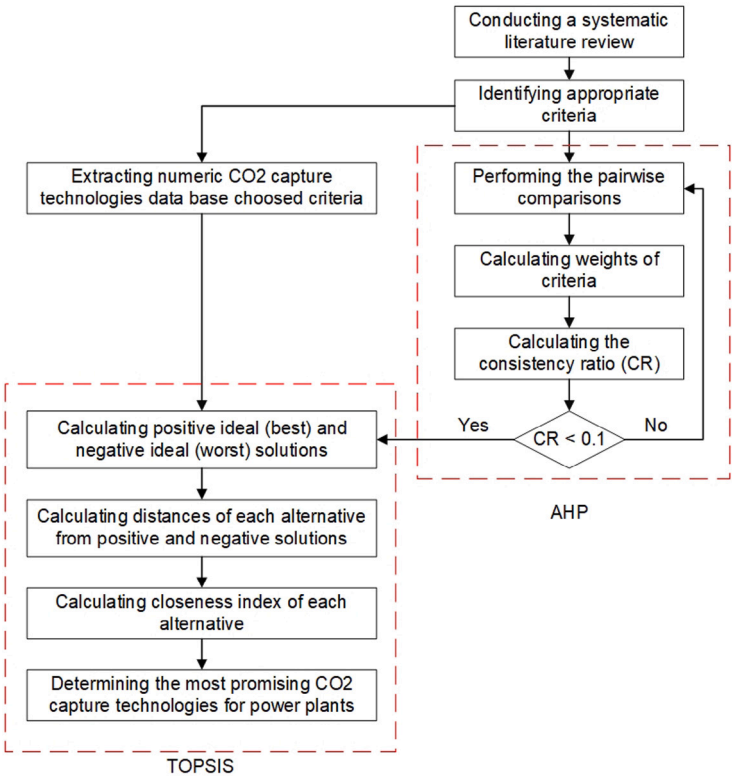

Fig. 2. The flowchart for the proposed AHP-TOPSIS process.

English-language publications, and restricting document types to peer-reviewed original and review articles. We also limited the search to engineering, energy, chemical engineering, and environmental science. This process ensured that the selected articles explicitly focused on CO_2 capture technologies.

After applying the search terms, we retrieved 4573 articles from Web of Science and 5138 articles from Scopus, for a total of 9711.

To ensure accuracy, duplicates were eliminated, reducing the total number of articles to 4215. Then, we conducted a detailed review of the titles and abstracts, narrowing the selection to 143 articles. We performed a comprehensive full-text screening on these remaining articles, resulting in a final set of 56 articles relevant to our research, as shown in Fig. 3.

As mentioned above, the literature review aimed to identify specific criteria that reflect the multifaceted nature of CO_2 capture technologies. It highlighted vital criteria commonly used for evaluating these technologies. By analyzing the methodology sections of the studies, we identified indicators categorized into technical, economic, and environmental dimensions, as shown in Fig. 4.

Subsequently, the most frequently used metrics were selected for evaluating CO_2 capture technologies in the articles. It should be emphasized that only a few studies employed life cycle assessment indicators, such as ozone depletion and freshwater ecotoxicity. Since specific CO_2 emissions (SE_{CO_2}) were the most commonly used indicator, only articles containing this data were considered for evaluation. Additionally, three social criteria — Technology Readiness Level (TRL), Social Readiness Level (SRL), and Commercial Readiness Level (CRL) — were included to assess the maturity and technological advancement of each system.

Given the varied temperature, pressure conditions, and fuel input flows across different CO_2 capture technologies, absolute criteria such as investment costs, operating costs, and power consumption could not be used for direct comparison, as these values differ significantly between technologies. Therefore, relative criteria such as LCOE (Levelized Cost of Electricity) and SPECCA (Specific Primary Energy Consumption for CO_2 Avoided) were chosen to ensure consistency and comparability in evaluating the technologies.

3.1.1. Selected criteria

The following quantitative indexes were used for evaluating CO_2 capture technologies:

- Net power plant efficiency refers to the ability of a power plant to generate energy while capturing CO_2 emissions. It is typically calculated as the net power output of the plant divided by the energy intake, taking into account the additional energy required for the capture process. The formula used is [39]:

$$\eta_{net} = \frac{\text{Net Power Output}}{\text{Energy Input}} = \frac{W_{net}}{Q_{Fuel}} \times 100 \quad (1)$$

where W_{net} is the net power output, calculated by subtracting the energy consumed during the CO_2 capture process from the plant's overall power production, and Q_{Fuel} is the total energy input, including the energy required for capture.

- Carbon capture efficiency (CCE) assesses how effectively a CO_2 capture process captures carbon dioxide emissions from a source. It is expressed as the percentage of CO_2 captured relative to the total CO_2 emissions produced. The formula is [40]:

$$CCE = \frac{\dot{m}_{CO_2,capt}}{\dot{m}_{CO_2,gen}} \quad (2)$$

where $\dot{m}_{CO_2,capt}$ is the mass flow rate of captured CO_2 (kg/h or kmol/h), and $\dot{m}_{CO_2,gen}$ is the mass flow rate of generated CO_2.

- SPECCA represents the amount of energy (kWh) required to prevent the emission of 1 kg of CO_2. The formula is [52,53]:

$$\text{SPECCA}\left[\frac{\text{kWh}}{\text{kg } CO_2}\right] = 3600 \times \frac{\left(\frac{1}{\eta_{CCS}} - \frac{1}{\eta_{Ref}}\right)}{SE_{Ref} - SE_{CCS}} \quad (3)$$

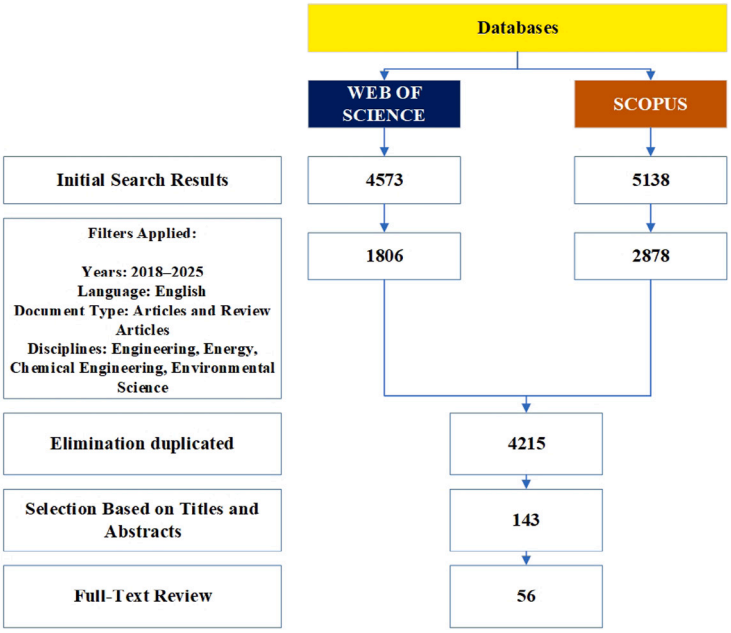

Fig. 3. Systematic literature review process.

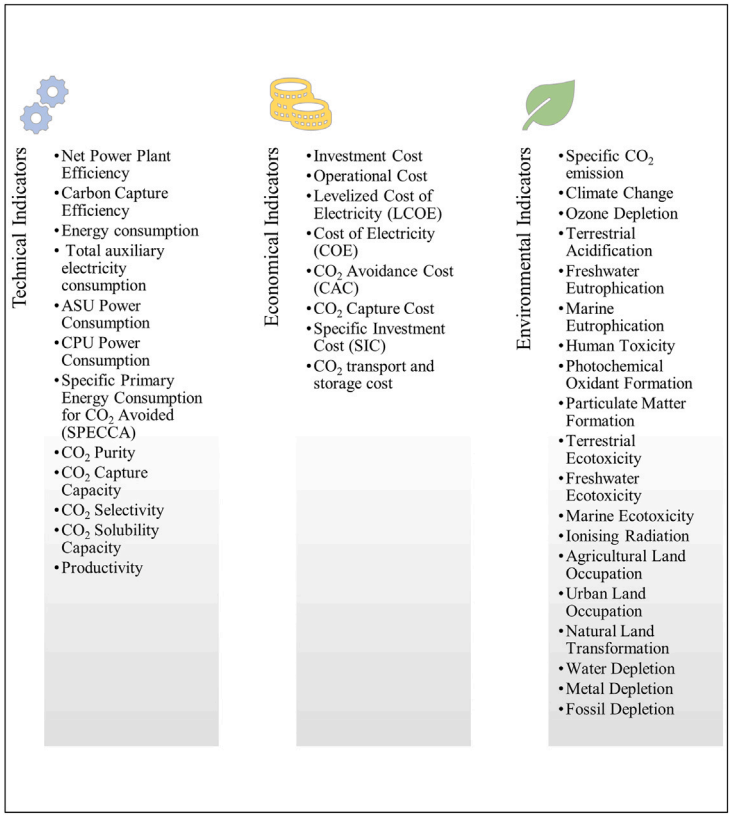

Fig. 4. Classification of indicators for evaluating CO_2 capture technologies.

where η_{CCS} is the net electric efficiency of the plant with carbon capture, η_{Ref} is the net electric efficiency of the reference plant without capture, and SE_{Ref} and SE_{CCS} are the specific CO_2 emission rates ($kgCO_2/MWhe$) for the reference plant and the plant with CO_2 capture, respectively.

- Cost of avoided carbon (CAC) measures the economic viability of CO_2 capture systems. It shows the difference in cost between a plant with CO_2 capture and a reference plant without capture, in terms of avoided emissions. The formula is [52]:

$$CAC = \frac{LCOE_{CO_2capture} - LCOE_{Ref}}{SE_{CO_2Ref} - SE_{CO_2capture}} \quad (4)$$

where $LCOE_{CO_2capture}$ and $LCOE_{Ref}$ are the levelized costs of electricity for plants with and without CO_2 capture, and SE_{CO_2Ref} and $SE_{CO_2capture}$ are the specific CO_2 emissions for the reference and capture plants.

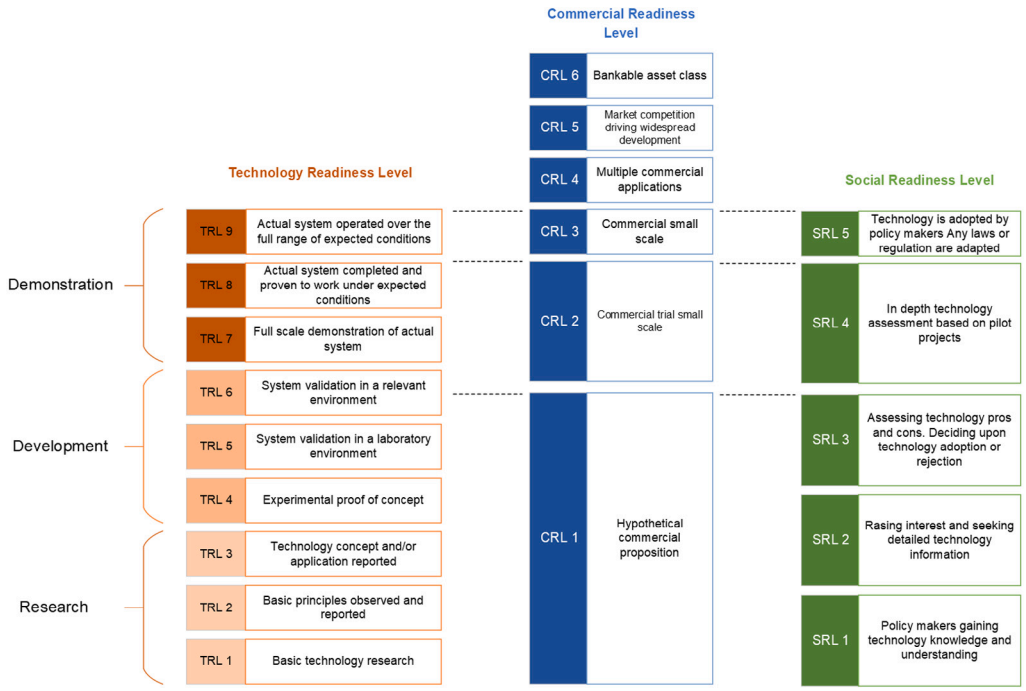

Fig. 5. Technology, commercial, and social readiness levels, derived from [55].

- LCOE shows the total cost of generating electricity for a plant, including capital, fixed, and variable operation, and fuel costs. It estimates the average electricity price needed to cover costs and is calculated as [54]:

$$\text{LCOE} = \frac{\text{TCC} \times \text{FCF} + \text{FOM}}{\text{CF} \times \text{MW} \times 8766} + \text{VOM} + (\text{HR} \times \text{FC}) \quad (5)$$

where TCC is the total capital cost, FCF is the fixed charge factor, FOM is fixed operation and maintenance costs, CF is the capacity factor, MW is the net plant capacity, VOM is variable non-fuel operation and maintenance costs, HR is the net power plant heat rate, and FC is the unit fuel cost.

- SE_{CO_2} measures the quantity of CO_2 emitted per unit of power generated. It is calculated as:

$$SE_{CO_2} = \frac{\text{Emitted } CO_2 \text{mass flow(kg/h)}}{\text{Generated net power output (MWe)}} \times 100 \quad (6)$$

where the emitted CO_2 mass flow is the mass of CO_2 emitted per hour, and the generated net power output is the net electrical power produced by the plant.

- TRL assesses how fully developed a technology is. It helps gauge the maturity of technologies like CCS in the development process.

- CRL evaluates parameters affecting market readiness and commercial viability in addition to technological development.

- SRL assesses the degree to which new technologies are socially accepted and whether they are likely to be adopted by communities and industries.

The relationship between TRL, CRL, and SRL is shown in Fig. 5, which highlights the progression from basic research through to commercial and societal adoption.

3.1.2. Data collection

After selecting the appropriate criteria, data were collected from the 56 reviewed articles. However, only 17 articles provided sufficient data on the selected criteria, which included η_{net}, CCE, SPECCA, CAC, LCOE, and SE_{CO_2}. The full-text screening focused on selecting articles that assessed CO_2 capture technologies using technical, economic, and environmental indicators. Many articles were excluded because they evaluated CO_2 capture processes from only a single perspective, such as technical, economic, or environmental. Additional exclusions were made for studies that addressed only two dimensions, such as techno-economic or techno-environmental assessments, without fully incorporating all three indicators. Only a few articles assessed TRL, and none directly evaluated SRL or CRL.

The TRL for each technology was determined based on a comprehensive review of the available literature. Whenever articles explicitly reported the TRL of a process, these values were adopted directly. However, many articles did not explicitly specify the TRL. In such cases, TRL was inferred based on the described development stage, the scale of deployment (laboratory, pilot, demonstration, or commercial), and the level of operational maturity indicated in the text. This approach is consistent with established practices in technology evaluation studies [27,31,56,57].

Since the reviewed articles did not report CRL and SRL, these values were assigned using the framework provided by the United Nations Economic Commission for Europe (UNECE) CCUS Technology Brief [55],as shown in Fig. 6. This framework defines CRL on a scale from 1 to 6, ranging from hypothetical commercial propositions to fully bankable projects, and SRL on a scale from 1 to 5, ranging from early awareness raising to full policy adoption. Based on this structured link between TRL, CRL, and SRL, technologies with higher TRL were assigned higher CRL and SRL. For example, MEA-based post-combustion capture, a fully commercial and widely deployed technology, was assigned TRL = 9, CRL = 6, and SRL = 4, reflecting its commercial maturity, regulatory acceptance, and broad public awareness. This structured assignment ensures consistency, transparency, and reproducibility across all evaluated technologies.

To organize the extracted data, an Excel matrix was created with columns representing the selected criteria, while the rows correspond to the DOIs of the reviewed articles. The data entries were populated based on the values extracted from these articles. To ensure more accurate comparisons, CO_2 capture technologies were categorized according to power plant type: NGCC, coal, and lignite. This classification was necessary because different fuel types result in varying levels of

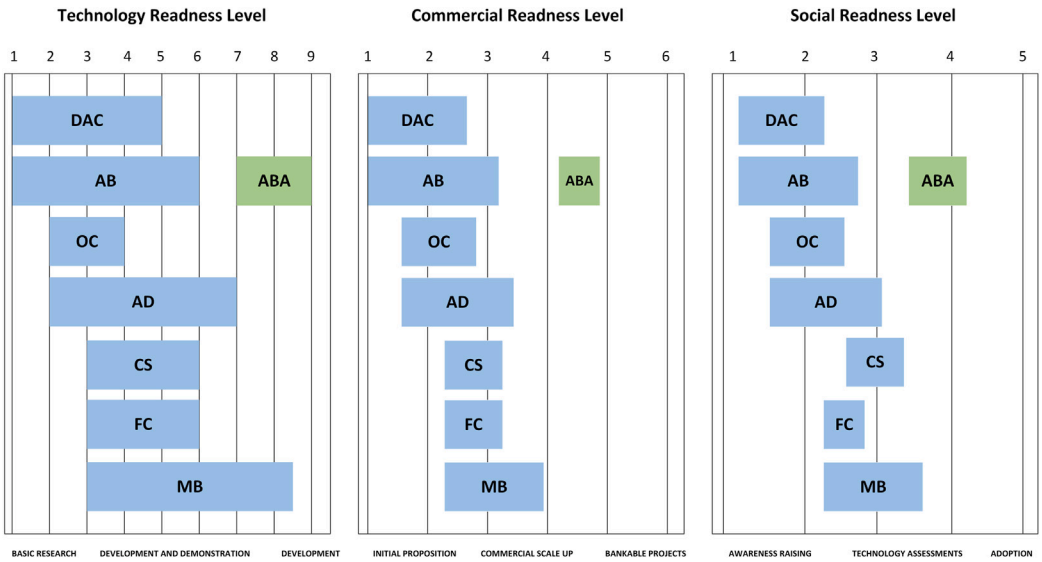

Fig. 6. TRL, CRL, and SRL of various carbon capture technologies. The evaluated technologies include Direct Air Capture (DAC), Absorption (AB), Oxy-Combustion (OC), Adsorption (AD), Cryogenic Separation (CS), Fuel Cells (FC), Membranes (MB), and Absorption using Amines (ABA). Reproduced from [55].

Table 3
Preference values for pairwise comparisons.

w_{ij}	Definition
1	Index i has the same importance as index j
3	Index i is slightly more important than index j
5	Index i is more important than index j
7	Index i is much more important than index j
9	Index i is extremely more important than index j
2, 4, 6, 8	The median of the two adjacent judgments

carbon emissions, making direct comparisons between technologies less reliable.

Data with differing units were standardized, particularly for LCOE and CAC, using the USD-to-Euro average exchange rate. Additionally, SPECCA was calculated in cases where it was not provided, following the formula in Eq. (3).

3.2. AHP method

AHP, developed by Saaty [58], is a robust multi-criteria decision-making tool that provides a structured approach for assessing the relative importance of various criteria. It enables a comprehensive understanding of their significance in decision-making [59]. AHP is favored over other weighting methods due to a number of its appealing qualities, including the following [60–62]:

- Use of hierarchical structure to present complex decision problems.
- It incorporates the consistency ratio to assess the reliability of the assigned weights and priorities.
- Converts subjective judgments into objective, numerical values for comparison.

The process of this method is as follows [63,64]:

3.2.1. Pairwise comparison matrix

A pairwise comparison matrix W is constructed, where each element w_{ij} represents the relative importance of criterion i compared to criterion j, based on Saaty's 1–9 scale, as shown in Table 3. The matrix W is expressed as follows:

$$W = (w_{ij})_{n\times n} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{bmatrix} \tag{7}$$

The matrix is reciprocal, meaning $w_{ij} = \frac{1}{w_{ji}}$, and $w_{ii} = 1$ for all i.

3.2.2. Geometric mean and normalization

The geometric mean GM_i for the ith row is calculated as:

$$GM_i = \left(\prod_{j=1}^{n} w_{ij}\right)^{\frac{1}{n}} \tag{8}$$

The normalized weight a_i for criterion i is derived by:

$$a_i = \frac{GM_i}{\sum_{k=1}^{n} GM_k} \tag{9}$$

3.2.3. Consistency check

The weighted sum vector is calculated as:

$$\mathbf{W}\cdot\mathbf{a} = \text{Weighted Sum Vector} \tag{10}$$

Then, the consistency vector is obtained by dividing the weighted sum vector by the normalized weights.

3.2.4. Principal eigenvalue and consistency index

The principal eigenvalue $\lambda_{\max}$ is calculated as the average of the consistency vector:

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n} \text{Consistency Vector}_i \tag{11}$$

Table 4
Random index (RI) values for different n [65].

Matrix Size	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The consistency index (CI) is computed using the following formula:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{12}$$

3.2.5. Consistency ratio (CR)

The consistency ratio is calculated as:

$$CR = \frac{CI}{RI} \tag{13}$$

Here, RI is the random consistency index based on the matrix size n, as shown in Table 4:

A CR of less than 0.10 indicates acceptable consistency, otherwise, the comparisons should be revised. One of the drawbacks of the AHP method is that the comparison matrix can be directly influenced by the selected pairwise comparisons, which may introduce bias in the calculation of weights and the prioritization of criteria. To mitigate this issue, expert opinions were utilized to enhance the accuracy of pairwise comparisons.

3.3. TOPSIS method

TOPSIS, is a method for multi-criteria decision-making. It assists in ranking and selecting several externally determined alternatives. The main idea of TOPSIS is to find the solution with the shortest distance from the ideal solution and the farthest distance from the negative ideal solution. The method involves the following steps [66,67]:

3.3.1. Construct the decision matrix

The decision matrix X contains i alternatives and j criteria. Each element x_{ij} represents the value of the ith alternative to the jth criterion.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{bmatrix} \tag{14}$$

3.3.2. Normalize the decision matrix

Normalization of the decision matrix is done by dividing each element by the square root of the sum of squares of each column. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{15}$$

3.3.3. Construct the weighted normalized decision matrix

Each column of the normalized decision matrix is multiplied by the corresponding weight w_j of the criteria. The weighted normalized value v_{ij} is calculated as:

$$v_{ij} = w_j \times r_{ij} \tag{16}$$

3.3.4. Determine the positive ideal and negative ideal solutions

For each criterion j:

- Select the highest value among all alternatives if it is a benefit criterion (maximization).
- Select the lowest value among all alternatives if it is a cost criterion.

$$v_j^+ = \begin{cases} \max(v_{ij}), & \text{if } j \text{ is a benefit attribute} \\ \min(v_{ij}), & \text{if } j \text{ is a cost attribute} \end{cases} \tag{17}$$

$$v_j^- = \begin{cases} \min(v_{ij}), & \text{if } j \text{ is a benefit attribute} \\ \max(v_{ij}), & \text{if } j \text{ is a cost attribute} \end{cases}$$

The positive ideal vector A^+ and the negative ideal vector A^- are then constructed as:

$$A^+ = [v_1^+, v_2^+, \ldots, v_n^+] \tag{18}$$

$$A^- = [v_1^-, v_2^-, \ldots, v_n^-]$$

3.3.5. Calculate the separation measures

Determine each alternative's Euclidean distance from the positive ideal solution S_i^+ and the negative ideal solution S_i^-:

$$S_i^+ = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_j^+)^2} \tag{19}$$

$$S_i^- = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_j^-)^2}$$

3.3.6. Calculate the relative closeness to the ideal solution

The relative closeness V_i of the ith alternative to the ideal solution is calculated as:

$$V_i = \frac{S_i^-}{S_i^- + S_i^+} \tag{20}$$

Following this, the alternatives are ranked according to their relative closeness values, where higher values indicate better performance.

4. Results and discussion

After collecting numeric data from 17 articles, three datasets were compiled, each focusing on CO_2 capture processes and their performance metrics. These metrics include η_{net}, CCE, SPECCA, CAC, LCOE, SE_{CO_2}, TRL, SRL, and CRL. The dataset for CO_2 capture technologies applied to NGCC, lignite, and coal power plants is presented in the Appendix. These datasets provide the possibility of a multi-criteria decision analysis of different CO_2 capture technologies across various power plant types.

4.1. Calculated weights

To determine the relative importance of CO_2 capture technology criteria, a pairwise comparison matrix was developed using the AHP approach. Each criterion was compared against others based on Saaty's scale of relative importance, ranging from 1 to 9. This systematic ranking of each criterion is illustrated in Table 3. The criteria considered include η_{net}, CCE, SPECCA, CAC, LCOE, SE_{CO_2}, CRL, and SRL. The matrix values represent the relative importance of these criteria. The pairwise comparison matrix is shown in Table 5.

We consulted with scientists experienced in CO_2 capture technologies in the decision-making process. The team engaged in structured discussions to reach a consensus-based evaluation of the importance of criteria based on pairwise comparisons used in the AHP process. The group of experts prioritized economic parameters, especially CO_2 avoidance cost (CAC) and Levelized Cost of Electricity (LCOE), which

Table 5
Pairwise comparison matrix.

Criteria	η_{net}	CCE	SPECCA	CAC	LCOE	SE_{CO_2}	TRL	CRL	SRL
η_{net}	1	2	2	1/3	1/2	2	1	3	4
CCE	1/2	1	1	1/2	1/3	3	1/2	2	4
SPECCA	1/2	1	1	1/2	1/3	3	1/2	2	4
CAC	3	2	2	1	2	4	2	3	4
LCOE	2	3	3	1/2	1	4	3	4	4
SE_{CO_2}	1/2	1/3	1/3	1/4	1/4	1	2	3	4
TRL	1	2	2	1/2	1/3	1/2	1	3	4
CRL	1/3	1/2	1/2	1/3	1/4	1/3	1/3	1	4
SRL	1/4	1/4	1/4	1/4	1/4	1/4	1/4	1/4	1

Table 6
Criteria weights.

Criteria	η_{net}	CCE	SPECCA	CAC	LCOE	SE_{CO_2}	TRL	CRL	SRL
Weights	0.1265	0.0930	0.0930	0.2197	0.2128	0.0705	0.1084	0.0489	0.0271

received the highest priority due to their central role in the economic feasibility of CO_2 capture technologies. Next in importance were η_{net} and TRL. CRL and SRL were assigned a lower priority. As CRL and SRL were not quantitatively measured in the reviewed articles, they received lower scores to minimize potential author bias. This ranking reflects a balanced consideration of economic feasibility, technical performance, and technological maturity.

However, the selection of comparative pairs in this study reflects relatively homogeneous opinions, which can differ from those of other stakeholders, such as investors, environmental advocates, or social activists, potentially leading to different outcomes. The framework of this work can easily be adapted for comprehensively evaluating carbon dioxide capture technologies by other stakeholders.

The AHP process yielded several key results. After calculating the row geometric mean and normalizing it, the weighted sum vector was derived, followed by the consistency vector. These calculations led to the estimation of λ_{max}, which was found to be 9.87, slightly higher than the matrix size of 9, indicating a good level of consistency.

With λ_{max} determined, the Consistency Index (CI) was calculated to be 0.109. This index was then used to compute the Consistency Ratio (CR) by dividing the CI by the Random Index (RI) for a 9 × 9 matrix (1.45). The resulting CR was 0.075, which is below the acceptable threshold of 0.1, confirming that the pairwise comparisons are sufficiently consistent for reliable decision-making.

The final criteria weights, calculated from the AHP process, are displayed in Table 6.

The updated analysis of the calculated weights indicates the relative importance of each criterion in the decision-making process. CAC and LCOE have the highest weights at 0.2197 and 0.2128, respectively, underscoring the significant emphasis on economic factors in evaluating CO_2 capture technologies. This highlights that minimizing the cost of carbon capture and maintaining a competitive electricity generation cost are top priorities in the decision-making process.

η_{net} follows with a weight of 0.1265, showing its critical role in ensuring that power plants can maintain high energy efficiency while incorporating CO_2 capture systems. The balance between energy output and CO_2 capture efficiency is crucial for making these technologies sustainable in the long term.

TRL, with a weight of 0.1084, reflects the importance of choosing technically mature and commercially viable technologies. Decision-makers prefer technologies that have reached higher levels of development and are ready for deployment, minimizing the risks associated with implementing newer, less-established systems.

CCE and SPECCA, both with weights of 0.0930, highlight the technical aspects of the capture technologies, emphasizing the need to balance CO_2 capture efficiency and energy consumption. This balance is necessary to ensure that the power plant's overall performance is not compromised by the carbon capture process.

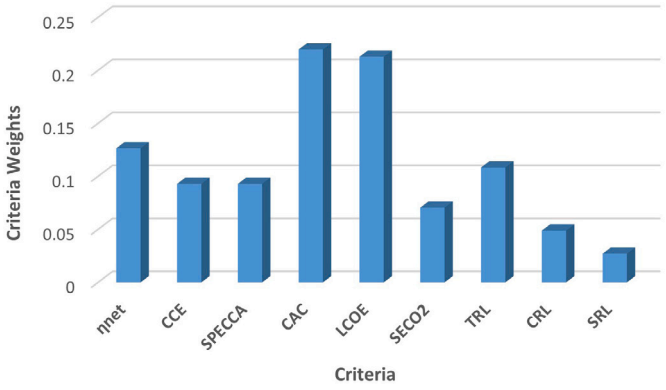

Fig. 7. Bar chart of criteria weights.

SE_{CO_2}, weighted at 0.0705, along with CRL and SRL, weighted at 0.0489 and 0.0271 respectively, suggest that while these criteria are relevant, they are considered less important than the economic and technical factors in this evaluation framework. The distribution of criteria weights calculated through the AHP process is visually summarized in Fig. 7.

4.2. AHP-TOPSIS results

This section presents the results of the TOPSIS analysis. The rankings of CO_2 capture technologies were obtained by applying the TOPSIS method to the normalized data sets for NGCC, coal, and lignite power plants. The criteria weights, as determined by AHP, ensured consistency in the evaluation. Each dataset was normalized and multiplied by the corresponding AHP-derived weights.

The technologies were evaluated based on their relative closeness to the ideal solution, considering both benefit and cost criteria. Benefit criteria included η_{net}, CCE, TRL, CRL, and SRL. Cost criteria included SPECCA, CAC, LCOE, SE_{CO_2}.

The following subsections rank CO_2 capture technologies for NGCC, coal, and lignite power plants based on their relative proximity to the ideal solution. These rankings provide insights into the most promising technologies for each power plant type.

Table 7
Results for NGCC power plants — CO_2 capture technologies ranked by relative closeness.

Process	Relative closeness	Rank
Post-combustion using calcium looping (CaL) - Case 1.c	0.789533	1
Post-combustion carbonate looping	0.784776	2
Post-combustion chemical absorption (MEA) using a 15-tray absorption column	0.725721	3
Post-combustion magnesium looping	0.717409	4
Post-combustion chemical absorption (MDEA)	0.715966	5
Post-combustion 41 wt% piperazine/amino-methyl-propanol solution in 1–2 M ratio	0.700470	6
Post-combustion using AMP (2-amino-2-methyl-1-propanol) solvent	0.617854	7
Post-combustion chemical absorption using MEA at 120 °C and 1.8 bar operating conditions	0.576184	8
Pre-combustion ATR + MDEA-based CO_2 capture	0.516038	9
Pre-combustion using calcium–copper looping (Optimized Case)	0.515866	10
Post-combustion MEA capture efficiency 90%	0.495591	11
Pre-combustion using calcium–copper looping (Compact Reactor)	0.470033	12
Pre-combustion using calcium–copper looping (Base Case)	0.388644	13
Post-combustion MEA capture efficiency 45%	0.339891	14

4.3. NGCC power plants

The TOPSIS analysis for NGCC CO_2 capture technologies, based on the dataset in Table 7, shows that Post-combustion using CaL - Case 1.c ranks first with a relative closeness value of 0.789533, indicating its strong performance across the selected criteria. This high ranking is supported by its moderate CAC (€33.80/tCO_2), relatively high η_{net} (48.31%), and a mature TRL of 7. Post-combustion carbonate looping ranks second with a relative closeness of 0.784776. Its strong performance is due to its low CAC (€35.34/tCO_2) and moderate SE_{CO_2} (31.50 kg/MWh). While it has a slightly lower η_{net} than CaL, its lower cost makes it highly competitive. Post-combustion chemical absorption (MEA) ranks third with a relative closeness of 0.725721. Despite its high TRL (9) and CCE (90%), it is impacted by its higher CAC (€64.75/tCO_2) compared to the top two processes.Post-combustion magnesium looping ranks fourth with a relative closeness of 0.717409. Its relatively low CAC (€38.86/tCO_2) is a strength, but its lower TRL (6) and higher SPECCA (5.40 MJ/kg) lower its overall ranking. Technologies like Pre-combustion ATR + MDEA-based CO_2 capture and calcium–copper looping processes rank lower, with relative closeness values ranging from 0.516038 to 0.388644. These technologies have higher operational costs and lower TRLs, which affect their rankings.

4.4. Lignite-based power plants

The TOPSIS results for CO_2 capture technologies in lignite power plants, as presented in Table 8, highlight that Post-combustion with chemical absorption (MDEA) ranks first with a relative closeness of 0.864981. This technology's high ranking is likely due to its favorable combination of economic and technical performance metrics, such as a relatively low CAC (€40.25/tCO_2) and a well-established TRL of 9. Its combination of maturity and cost-effectiveness makes it a promising choice for implementation in lignite power plants.

Post-combustion-carbonate looping ranks second and fourth with reactor temperatures of 900-945 °C and 900-980 °C, respectively. Both processes perform well due to their relatively low SPECCA values (2.58 MJ/kg) and competitive CAC (€37.71 and €37.82/tCO_2), resulting in relative closeness values of 0.838602 and 0.802449. These processes' ability to minimize energy penalties while maintaining high CCE (90%) ensures their competitive position in the rankings.

Post-combustion with chemical absorption (MEA) using a 15-tray absorption column ranks third with a relative closeness of 0.802995. This technology benefits from a balanced performance across key criteria, including a CAC of €40.10/tCO_2 and a high TRL of 9, though its higher LCOE (€84.95/MWh) slightly limits its relative performance compared to the top-ranking technologies.

Technologies such as Oxy-fuel combustion with Mn-based looping system & CO_2 capture and Pre-combustion using Selexol process with Mn-based chemical looping air separation unit also rank competitively, with relative closeness values of 0.708011 and 0.680824, respectively. These processes benefit from their high technological maturity and relatively moderate CAC values.

In contrast, technologies such as Pre-combustion with CO_2-selective membrane and Oxy-combustion with cryogenic air separation unit, with relative closeness values of 0.120823 and 0.370169, rank lower. These technologies face challenges. Membrane separation has low CO_2 selectivity, making it unsuitable for large-scale applications [68]. It also struggles to achieve high-purity CO_2 and requires multiple stages or high-pressure operation when CO_2 concentration is low (below 20%) [15,44]. Additionally, membranes degrade under high temperatures and are sensitive to corrosive gases, requiring pretreatment and frequent maintenance [15]. Cryogenic separation, while achieving high CO_2 purity, is only effective for high CO_2 concentrations and is not suitable for flue gases with low CO_2 partial pressure [68]. It also has high energy consumption due to compression and refrigeration needs, with an energy penalty of 600–660 kWh/tCO_2 [14,39]. Moreover, CO_2 freezing can cause pipeline blockages, increasing operational complexity and costs [68].

Overall, the results suggest that post-combustion processes, particularly those involving chemical absorption and carbonate looping, are the most favorable for lignite power plants, balancing technical maturity, economic performance, and energy efficiency.

4.5. Coal-based power plants

The TOPSIS analysis for CO_2 capture technologies applied to coal power plants, as shown in Table 9, ranks Pre-combustion using the Selexol process with Mn-based chemical looping air separation unit as the most promising technology, with a relative closeness of 0.829189. This high ranking is due to its favorable combination of economic and technical factors, including low CAC (€19.94/tCO_2) and high η_{net} (37.13%).

In second place is the Oxy-combustion with circulating fluidized bed (CFB), with a relative closeness of 0.815831. This technology performs well due to its high TRL (6) and moderate CAC (€54.43/tCO_2), making it a competitive option despite higher LCOE. Pre-combustion using the Selexol process with a cryogenic air separation unit ranks third with a relative closeness of 0.811617. It benefits from a low CAC (€14.27/tCO_2) and a good η_{net} of 37.19%. However, its lower maturity level, with a TRL of 6, slightly impacts its ranking compared to more mature technologies.

Pre-combustion using reactive gas-liquid absorption (MDEA) ranks fourth with a closeness of 0.810290. While it has a moderate TRL (8) and favorable technical characteristics like a high η_{net} (36.61%), its

Table 8
Results for lignite power plants — CO_2 capture technologies ranked by relative closeness.

Process	Relative closeness	Rank
Post-combustion with chemical absorption (MDEA)	0.864981	1
Post-combustion-carbonate looping with calciner reactor temperature of 900-945 °C	0.838602	2
Post-combustion with chemical absorption (MEA) with 15 trays absorption column	0.802995	3
Post-combustion-carbonate looping with calciner reactor temperature of 900-980 °C	0.802449	4
Post-combustion-magnesium looping	0.752635	5
Pre-combustion with Rectisol process	0.725602	6
Oxy-fuel combustion with Mn-based looping system & CO_2 capture	0.708011	7
Pre-combustion using Selexol process with Mn-based chemical looping air separation unit	0.680824	8
Pre-combustion with low-temperature CO_2 capture	0.666536	9
Oxy-combustion with copper-based chemical looping air separation unit	0.564635	10
Pre-combustion with amine modified PVAm membrane	0.557800	11
Oxy-fuel combustion with cryogenic air separation & CO_2 capture	0.549197	12
Pre-combustion using Selexol process with cryogenic air separation unit	0.542834	13
Pre-combustion using Selexol process with copper-based chemical looping air separation unit	0.490987	14
Pre-combustion using Selexol process with cryogenic air separation unit	0.394972	15
Oxy-combustion with cryogenic air separation unit	0.370169	16
Pre-combustion with CO_2-selective membrane	0.120823	17

Table 9
Results for coal power plants — CO_2 capture technologies ranked by relative closeness.

Process	Relative Closeness	Rank
Pre-combustion using Selexol process with Mn-based chemical looping air separation unit	0.829189	1
Oxy-combustion circulating fluidized bed (CFB)	0.815831	2
Pre-combustion using Selexol process with cryogenic air separation unit	0.811617	3
Pre-combustion using reactive gas-liquid absorption (MDEA)	0.810290	4
Post-combustion using calcium looping	0.804424	5
Post-combustion using calcium looping	0.803861	6
Pre-combustion using membrane	0.801507	7
Post-combustion with MDEA	0.794984	8
Pre-combustion using calcium looping	0.792474	9
Post-combustion using MEA-based absorption (15 trays absorption column)	0.787090	10
Pre-combustion using MDEA	0.785067	11
Pre-combustion using Selexol™	0.784695	12
Post-combustion-magnesium looping	0.783051	13
Pre-combustion using hybrid membrane–MDEA system	0.773973	14
Post-combustion + MDEA-based gas–liquid absorption system (absorption intercooling and lean vapor recompression)	0.773678	15
Post-combustion using a 13% PZ/27% AMP solution and absorber intercooling with rich split	0.773223	16
Post-combustion + MDEA-based gas–liquid absorption system with intercooling	0.764142	17
Post-combustion + MDEA-based gas–liquid absorption system (lean vapor recompression)	0.764077	18
Oxy-fuel combustion with Mn-based looping system & CO_2 capture	0.759581	19
Oxy-combustion with copper-based chemical looping air separation (CLAS) system & CO_2 capture	0.744347	20
Oxy-combustion circulating fluidized bed (CFB) power plant	0.739237	21
Oxy-fuel combustion with cryogenic air separation & CO_2 capture	0.711893	22
Post-combustion using fixed bed adsorption (FBA) and PEI-silica sorbent with internal heat recovery	0.695178	23
Post-combustion using moving bed adsorption (MBA) and PEI-silica sorbent with internal heat recovery	0.680342	24
Post-combustion using rapid thermal swing adsorption (RTSA) and PEI-silica sorbent with internal heat recovery	0.679958	25
Post-combustion using fluidized bed adsorption (FLBA) and PEI-silica sorbent with internal heat recovery	0.570755	26
Post-combustion using Membrane area = 400,000 (m^2), CP1 = 8 (bar)	0.569004	27
Post-combustion using Membrane area = 600,000 (m^2), CP1 = 6 (bar)	0.550124	28
Post-combustion using Membrane area = 600,000 (m^2), CP1 = 8 (bar)	0.537106	29
Post-combustion using Membrane area = 200,000 (m^2), CP1 = 10 (bar)	0.530880	30
Post-combustion using Membrane area = 400,000 (m^2), CP1 = 10 (bar)	0.523461	31
Post-combustion using Membrane area = 400,000 (m^2), CP1 = 6 (bar)	0.468762	32
Post-combustion using Membrane area = 200,000 (m^2), CP1 = 8 (bar)	0.448787	33
Post-combustion using Membrane area = 600,000 (m^2), CP1 = 10 (bar)	0.385181	34
Post-combustion using Membrane area = 200,000 (m^2), CP1 = 6 (bar)	0.207161	35

relatively higher CAC (€28.38/tCO_2) and LCOE (€73.28/MWh) reduce its overall ranking.

Technologies like Oxy-fuel combustion with Mn-based looping system & CO_2 capture and Oxy-combustion with copper-based chemical looping air separation (CLAS) system & CO_2 capture rank lower, with relative closeness values of 0.759581 and 0.744347, respectively. These technologies face higher operational costs and lower technological maturity levels, impacting their rankings.

The analysis underscores the importance of selecting technologies with a balance between economic performance and technical maturity. Pre-combustion processes like Selexol-based technologies tend to outperform other options due to their strong economic performance and technical efficiency. However, post-combustion processes, especially calcium looping, also present viable alternatives for large-scale implementation in coal power plants.

5. Conclusion

The comprehensive analysis of CO_2 capture technologies across NGCC, lignite, and coal power plants has demonstrated clear distinctions in the effectiveness of different approaches. For NGCC plants, post-combustion calcium looping (CaL) emerged as the most favorable technology, balancing cost-effectiveness, technical efficiency, and maturity (TRL 7). In lignite-based plants, post-combustion with chemical

absorption (MDEA) stood out due to its high TRL (9) and strong economic performance, while for coal power plants, pre-combustion using the Selexol process with Mn-based chemical looping showed the best balance of low CO_2 avoidance cost (€19.94/tCO_2) and efficiency.

The results across all plant types emphasize the importance of considering both economic performance and technology readiness in selecting CO_2 capture solutions. Technologies that offer a high TRL combined with cost-efficient operation, such as chemical absorption and CaL, are well-positioned for large-scale adoption. However, emerging solutions like pre-combustion Selexol processes also show promise, particularly in coal applications, where their strong economic metrics make them competitive.

The study faced some limitations. Data collection relies heavily on existing literature, which may not always provide consistent or comprehensive datasets across all environmental indicators. For instance, specific CO_2 emissions were used as a primary environmental criterion, but other important environmental factors were not always covered due to data availability constraints. Additionally, the study was limited to the criteria for which there were available and reliable datasets, which may have excluded emerging or less-studied technologies.

Future research could address these limitations by creating a broader database of CO_2 capture technologies, including more detailed environmental, social, and operational data. Establishing a comprehensive dataset could enable using machine learning algorithms to enhance the comparison and ranking of technologies, providing more accurate predictions for performance under various operational conditions. Further studies should also focus on the scale-up and integration of promising low-TRL technologies to ensure their viability for future industrial applications.

CRediT authorship contribution statement

Nima Sepahi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Adrian Ilinca:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Daniel R. Rousse:** Conceptualization, Investigation, Methodology, Project administration, Resources, Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this work, the author(s) did not use generative AI technologies. The authors used AI-assisted technologies, Grammarly (http://www.grammarly.com/) and Antidote (http://www.antidote.info/), to improve formulation and eliminate grammatical errors. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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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.

Appendix. Supplementary data: CO_2 capture technologies data

See Tables A.1 and A.2.

Data availability

Data will be made available on request.

Table A.1
Dataset of CO_2 capture technologies for NGCC power plants.

Process	η_{net} (%)	CCE (%)	SPECCA (MJ/kg)	CAC (€/tCO_2)	LCOE (€/MWh)	SE_{CO_2} (kg/MWh)	TRL	CRL	SRL	Reference
Post-combustion chemical absorption (MEA) using a 15-tray absorption column	52.08	90.00	2.62	64.75	65.00	38.52	9	5	4	[69]
Post-combustion carbonate looping	48.20	90.00	4.30	35.34	56.05	31.50	7	4	3	[69]
Post-combustion magnesium looping	46.10	90.00	5.40	38.86	57.10	33.45	6	3	2	[69]
Post-combustion chemical absorption using MEA at 120 °C and 1.8 bar	44.70	90.00	3.96	86.31	69.12	33.50	9	5	4	[70]
Post-combustion using AMP (2-amino-2-methyl-1-propanol) solvent	46.70	90.00	3.12	77.07	64.59	51.10	7	3	3	[70]
Post-combustion chemical absorption (MDEA)	52.08	90.00	2.63	65.10	65.10	38.75	8	4	3	[23]
Post-combustion using calcium looping (CaL) - Case 1.c	48.31	90.00	4.24	33.80	55.88	30.75	7	4	3	[23]
Post-combustion 41 wt% piperazine/amino-methyl-propanol solution in 1–2 M ratio	50.82	90.00	0.90	67.10	73.80	39.00	7	4	3	[71]
Pre-combustion ATR + MDEA-based CO_2 capture	47.12	91.56	4.75	85.38	84.80	39.60	8	4	3	[72]
Pre-combustion using calcium–copper looping (Base Case)	45.29	89.14	5.97	108.01	90.55	51.53	6	3	2	[72]
Pre-combustion using calcium–copper looping (Compact Reactor)	46.31	89.14	5.36	87.48	84.51	50.39	6	3	2	[72]
Pre-combustion using calcium–copper looping (Optimized Case)	47.61	89.14	4.64	80.75	82.60	49.01	6	3	2	[72]
Post-combustion MEA capture efficiency 45%	53.70	45.00	1.27	93.25	93.73	202.80	9	5	4	[73]
Post-combustion MEA capture efficiency 90%	48.91	90.00	1.16	93.25	108.94	40.50	9	5	4	[73]

Table A.2
Dataset of CO_2 capture technologies for lignite power plants.

Process	η_{net} (%)	CCE (%)	SPECCA (MJ/kg)	CAC (€/tCO_2)	LCOE (€/MWh)	SE_{CO_2} (kg/MWh)	TRL	CRL	SRL	Reference
Pre-combustion with Rectisol process	33.64	89.0	3.58	47.00	96.00	103.00	9.00	5.00	4.00	[74]
Pre-combustion with CO_2-selective membrane	26.42	86.9	8.17	84.00	120.00	117.00	6.00	3.00	2.00	[74]
Pre-combustion with amine modified PVAm membrane	30.74	86.9	5.22	51.00	98.00	118.00	6.00	3.00	2.00	[74]
Pre-combustion with low-temperature CO_2 capture	33.70	84.1	3.75	42.00	91.00	139.00	6.00	2.00	2.00	[74]
Oxy-fuel combustion with cryogenic air separation & CO_2 capture	32.22	90.0	4.21	50.74	98.10	118.75	4.00	2.00	2.00	[52]
Oxy-fuel combustion with Mn-based looping system & CO_2 capture	35.30	90.0	2.74	32.94	86.33	107.94	4.00	2.00	2.00	[52]
Pre-combustion using Selexol process with cryogenic air separation unit	32.03	90.0	5.15	56.38	110.57	98.55	9.00	5.00	4.00	[52]
Pre-combustion using Selexol process with Mn-based chemical looping air separation unit	33.95	90.0	4.14	43.26	102.17	91.95	7.00	3.00	3.00	[52]
Oxy-combustion with cryogenic air separation unit	32.21	90.0	4.22	71.54	96.54	118.28	4.00	2.00	2.00	[75]
Oxy-combustion with copper-based chemical looping air separation unit	35.1	90.0	2.83	56.06	86.55	108.56	4.00	2.00	2.00	[75]
Pre-combustion using Selexol process with cryogenic air separation unit	32.03	90.0	5.15	75.56	100.77	98.52	9.00	5.00	4.00	[75]
Pre-combustion using Selexol process with copper-based chemical looping air separation unit	33.8	90.0	4.22	63.24	99.98	92.52	7.00	3.00	3.00	[75]
Post-combustion with chemical absorption (MEA) with 15 trays absorption column	32.47	90.0	3.27	40.10	84.95	87.50	9.00	5.00	4.00	[69]
Post-combustion-carbonate looping with calciner reactor temperature of 900–980 C	34.00	90.0	2.58	37.71	79.57	76.00	7.00	3.00	3.00	[69]
Post-combustion-magnesium looping	32.97	90.0	3.03	39.95	80.77	82.50	6.00	3.00	2.00	[69]
Post-combustion with chemical absorption (MDEA)	32.48	90.0	3.26	40.25	85.01	87.49	9.00	5.00	4.00	[23]
Post-combustion-carbonate looping with calciner reactor temperature of 900-945 C	34.00	90.0	2.58	37.82	79.56	76.20	9.00	3.00	3.00	[23]

Table A.A.3
Dataset of CO_2 capture technologies for coal power plants.

Process	η_{net} (%)	CCE (%)	SPECCA (MJ/kg)	CAC (€/tCO_2)	LCOE (€/MWh)	SE_{CO_2} (kg/MWh)	TRL	CRL	SRL	Reference
Pre-combustion using Selexol™	37.13	90	2.83	19.94	93.22	92.05	8	4	3	[24]
Pre-combustion using MDEA	37.45	90	2.70	20.24	93.43	91.58	8	4	3	[24]
Pre-combustion using membrane	38.10	90	2.46	9.90	86.53	91.41	6	3	2	[24]
Pre-combustion using hybrid membrane–MDEA system	37.55	90	2.66	21.92	94.56	91.33	6	3	2	[24]
Pre-combustion using reactive gas-liquid absorption (MDEA)	36.61	90	2.94	28.38	73.28	85.48	8	4	3	[49]
Pre-combustion using calcium looping	36.08	90	3.14	32.40	76.07	83.02	6	3	3	[49]
Oxy-fuel combustion with cryogenic air separation & CO_2 capture	34.64	90	2.98	84.43	29.87	100.25	6	3	2	[52]
Oxy-fuel combustion with Mn-based looping system & CO_2 capture	38.17	90	1.59	73.54	14.10	90.10	6	3	2	[52]
Pre-combustion using Selexol process with cryogenic air separation unit	37.19	90	2.74	14.27	82.89	85.95	7	4	3	[52]
Pre-combustion using Selexol process with Mn-based chemical looping air separation unit	39.13	90	2.01	5.97	77.31	82.24	6	3	2	[52]
oxy-combustion circulating fluidized bed (CFB)	39.20	90	2.09	54.43	21.70	80.00	6	3	3	[76]
Oxy-combustion with copper-based chemical looping air separation (CLAS) system and CO_2 capture	37.83	90	1.72	74.04	37.12	91.70	6	3	2	[75]
oxy-combustion circulating fluidized bed (CFB) power plant	35.40	98	1.67	79.20	34.84	23.80	6	3	2	[77]
Post-combustion using MEA-based absorption (15 trays absorption column)	33.73	90	3.34	37.00	74.85	94.00	9	5	4	[69]
Post-combustion using calcium looping	35.94	90	2.34	35.38	71.02	71.00	6	3	3	[69]
Post-combustion-magnesium looping	34.56	90	2.92	38.21	72.15	79.50	6	3	3	[69]
Post-combustion with MDEA	33.74	90	2.43	37.12	74.81	94.03	8	4	3	[23]
Post-combustion using calcium looping	35.91	90	2.35	35.43	70.59	70.98	6	3	3	[23]
Post-combustion using Membrane area = 200,000 (m2), CP1 = 6(bar)	40.49	90	4.71	234.94	126.90	522.84	6	3	3	[78]
Membrane area = 200,000 (m2), CP1 = 8(bar)	36.67	90	5.01	124.95	124.30	351.46	6	3	3	[78]
Membrane area = 200,000 (m2), CP1 = 10(bar)	33.23	90	5.73	97.75	126.30	222.77	6	3	3	[78]
Membrane area = 400,000 (m2), CP1 = 6(bar)	37.71	90	4.34	120.58	122.40	353.25	6	3	3	[78]
Membrane area = 400,000 (m2), CP1 = 8(bar)	32.54	90	5.54	86.72	125.70	163.41	6	3	3	[78]
Membrane area = 400,000 (m2), CP1 = 10(bar)	27.82	90	7.48	96.34	141.00	62.28	6	3	3	[78]
Membrane area = 600,000 (m2), CP1 = 6(bar)	35.08	90	4.76	94.27	123.10	237.37	6	3	3	[78]
Membrane area = 600,000 (m2), CP1 = 8(bar)	28.69	90	6.98	93.28	138.20	69.73	6	3	3	[78]
Membrane area = 600,000 (m2), CP1 = 10(bar)	22.87	90	10.82	137.52	175.70	13.05	6	3	3	[78]
Post-combustion using fluidized bed adsorption (FLBA) and PEI-silica sorbent with internal heat recovery	28.20	86	3.70	89.36	137.69	99.90	7	4	3	[79]
Post-combustion using moving bed adsorption (MBA) and PEI-silica sorbent with internal heat recovery	32.60	87	0.96	61.55	116.81	97.70	7	4	3	[79]
Post-combustion using fixed bed adsorption (FBA) and PEI-silica sorbent with internal heat recovery	33.10	87	0.70	57.11	113.94	97.80	7	4	3	[79]
Post-combustion using rapid thermal swing adsorption (RTSA) and PEI-silica sorbent with internal heat recovery	33.40	86	0.55	61.82	117.73	100.10	7	4	3	[79]
Post-combustion using a 13% PZ/27% AMP solution and absorber intercooling with rich split	37.23	90	2.39	42.80	79.50	84.00	6	3	3	[71]
Post-combustion + MDEA-based gas–liquid absorption system with intercooling	33.09	90	2.93	44.81	80.96	104.41	8	5	4	[80]
Post-combustion + MDEA-based gas–liquid absorption system (lean vapor recompression)	33.18	90	2.89	44.95	81.10	103.67	8	5	4	[80]
Post-combustion + MDEA-based gas–liquid absorption system (absorption intercooling and lean vapor recompression)	33.70	90	2.66	42.74	79.51	102.08	8	5	4	[80]

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