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Recent Advances in Integrated Carbon Dioxide Capture: Exploring Carbon Capture Methods and AI Integration

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ABSTRACT

Achieving the Sustainable Development Goals depends on decarbonizing the industrial sector, as it still contributes the most to global greenhouse gas emissions and energy consumption. Reducing emissions from fossil fuel-based energy systems critically depends on carbon capture, especially post-combustion carbon capture (PCC). Absorption-based carbon capture (ACC) is the most developed and extensively applied PCC system. However, ACC systems are quite energy-intensive and require major heating and cooling utilities, which increases the running costs and makes large-scale adoption difficult. This study investigates the current developments in carbon capture technology and emphasizes the integration of artificial intelligence (AI) to address optimization challenges. In particular, it suggests an artificial intelligence-based approach for improving ACC system design, operation, and utility consumption forecasting. AI-driven solutions can promote scalable and reasonably priced carbon capture technologies by allowing accurate and fast assessments of technical and financial viability. This study emphasizes how artificial intelligence might hasten the shift toward more environmentally friendly industrial methods and significantly support global climate action targets (SDG 13).

INTRODUCTION

In recent years, extreme weather events, including heatwaves, droughts, wildfires, hurricanes, and flooding, have become increasingly severe, resulting in substantial damage to human life, infrastructure, and ecosystems (Cotterill et al. 2021, Jain et al. 2022). The World Meteorological Organization (WMO) has projected that severe weather events have caused over 2 million fatalities and US$4.3 trillion in economic damages from 1970 to 2020. Global warming and anthropogenic carbon emissions are widely acknowledged as the causes of the escalating frequency and severity of extreme weather events, although the attribution of individual events is frequently a topic of debate (Bellprat et al. 2019, Schiermeier 2018). With 29.4% of all greenhouse gas emissions coming from energy usage in industry and direct industrial processes, the industry sector has the highest carbon emissions. Consequently, it is imperative to implement industry decarbonization to mitigate extreme weather events. Energy efficiency improvement, carbon capture, and hydrogen energy are among the primary techniques for industrial decarbonization (Baker et al. 2018, Ritchie & Roser 2024, Schiermeier 2018).

Carbon emissions can be reduced by implementing strategies such as improving the energy structure, electrification, decreasing excessive energy usage, and carbon sequestration. Carbon dioxide capture and storage (CCS) is a method that utilizes pipeline transportation to extract carbon dioxide (CO_2) from the atmosphere or industrial waste gas and stores it in the ocean or underground at a significant concentration. This process has the potential to reduce the concentration of CO_2 in the atmosphere (Zhang et al. 2021). Nevertheless, its development is constrained by its high cost and potential long-term environmental impact. In recent years, the field of CO_2 capture and utilization (CCU) has garnered growing interest because of its capacity to convert CO_2 into value-added products through chemical conversion, including thermal, electrical, and photocatalysis techniques (Liang et al. 2021, Moss et al. 2017). Table 1 summarizes the relevant carbon dioxide capture and utilization technologies in terms of their features, benefits, and drawbacks. By capturing and using CO_2 gas on-site, the integrated carbon dioxide captures and utilization (ICCU) system makes CO_2 use efficient and economical by lowering transportation and compression costs (Guo et al. 2023).

Geological carbon storage (GCS) is an essential part of carbon capture, use, and storage (CCUS) to reduce greenhouse gas emissions and meet climate objectives (Ringrose & Meckel 2019). With the potential to manage over 220 Mton of CO_2 annually, project developers expect to put more than 200 new capture and storage facilities into operation globally by 2030, according to the International

Table 1: An overview of CO_2 collecting and use technologies.

	Technology	Description	Advantages	Disadvantages	References
Technology to collect CO_2	Capture of oxyfuel combustion	Combusting fuel with either pure oxygen or a combination of oxygen and carbon dioxide (CO_2) in the exhaust gas can be captured.	It is possible to store things directly.	The generation of oxygen has a high cost and is susceptible to air leakage.	(Martin et al. 2011)
	Pre-combustion capture	Before burning fuel derived from carbon, separate other combustibles from CO_2	Significant CO_2 concentration and effortless separation	Require the enhancement of the existing power plant, a task that is challenging and entails significant expenses	(Martin et al. 2011)
	Absorption separation	Gas mixtures can be separated based on their varying solubility	high yield and elevated CO_2 concentration	significant energy usage, significant equipment investment	(Guo et al. 2023)
	Post-combustion capture, adsorption, and separation	The separation of gas mixtures is achieved by exploiting the distinct binding force between gases and porous materials.	Flexible operation, safety, and affordability	Inorganic adsorbents exhibit poor selectivity and unpredictable performance.	(Gu et al. 2015, Tang et al. 2022)
	Membrane separation	Utilize variations in solubility and diffusivity to capture	High selectivity with low energy usage	restricted application, weak stability	(Yan et al. 2012)
Technology for using CO_2	Solar thermochemical conversion technology	Solar radiation is employed to generate a robust endothermic reaction that is suitable for utilization by driving CO_2 and H_2O	low usage of energy	minimal efficiency of conversion	(Ishaq et al. 2021)
	Electrochemical conversion	The voltage difference between the two electrodes is what drives the reduction of carbon dioxide into compounds	flexible running circumstances, moderate reaction environment	Electrocatalyst instability and elevated energy consumption	(Meng et al. 2021)
	Catalytic conversion	Chemical bond formation and breakage are facilitated by the employment of catalysts	cheap cost and excellent safety	Improvements are needed in stability and conversion efficiency	(Rahimi et al. 2016)
	Photochemical conversion	The absorption of thermal energy and the overriding of activation energy facilitate the CO_2 conversion reaction	moderate reaction circumstances and potent oxidation capacity	low light energy utilization rate, efficiency, and control issues	(Guo et al. 2023)

Energy Agency (IEA) (Lin et al. 2022). Because one of the largest CCUS projects to date, the water-alternating gas (WAG) injection project in the Brazilian Pre-Salt, has only injected 20 Mton of CO_2 over a decade into the four largest carbonate reservoirs in Brazil, or less than 10% of the IEA target, it is important to put this ambitious goal into perspective. When fossil fuels are burned, carbon dioxide (CO_2) is released into the atmosphere. The quantity of CO_2 increases as global energy consumption increases to support energy-intensive activities (Seabra et al. 2024). For the foreseeable future, fossil fuels will remain the primary source of energy globally, despite the grave environmental problems often linked to CO_2 emissions. Numerous carbon dioxide storage locations are found in geologically intricate formations, such as channelized reservoirs or fractured carbonate rocks (March et al. 2018). Consequently, it is imperative to identify and develop a technological solution that is both feasible and effective in reducing carbon dioxide emissions into the atmosphere.

Most carbon capture and storage methods involve post-combustion carbon capture, oxy-fuel combustion carbon capture, or pre-combustion carbon capture. The development and deployment of combustion systems suitable for their intended purpose are necessary for both pre-combustion and oxyfuel carbon capture (Al-Hamed & Dincer 2022, Park et al. 2015). Alternatively, post-combustion carbon capture technology may be used to upgrade and modify existing fossil-fuel burning facilities (Khalilpour 2014). Thus, it may reduce emissions without replacing the infrastructure (Aliyon et al. 2020). Absorption, adsorption, and membrane separation are the three most prevalent methods for capturing carbon after burning (Akinola et al. 2022, Aliyon et al. 2020, Zhang et al. 2021).

This study developed a substitute machine learning (SML) model to predict the heating and cooling utility consumption of ACC plants using machine learning (ML) techniques. System engineering models are enhanced or replaced by SML models. SML models outperform

Table 2: Literature reviews that have used ML within the ACC.

ML model(s)	Purpose	Model Inputs	Model Outputs	Data Generation Software	References
An ensemble neural network using bootstrap aggregation, often known as bagging, with a single-layer neural network.	Forecasting the efficiency of CO_2 capture	Flow rate of flue gas, pressure, temperature, and concentration of CO_2, flow rate and temperature of lean fluid, concentration of MEA, and temperature of the reboiler	Efficiency in CO_2 capture	gPROMS	(Li et al. 2015)
Single-layer neural network	Predicting the specified duty of a reboiler and the rich loading	Temperature, CO_2 concentration, lean load, removal efficiency, solvent circulation rate, and flue gas flow rate	The flow rate of captured CO_2, plus the specific duty of the reboiler, plus a solvent-rich load	CO2SIM	(Sipöcz et al. 2011)
Network of profound convictions	Forecasting the efficiency of CO_2 capture	Flow rate of flue gas, pressure, temperature, and concentration of CO_2, flow rate and temperature of lean fluid, concentration of MEA, and temperature of the reboiler	Efficiency in CO_2 capture	gPROMS	(Li et al. 2018)
The extreme learning machine is used to build a bootstrap combined neural network with a single-layer neural network.	Forecasting the efficiency of CO_2 capture	Flow rate of flue gas, pressure, temperature, and concentration of CO_2, flow rate and temperature of lean fluid, concentration of MEA, and temperature of the reboiler	Efficiency in CO_2 capture	gPROMS	(Li et al. 2017)
Single-layer neural network	Improvement of operational control	The flow rates of lean solvent, flue gas, and reboiler steam	Amount of CO_2 collection plus the temperature of the reboiler	gPROMS (gCCS module)	(Wu et al. 2020)
A single-layer neural network and a few other components	Optimisation of processes	factors such as reboiler and condenser responsibilities, reboiler pressure, flow rate, temperature, and flue gas pressure	Total work for reboilers, condensers, and amine coolers, plus the rate of capture, plus the purity of CO_2	gPROMS	(Shalaby et al. 2021)

engineering models in several ways, such as quick running times, robustness in predicting system performance that engineering models are unable to fully capture, robustness in predicting system performance as components age, ability to make predictions without in-depth knowledge of the system, and ability to make predictions with few inputs (Chegari et al. 2022, Li et al. 2022, Spinti et al. 2022, H. Zhang et al. 2021). This study used SML models to provide rapid and accessible utility consumption prediction models to help build energy-efficient ACC procedures.

Active sites for CO_2 adsorption and conversion are the primary components of dual-function materials, which facilitate the adsorption, desorption, and in situ conversion of CO_2. Because fresh dual-function material samples tend to absorb carbon dioxide and water from the surrounding air, a pre-reduction step is often necessary before the reaction (Bermejo-López et al. 2022). Initially, CO_2 was drawn at a particular temperature until the adsorbent was fully saturated. Second, the adsorbed CO_2 in the saturated materials interacts with hydrogen to form CH_4 when placed in a reducing environment. The integrated carbon dioxide capture and methanation procedure primarily comprises this two-step process. Carbon dioxide can be consistently captured and transformed in a single reactor throughout multiple cycles. The reaction exhibited a favorable cyclic performance and could be conducted at a moderate temperature of approximately 300°C. This streamlines the procedure and improves the energy efficiency. Integrated carbon dioxide capture and utilization (ICCU) technology has gained significant attention owing to its ability to efficiently convert carbon dioxide into fuels, such as carbon, using dual-function materials. This approach delivers high efficiency with low energy usage by combining carbon dioxide adsorption and in situ conversion (Guo et al. 2023). Table 2 presents the various studies that have used ML in the ACC.

Carbon capture research has primarily focused on developing new methods to reduce the cost of CO_2 collection. Some of the methods used include the development of new solvents, the use of catalysts to enhance the performance of existing solvents, the application of artificial intelligence to the CO_2 capture process, and the development of new repair methods. In this section, several approaches for determining the column height of the CO_2 absorbent are thoroughly examined. Some of the methods used include empirical design, theoretical design, laboratory and pilot plant processes, and so on. This review is based on the idea of using AI to capture CO_2. The coming together of many AI programs. The potential for AI-assisted CO_2 collection is examined, along with the difficulties involved. A comparative summary of common machine learning models used in CO_2 capture, along with their advantages and limitations, is presented in Table 3.

MATERIALS AND METHODS

A Summary of the Process of Capturing Carbon Dioxide

Extensive research has been conducted on CO_2 capture systems, which are crucial for reducing industrial carbon emissions. Among the most significant contributors to carbon monoxide emissions are high-temperature industrial activities, including the manufacturing of steel, cement, oil, and gas. Post-combustion capture technologies, more especially absorption, adsorption, and membrane separation, are among the many ways that have been extensively researched and utilized (Chao et al. 2021). Amine-based chemical absorption is the post-combustion capture method with the greatest documented track record and is potentially economically viable. This technique involves the use of aqueous amine solvents to selectively absorb carbon monoxide from exhaust gases (Raganati et al. 2021). In real time, intelligent control systems that use artificial intelligence can monitor membrane performance, identify fouling or degradation, and dynamically alter operating settings. Data-driven models also support the selection of materials and the creation of hybrid systems (e.g., coupling membranes with adsorption or absorption).

The procedure involves the absorption of CO_2 from flue gas using an amine solvent, followed by the separation of CO_2 from the solvent using a stripping column. The solvent is recycled back into the absorber, and the concentrated CO_2 is collected for storage or use after extraction (Yamada 2021). The capture of CO_2 is essential in petrochemical activities, particularly in the production of ammonia, because of the significant volume of CO_2 emissions produced during the process (Takht Ravanchi & Sahebdelfar 2014). This cycle process is commonly implemented in large-scale industrial processes, such as natural gas processing and ammonia manufacturing, when the amount of carbon dioxide produced is significant. The solvent-based approach is frequently followed by a sorbent method. At present, fewer than one-third of the processes are membrane-based. In the collection of CO_2 through absorption, adsorption, and membrane separation technologies, the selection of a solvent, adsorbent, or membrane material, as well as the optimization of the operating pressure and temperature, are all critical operational factors. These characteristics significantly influence the efficiency and efficacy of the capture process; therefore, it is necessary to comprehensively select and optimize these parameters to achieve the desired results. The subsequent discourse provides a comprehensive examination of diverse techniques for CO_2 capture, including membrane-based, adsorption, and absorption techniques (Priya et al. 2023).

Adsorption is a relatively new alternative to absorption, offering several benefits similar to those of absorption, including reduced energy usage and simpler regeneration. In this approach, carbon monoxide molecules can attach themselves to the surface of a solid porous substance, referred to as an adsorbent. Temperature, pressure, pore size, surface area, and adsorption kinetics are key operating parameters that significantly affect performance. High CO_2 selectivity, rapid adsorption and desorption rates, mechanical durability, and economic viability for regeneration are only a few of the characteristics that should be present in effective adsorbents (Abd et al. 2020). Absorption-based systems consume significant energy, particularly due to the requirements for thermal regeneration. Predicting the performance of a solvent, optimizing the amount of energy required for regeneration, and simulating the behavior of a process under a variety of different operating circumstances are all possible applications of artificial intelligence models. AI-driven predictive modeling can considerably improve the design and control of absorption systems in terms of energy efficiency and economic feasibility.

Additionally, the adsorbent material must fulfill the operational and budgetary requirements for efficient CO_2 removal by demonstrating CO_2 selectivity, rapid adsorption and desorption kinetics, sufficient mechanical strength, and economically feasible regeneration (Abd et al. 2020). Most of the area in the column is occupied by the adsorbent, which allows CO_2 to flow over the system unhindered. The adsorbent captures CO_2 through its surface. Once the balancing condition is reached, the duplicated adsorbent can be employed for the next CO_2 intake. Pressure swing adsorption is a technique that includes controlling the pressure to improve both the absorption and desorption of CO_2 by the adsorbent to separate CO_2 from a gas mixture. This technique continues until the necessary amount of CO_2 is removed, at which point the gas mixture exits the adsorbent bed with a decreased concentration of CO_2 (Siqueira et al. 2017). When optimizing adsorption processes, it is necessary to solve complex problems involving multiple variables. Modeling nonlinear interactions among parameters, predicting breakthrough curves, and optimizing PSA cycle times and operating conditions are all possible using artificial intelligence and machine learning techniques.

The performance of the system is heavily dependent on the following factors, regardless of capture technology:

- The selection of the material for the membrane, the adsorbent, or the solvent.
- Temperature, pressure, and flow rate are examples of the operating parameters.
- In terms of energy efficiency and capacity for regeneration.

Artificial intelligence-based techniques play a crucial role in optimizing these variables. This study highlights the growing body of research that employs artificial intelligence to enhance the scalability, responsiveness, and sustainability of carbon capture systems.

RESULTS AND DISCUSSION

Technologies for Sequestering Carbon

Deep-ground injection, ocean storage, and improved oil recovery (EOR) are the main approaches to carbon sequestration (Alvarado & Manrique 2010, Lemieux 2011). Deep-ground injection involves the use of geological formations to store CO_2, whereas ocean storage takes advantage of the vast carbon-absorbing capacity of oceans. Enhanced oil recovery (EOR) combines CO_2 storage with practical energy generation. These techniques demonstrate the complex endeavors to tackle carbon emissions, with each strategy employing distinct natural and technological mechanisms to reduce atmospheric CO_2. Deep ground injection is a procedure in which carbon dioxide (CO_2) is crushed and injected into geological formations beneath the Earth's surface. As a result of the intense pressure and temperature at extreme depths, CO_2 frequently becomes supercritical, leading to improved storage efficiency because of its higher density (Bloom Energy 2024). Trapping by it structurally beneath impermeable caprocks, residual trapping within rock fissures, solubility trapping as CO_2 dissolves in water, and mineral trapping as it combines with minerals to produce stable carbonates are some of the methods that sequester CO_2 over time. The integrity and continuity of caprocks are essential for structural entrapment, as they serve as seals that prevent upward migration (Arif et al. 2016). Residual trapping is a process that effectively prevents migration by utilizing capillary forces to hold CO_2 in pore spaces, even if the structural trap is compromised (El-Maghraby & Blunt 2013). Carbonic acid is produced when CO_2 dissolves in the formation water during solubility trapping. This process also reduces buoyancy and leakage potential by reacting to generate bicarbonate ions (Adamczyk et al. 2009). Mineral trapping refers to the process in which carbon dioxide (CO_2) reacts with minerals in the formation of stable carbonate minerals. This reaction occurs over a long period and helps improve the long-term security of CO_2 storage (Soong et al. 2004). The longevity of this method's ability to store large volumes of CO_2 is heavily contingent upon geological and technical conditions. Fissures in the rock, which may be worsened by seismic activity, have the potential to weaken this seal, resulting in the release of CO_2 back into the environment (Blake et al. 2022). Furthermore, permanent sequestration is complicated by the substantial technical challenges associated with the monitoring and verification of the stored CO_2.

AI-Based Carbon Capture Applications

As computer technology has improved significantly over the last two decades, the numerical simulation of processes has gained importance and popularity across a wide range of engineering and academic disciplines. Many researchers are currently investigating artificial intelligence (AI) technologies, namely machine learning approaches,

Table 3: Machine Learning approaches: Advantages and Limitations.

ML Model	Typical Use in CO_2 Capture	Advantages	Limitations	References
Artificial Neural Networks (ANN)	Prediction of energy use, solvent recovery, and system optimization	High predictive accuracy, handles non-linear systems well	Prone to overfitting, requires large datasets	(Alabdraba et al. 2017)
Support Vector Machines (SVM)	Classifying optimal operating conditions, CO_2 selectivity prediction	Effective in high-dimensional space, good for classification/ regression	Computationally intensive, kernel selection is critical	(Afkhamipour and Mofarahi, 2016)
Random Forest (RF)	Sensitivity analysis, feature importance ranking	Robust to noise, handles missing data well	Less interpretable, can be slow for large datasets	(Chen et al. 2021)
Gradient Boosting Machines (e.g., XGBoost)	Performance prediction and fault detection	High accuracy, handles heterogeneous data	Risk of overfitting, tuning complexity	(Zhang et al. 2022)
Reinforcement Learning (RL)	Dynamic control system optimization	Suitable for real-time control and adaptive optimization	Limited industrial deployment needs well-defined reward structures	(Moradi et al. 2022)
Hybrid AI models (e.g., ANN+GA, SVM+PSO)	Optimizing operating conditions	Combines the benefits of multiple techniques for improved optimization	Complex to implement and validate	(Ehteram et al. 2021)

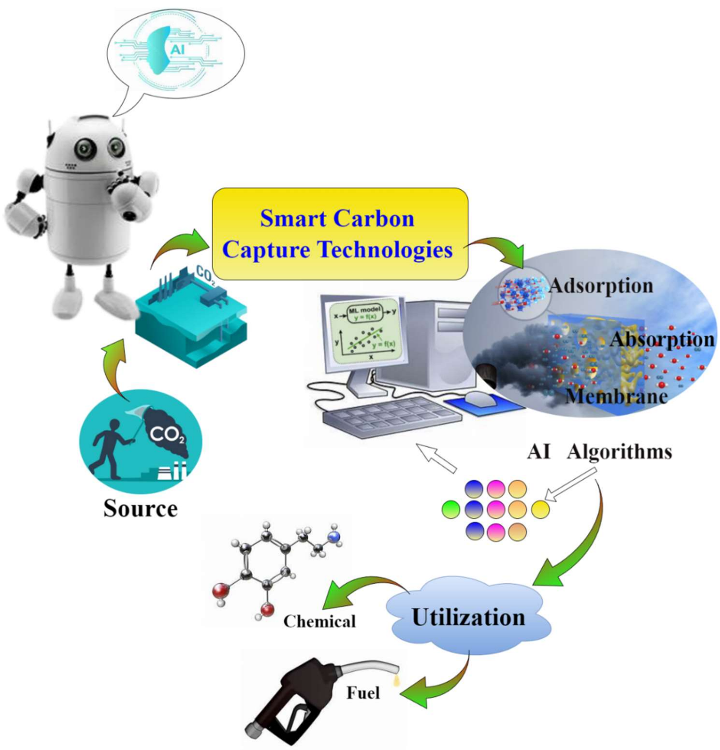

Fig. 1: Smart carbon capture technologies and utilization.

because of their potential as attractive alternative solutions (Alabdraba et al. 2017). Significant post-combustion CO_2 collection facilities, such as TMC Mongstad in Norway and BD3 SaskPower in Canada, generate large amounts of operating process data. This information can be used as a great source of input to create knowledge that enhances the CO_2 capture mechanism (Chan & Chan 2017). Artificial neural networks (ANN are widely utilized and popular techniques of artificial intelligence applied for mass transfer and property prediction in the CO_2 capture process, owing to several factors. The quick formulation of ANN predictive models, including several parameters, is possible. They possess a high degree of adaptability and often yield more accurate outcomes than numerical simulations and correlations (Li et al. 2015). The ANN method is briefly described as follows. Fig. 1 shows smart carbon-capture technologies and their utilization.

An Artificial Neural Network (ANN) model can display both linear and nonlinear relationships in its input and output data (Fu et al. 2014). The network has many processing units that work simultaneously and are linked to each other. These are called neurons, and they are based on the nervous system of the human brain and biological neurons (Mohagheghian et al. 2015). The neuron units in the adjacent layers were fully coupled to each other in the hidden layer. The following formula can be used to determine the output of each neuron (yj): Activation or transfer functions include sigmoid, piecewise linear, radial basis, and Gaussian functions. (Adeyemi et al. 2018). Utilizing either the sigmoid or hyperbolic functions as the concealed activation mechanism, the multilayer perceptron is the most frequently employed feedforward neural network (Chan & Chan 2017). AI applications in CO_2 capture currently face several significant constraints.

- For CO_2 capture procedures at the plant scale, there is a lack of high-quality datasets, particularly for more recent technologies such as membranes.
- The inability to generalize from small training sets is a common problem with many ML models, especially DNNs.
- Adaptability in real-time, reaction with minimal latency, and integration with existing control systems are essential for using AI in dynamic industrial environments.
- Companies that place a premium on safety may be hesitant to use black-box models like ANN because of the lack of understanding they provide on process dynamics.
- Retraining or substantial recalibration may be necessary to make models trained on data from lab-scale plants work well on data from full-scale plants.

AI's Application to Physical Attributes and Solubility

The physical and chemical properties of CO_2 and amines, such as viscosity, density, heat capacity, reaction rate, diffusivity, and conductivity, can substantially influence the efficiency and effectiveness of the carbon capture process in CCS (Tantikhajorngosol et al. 2019). These properties are frequently utilized in the process simulations of the CO_2 capture process and are necessary for the calculation of heat duty. The values of these properties are frequently determined by measuring them in a laboratory environment using costly instruments (Pouryousefi et al. 2016). However, experiments and the collection of experimental data require a high level of expertise and a comprehensive understanding of the process. The data capture process is intricate and time-consuming, often involving repetitive procedures (Adeyemi et al. 2018).

Based on notable empirical and semi-empirical connections, numerical simulations and models tend to be simpler methods for determining feature values than experimental techniques (Fu et al. 2014, Mohagheghian et al. 2015). However, there are several downsides to the modeling technique, including: (i) the correlations cannot capture the nonlinear relationships between the parameters, (ii) there needs to be a guarantee of access to massive amounts of data, (iii) function evaluations need to be carried out to ensure that the models and numerical simulations are correct, (iv) it might take a lot of computing power to develop the solutions, (v) there is a chance that the models and simulations developed for certain conditions will not work outside of those parameters, and (vi) the unfavorable characteristics of gases and amines might complicate computations relying on correlations (Bahadori & Mokhatab 2008, Zhou et al. 2009). Many studies have proposed the use of machine-learning methods, such as artificial neural networks (ANN) and Support Vector machines (SVM), to forecast several properties connected with the CO_2 capture process to solve these problems (Afkhamipour & Mofarahi 2016).

Baghban et al. (2015) created artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models to accurately predict the solubility of CO_2 in the carbon-capture process (Baghban et al. 2015). These models can provide precise predictions across a wide range of temperatures, pressures, and concentrations. The CO_2 concentration was the output variable, with the following variables serving as inputs: acentric factor, molecular weight, critical pressure, temperature and pressure. The solubility of CO_2 in aqueous TBAB solutions was predicted using

RBFNN and ANFIS (Hoseinpour et al. 2018). The CO_2 solubility served as the end parameter, and the mass and mole percent of TBAB, temperature, and pressure were the inputs. The accuracy of the AI model predictions was confirmed using statistical and graphical analytical methods. The CO_2 solubility in the aqueous sodium salt of L-phenylalanine was precisely predicted by the ANN model employing Lvenberg-Marquardt (LM) (Garg et al. 2017). When contrasted with the solubility predictions offered by the Kent-Eisenberg model, the results produced by Artificial Neural Networks (ANN) showed a higher degree of agreement with the experimental data. The integration of a genetic algorithm with a least-squares support vector machine (GA-LSSVM) enabled precise predictions of hydrocarbon solubility in water (Helei et al. 2021).

AI Application for CO_2 Mass Transfer

To design, simulate, and improve the CO_2 collection process, it is especially important to obtain accurate measurements of the mass transfer rate. Over the past 15 years, experts have investigated the use of artificial intelligence (AI) to copy the process of moving mass and test how well CO_2 can be captured. The purpose of this study was to develop accurate and reliable estimates of the speed at which mass moves (Meesattham et al. 2020). Predicting properties such as CO_2 concentration, temperature, heat duty, and removal efficiency is a common focus in these applications. In contrast, the conditions of the CO2 collection process are the input predictors (Afkhamipour & Mofarahi 2016, Fu et al. 2014). The research comprised several crucial elements: soliciting input from experts regarding the intricate interdependencies among the parameters required for particular algorithms, building artificial neural networks (ANNs), fine-tuning the internal connection weights to minimize disparities between the inputs to the network and the desired output, and optimizing the networks to handle weird data that do not fit in with the training samples. Moreover, the tests produced a limited data sample that accurately represented the population. Some instances of sample investigations are as follows: The current research states that hybrid models integrating experimental and simulation datasets have improved the prediction of CO_2 transfer coefficients. To illustrate this point, accurate estimates of the total mass transfer rates in absorber columns have been achieved by estimating the Sherwood and Reynolds numbers using ANN+PSO models (Hoseinpour et al. 2018).

The Potential and Difficulties of AI-Assisted Carbon Capture

An estimated 53 gigatonnes of CO_2 equivalent greenhouse gas emissions have been released into the atmosphere worldwide, intensifying the already severe climate change. The primary objective of the 2016 Paris Agreement is to limit the rise in average global temperature to 1.5°C. By the conclusion of this decade, emissions must be reduced by 50% to accomplish this objective. Artificial intelligence is believed to be capable of achieving a reduction of 5% to 10% of the required reduction, which is within the range of 2.6 to 5.3 gigatonnes of CO_2 equivalent (Degot et al. 2021). An important advantage of AI-assisted carbon capture is its ability to significantly decrease the cost associated with capturing CO_2. Artificial intelligence algorithms can analyze vast quantities of data in real time, resulting in enhanced performance of CO_2 capture systems that are efficient and cost-effective. AI-assisted CO_2 capture enhances the reliability and accuracy of CO_2 capture systems. Artificial intelligence algorithms can observe and evaluate the operation of CO_2 extraction devices and make immediate adjustments to enhance efficiency. This can reduce the likelihood of costly malfunctions and guarantee the ongoing functionality of the system. A novel AI-based instrument was recently created by a team of scientists to facilitate the faster and more precise locking of greenhouse gases, including CO_2, in porous rock formations with unprecedented speed. A Fourier neural operator-based deep-learning model, which is a unique neural operator architecture, was employed to efficiently mimic the pressure levels in carbon storage. This model significantly improved the precision of specific jobs, enabling scientists to identify the most efficient injection rates and sites with twice the accuracy (Wen et al. 2022). The use of artificial intelligence (AI) in carbon capture has shown promise in the laboratory, but practical implementations have been slow to materialize. Compact carbon-capture systems assisted by artificial intelligence have been developed by Carbon Clean for use in small and medium-scale companies. To achieve zero-emission power generation, Net Power incorporates predictive controls powered by artificial intelligence into its Allam Cycle technology. As part of their goal to remove carbon emissions, Microsoft and Climeworks, a software company, invested in direct air capture (DAC) systems powered by artificial intelligence (AI). The shift from AI models in laboratories to real-world control systems in manufacturing is illustrated by these examples (Allam et al. 2017).

AI Application in the Future for the Complete Process of CO_2 Capture

Artificial intelligence technology enables accurate predictions of the entire CO_2 capture process, encompassing the absorber and desorber columns and the rich/lean amine heat exchanger. Sipocz et al. applied artificial neural networks (ANNs) to model the complex relationships between input and output parameters in a post-combustion CO_2 capture system that utilizes amines (Sipöcz et al. 2011). A rate-based process simulation (CO2SIM) was implemented to generate the data required for ANN training and validation. The lean loading, circulation rate, temperature, mass percentage of CO_2 in the inlet gas, removal efficiency, inlet gas flow rate, and inlet gas percentage were all input data that could be used as predictors. The anticipated or resulting parameters were as follows: (i) the pace at which CO_2 was captured, (ii) the amount of CO_2 absorbed, and (iii) the amount of heat required for operation. The LM and Scaled Conjugate Gradient (CG) algorithms were used to improve the accuracy of the predictions. The study found that the LM approach produced the most accurate forecasts for all three parameters in this study. The pre-design of a power plant that can capture CO_2 relies on these anticipated values (Aliyon et al. 2023). Fig. 2 shows the SWOT Analysis of AI Applications in CO_2 Capture Technologies.

Emphasizing Research Needs and Prospects:

There are still significant research gaps, even though we've made a lot of progress:

- There is an immediate need to develop publicly available benchmark datasets for CO_2 capture across various processes and scales.
- Improved industrial trust and transparency can be achieved through explainable AI, which aims to make AI models more interpretable.
- Combining artificial intelligence with digital twins, which are representations of processes in real time, is an exciting new development in the field of predictive control and problem detection.
- Few studies have combined artificial intelligence with energy-economic or life cycle models to evaluate comprehensive CO_2 capture strategies.
- Artificial intelligence for multi-objective optimization: little is known about how to optimise cost, energy, emissions, and operability all at once.

CONCLUSIONS

Modelling studies that attempt to predict the physical and chemical properties of the PCC process account for a large portion of the work; this study has also updated research activity on artificial intelligence applications in PCC technology. Artificial intelligence methodology typically outperforms numerical simulation and empirical correlation techniques in terms of speed and accuracy. Furthermore, artificial intelligence technology can help with design and PCC technology optimization. There is a substantial need for additional studies on the use of artificial intelligence in PCC. Hence, it is imperative to foster collaboration between PCC

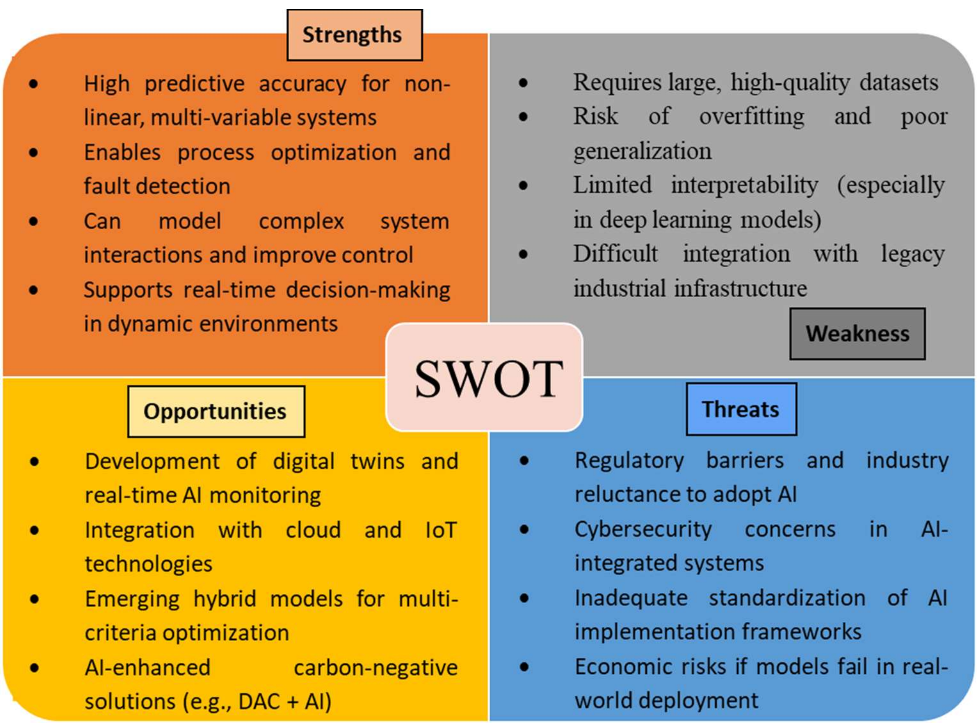

Fig. 2: SWOT Analysis: AI applications in CO_2 capture technologies.

specialists and AI researchers to advance research in this field. This study utilized surrogate machine learning models to estimate the energy and cooling utility consumption of an ACC process plant. The results indicate that surrogate machine learning models have significant potential for application in energy-related operations. Furthermore, studies suggest that specific models exhibit superior performance when provided with a limited number of data points, whereas other models outperform others when given a reduced number of input sets. Based on the data that are now accessible, one model may exhibit more superiority than the other. The economic viability of carbon-capture technologies is increasing. It is imperative to evaluate the most efficient and viable technology to minimize CO_2 emissions and achieve optimal CO_2 removal, considering economic and energy considerations. Furthermore, optimal outcomes can be attained by integrating a diverse range of machine and deep learning models with hybrid ones. As technological advancements progress, artificial intelligence techniques are likely to offer advantages in CO_2 capture. Artificial intelligence models can produce accurate outcomes by leveraging their ability to estimate variables and acquire knowledge from data. Despite the growing use of these algorithms in current research, further work is required to improve their capacities to simultaneously manage combustion and CO_2 capture systems to obtain the best possible performance. The fusion of oxy-fuel combustion technology and artificial intelligence is one such example. This process involves the combustion of fuel with oxygen instead of air, which leads to the generation of a stream of CO_2 that can be gathered and stored. Artificial intelligence can enhance the oxygen combustion process by accurately predicting the ideal conditions for CO_2 capture and burning, thereby maximizing efficiency.

As covered in the previous section, some possible CO_2 capture methods include customized greenhouse gas-absorbing devices and artificial intelligence-assisted output stream control. Many more approaches could help to reduce CO_2 emissions, however, researchers must find a good approach to allow a route to see the expansion of this industry. Analyzing the implementation of artificial intelligence in patent landscape analysis and CO_2 capture will provide carbon capture professionals with new insights. The development of emerging AI technologies will facilitate the realization of our future goals by enabling precise and instantaneous predictions.

REFERENCES

Abd, A.A., Naji, S.Z., Hashim, A.S. and Othman, M.R., 2020. Carbon dioxide removal through physical adsorption using carbonaceous and non-carbonaceous adsorbents: a review. *Journal of Environmental Chemical Engineering*, 8(3), pp.104142. [DOI]

Adamczyk, K., Prémont-Schwarz, M., Pines, D., Pines, E. and Nibbering, E.T.J., 2009. Real-time observation of carbonic acid formation in aqueous solution. *Science*, 326(5957), pp.1690–1694. [DOI]

Adeyemi, I., Abu-Zahra, M.R.M. and AlNashef, I.M., 2018. Physicochemical properties of alkanolamine-choline chloride deep eutectic solvents: measurements, group contribution and artificial intelligence prediction techniques. *Journal of Molecular Liquids*, 256, pp.581–590. [DOI]

Afkhamipour, M. and Mofarahi, M., 2016. Modeling and optimization of CO_2 capture using 4-diethylamino-2-butanol (DEAB) solution. *International Journal of Greenhouse Gas Control*, 49, pp.24–33. [DOI]

Akinola, T.E., Prado, P.L.B. and Wang, M., 2022. Experimental studies, molecular simulation and process modelling\simulation of adsorption-based post-combustion carbon capture for power plants: a state-of-the-art review. *Applied Energy*, 317, pp.119156. [DOI]

Al-Hamed, K.H.M. and Dincer, I., 2022. Exergoeconomic analysis and optimization of a solar energy-based integrated system with oxy-combustion for combined power cycle and carbon capturing. *Energy*, 250, pp.123814. [DOI]

Alabdraba, W.M.S., Arslan, C.A. and Mohammed, Z.B., 2017. Application of artificial neural networks (ANN) and adaptive neuro fuzzy inference system (ANFIS) models in water quality simulation of Tigris River at Baghdad City. *Transactions on Machine Learning and Artificial Intelligence*, 5(1), pp.47–58. [DOI]

Aliyon, K., Mehrpooya, M. and Hajinezhad, A., 2020. Comparison of different CO_2 liquefaction processes and exergoeconomic evaluation of integrated CO2 liquefaction and absorption refrigeration system. *Energy Conversion and Management*, 211, pp.112752. [DOI]

Aliyon, K., Rajaee, F. and Ritvanen, J., 2023. Use of artificial intelligence in reducing energy costs of a post-combustion carbon capture plant. *Energy*, 278, pp.127834. [DOI]

Allam, R., Martin, S., Forrest, B., Fetvedt, J., Lu, X., Freed, D., Brown Jr, G.W., Sasaki, T., Itoh, M. and Manning, J., 2017. Demonstration of the Allam Cycle: an update on the development status of a high efficiency supercritical carbon dioxide power process employing full carbon capture. *Energy Procedia*, *114*, pp.5948-5966. [DOI]

Alvarado, V. and Manrique, E., 2010. Enhanced oil recovery: an update review. *Energies*, 3(8), pp.1529–1575. [DOI]

Arif, M., Barifcani, A., Lebedev, M. and Iglauer, S., 2016. Structural trapping capacity of oil-wet caprock as a function of pressure, temperature and salinity. *International Journal of Greenhouse Gas Control*, 50, pp.112–120. [DOI]

Baghban, A., Ahmadi, M.A. and Shahraki, B.H., 2015. Prediction of carbon dioxide solubility in presence of various ionic liquids using computational intelligence approaches. *Journal of Supercritical Fluids*, 98, pp.50–64. [DOI]

Bahadori, A. and Mokhatab, S., 2008. Estimating thermal conductivity of hydrocarbons. *Chemical Engineering*, 115(4), pp.200–210.

Baker, H.S., Millar, R.J., Karoly, D.J., Beyerle, U., Guillod, B.P., Mitchell, D., Shiogama, H., Sparrow, S., Woollings, T. and Allen, M.R., 2018. Higher CO_2 concentrations increase extreme event risk in a 1.5 C world. *Nature Climate Change*, 8(7), pp.604–608. [DOI]

Bellprat, O., Guemas, V., Doblas-Reyes, F. and Donat, M.G., 2019. Towards reliable extreme weather and climate event attribution. *Nature Communications*, 10, pp.1732. [DOI]

Bermejo-López, A., Pereda-Ayo, B., Onrubia-Calvo, J.A., González-Marcos, J.A. and González-Velasco, J.R., 2022. Tuning basicity of dual function materials widens operation temperature window for efficient CO_2 adsorption and hydrogenation to CH4. *Journal of CO_2 Utilization*, 58, pp.101922. [DOI]

Blake, O.O., Faulkner, D.R., Worden, R.H., Armitage, P.J. and Espie, A.A., 2022. Effect of thermal shock on the permeability and seismic wave velocity of the caprock and reservoir during CO_2 injection. *International Journal of Greenhouse Gas Control*, 118, pp.103691. [DOI]

Bloom Energy, 2024. Carbon capture technology for carbon capture and sequestration. pp.13. [DOI]
Chan, V. and Chan, C., 2017. Learning from a carbon dioxide capture system dataset: application of the piecewise neural network algorithm. *Petroleum*, 3(1), pp.56–67. [DOI]
Chao, C., Deng, Y., Dewil, R., Baeyens, J. and Fan, X., 2021. Post-combustion carbon capture. *Renewable and Sustainable Energy Reviews*, 138, pp.110490. [DOI]
Chegari, B., Tabaa, M., Simeu, E., Moutaouakkil, F. and Medromi, H., 2022. An optimal surrogate-model-based approach to support comfortable and nearly zero energy buildings design. *Energy*, 248, pp.123584. [DOI]
Cotterill, D., Stott, P., Christidis, N. and Kendon, E., 2021. Increase in the frequency of extreme daily precipitation in the United Kingdom in autumn. *Weather and Climate Extremes*, 33, pp.100340. [DOI]
Degot, C., Duranton, S., Frédeau, M. and Hutchinson, R., 2021. Reduce carbon and costs with the power of AI. *Boston Consulting Group*, pp.15. [DOI]
El-Maghraby, R.M. and Blunt, M.J., 2013. Residual CO_2 trapping in Indiana limestone. *Environmental Science & Technology*, 47(1), pp.227–233. [DOI]
Fu, K., Chen, G., Liang, Z., Sema, T., Idem, R. and Tontiwachwuthikul, P., 2014. Analysis of mass transfer performance of monoethanolamine-based CO_2 absorption in a packed column using artificial neural networks. *Industrial & Engineering Chemistry Research*, 53(11), pp.4413–4423. [DOI]
Garg, S., Shariff, A.M., Shaikh, M.S., Lal, B., Suleman, H. and Faiqa, N., 2017. Experimental data, thermodynamic and neural network modeling of CO_2 solubility in aqueous sodium salt of l-phenylalanine. *Journal of CO_2 Utilization*, 19, pp.146–156. [DOI]
Gu, M., Zhang, B., Qi, Z., Liu, Z., Duan, S., Du, X. and Xian, X., 2015. Effects of pore structure of granular activated carbons on CH4 enrichment from CH4/N2 by vacuum pressure swing adsorption. *Separation and Purification Technology*, 146, pp.213–218. [DOI]
Guo, Z.L., Bian, X.L., Du, Y.B., Zhang, W.C., Yao, D.D. and Yang, H.P., 2023. Recent advances in integrated carbon dioxide capture and methanation technology. *Journal of Fuel Chemistry and Technology*, 51, pp.293–303. [DOI]
Helei, L., Tantikhajorngosol, P., Chan, C. and Tontiwachwuthikul, P., 2021. Technology development and applications of artificial intelligence for post-combustion carbon dioxide capture: critical literature review and perspectives. *International Journal of Greenhouse Gas Control*, 108, pp.103307. [DOI]
Hoseinpour, S., Barati-Harooni, A., Nadali, P., Mohebbi, A., Najafi-Marghmaleki, A. and Tatar, A., 2018. Accurate model based on artificial intelligence for prediction of carbon dioxide solubility in aqueous tetra-n-butylammonium bromide solutions. *Journal of Chemometrics*, 32, e2956. [DOI]
Ishaq, H., Siddiqui, O., Chehade, G. and Dincer, I., 2021. A solar and wind driven energy system for hydrogen and urea production with CO_2 capturing. *International Journal of Hydrogen Energy*, 46, pp.4749–4760. [DOI]
Jain, P., Castellanos-Acuna, D., Coogan, S.C.P., Abatzoglou, J.T. and Flannigan, M.D., 2022. Observed increases in extreme fire weather driven by atmospheric humidity and temperature. *Nature Climate Change*, 12, pp.63–70. [DOI]
Khalilpour, R., 2014. Multi-level investment planning and scheduling under electricity and carbon market dynamics: retrofit of a power plant with PCC (post-combustion carbon capture) processes. *Energy*, 64, pp.172–186. [DOI]
Lemieux, J.-M., 2011. The potential impact of underground geological storage of carbon dioxide in deep saline aquifers on shallow groundwater resources. *Hydrogeology Journal*, 19, pp.757–768. [DOI]
Li, A.G., West, A.C. and Preindl, M., 2022. Towards unified machine learning characterization of lithium-ion battery degradation across multiple levels: a critical review. *Applied Energy*, 316, pp.119030. [DOI]
Li, F., Zhang, J., Oko, E. and Wang, M., 2015. Modelling of a post-combustion CO_2 capture process using neural networks. *Fuel*, 151, pp.156–163. [DOI]
Li, F., Zhang, J., Oko, E. and Wang, M., 2017. Modelling of a post-combustion CO_2 capture process using extreme learning machine. *International Journal of Coal Science & Technology*, 4, pp.33–40. [DOI]
Li, F., Zhang, J., Shang, C., Huang, D., Oko, E. and Wang, M., 2018. Modelling of a post-combustion CO_2 capture process using deep belief network. *Applied Thermal Engineering*, 130, pp.997–1003. [DOI]
Liang, J., Wu, Q. and Cao, R., 2021. Reticular frameworks and their derived materials for CO_2 conversion by thermo-catalysis. *EnergyChem*, 3, pp.100064. [DOI]
Lin, Q., Zhang, X., Wang, T., Zheng, C. and Gao, X., 2022. Technical perspective of carbon capture, utilization, and storage. *Engineering*, 14, pp.27–32. [DOI]
March, R., Doster, F. and Geiger, S., 2018. Assessment of CO_2 storage potential in naturally fractured reservoirs with dual-porosity models. *Water Resources Research*, 54, pp.1650–1668. [DOI]
Martin, C.F., Garcia, S., Pis, J.J., Rubiera, F. and Pevida, C., 2011. Doped phenol-formaldehyde resins as precursors for precombustion CO_2 capture adsorbents. *Energy Procedia*, 4, pp.1222–1227. [DOI]
Meesattham, S., Charoensiritanasin, P., Ongwattanakul, S., Liang, Z., Tontiwachwuthikul, P. and Sema, T., 2020. Predictions of equilibrium solubility and mass transfer coefficient for CO_2 absorption into aqueous solutions of 4-diethylamino-2-butanol using artificial neural networks. *Petroleum*, 6, pp.385–391. [DOI]
Meng, Y., Kuang, S., Liu, H., Fan, Q., Ma, X.B. and Zhang, S., 2021. Recent advances in electrochemical CO_2 reduction using copper-based catalysts. *Acta Phys.-Chim. Sin*., 37. [DOI]
Mohagheghian, E., Zafarian-Rigaki, H., Motamedi-Ghahfarrokhi, Y. and Hemmati-Sarapardeh, A., 2015. Using an artificial neural network to predict carbon dioxide compressibility factor at high pressure and temperature. *Korean Journal of Chemical Engineering*, 32, pp.2087–2096. [DOI]
Moss, M., Reed, D.G., Allen, R.W.K. and Styring, P., 2017. Integrated CO_2 capture and utilization using non-thermal plasmolysis. *Frontiers in Energy Research*, 5, pp.20. [DOI]
Park, S.H., Lee, S.J., Lee, J.W., Chun, S.N. and Lee, J. Bin, 2015. The quantitative evaluation of two-stage pre-combustion CO_2 capture processes using the physical solvents with various design parameters. *Energy*, 81, pp.47–55. [DOI]
Pouryousefi, F., Idem, R., Supap, T. and Tontiwachwuthikul, P., 2016. Artificial neural networks for accurate prediction of physical properties of aqueous quaternary systems of carbon dioxide (CO_2)-loaded 4-(Diethylamino)-2-butanol and Methyldiethanolamine blended with Monoethanolamine. *Industrial & Engineering Chemistry Research*, 55, pp.11614–11621. [DOI]
Priya, A.K., Devarajan, B., Alagumalai, A. and Song, H., 2023. Artificial intelligence enabled carbon capture: a review. *Science of the Total Environment*, 886, pp.163913. [DOI]
Raganati, F., Miccio, F. and Ammendola, P., 2021. Adsorption of carbon dioxide for post-combustion capture: a review. *Energy & Fuels*, 35, pp.12845–12868. [DOI]
Rahimi, N., Moradi, D., Sheibak, M., Moosavi, E. and Karimzadeh, R., 2016. The influence of modification methods on the catalytic cracking of LPG over lanthanum and phosphorus modified HZSM-5 catalysts. *Microporous and Mesoporous Materials*, 234, pp.215–223. [DOI]
Ringrose, P.S. and Meckel, T.A., 2019. Maturing global CO_2 storage resources on offshore continental margins to achieve 2DS emissions reductions. *Scientific Reports*, 9, pp.1–10. [DOI]
Ritchie, H. and Roser, M., 2024. Sector by sector: where do global greenhouse gas emissions come from? *Our World in Data,* 17, p.91.

Schiermeier, Q., 2018. Climate as culprit. *Nature*, 560, pp.20–22.
Seabra, G.S., Mücke, N.T., Silva, V.L.S., Voskov, D. and Vossepoel, F., 2024. AI enhanced data assimilation and uncertainty quantification applied to geological carbon storage. *International Journal of Greenhouse Gas Control*, 136, pp.104190. [DOI]
Shalaby, A., Elkamel, A., Douglas, P.L., Zhu, Q. and Zheng, Q.P., 2021. A machine learning approach for modeling and optimization of a CO_2 post-combustion capture unit. *Energy*, 215, pp.119113. [DOI]
Sipöcz, N., Tobiesen, F.A. and Assadi, M., 2011. The use of artificial neural network models for CO_2 capture plants. *Applied Energy*, 88, pp.2368–2376. [DOI]
Siqueira, R.M., Freitas, G.R., Peixoto, H.R., Do Nascimento, J.F., Musse, A.P.S., Torres, A.E.B., Azevedo, D.C.S., and Bastos-Neto, M., 2017. Carbon dioxide capture by pressure swing adsorption. *Energy Procedia*, 114, pp.2182–2192. [DOI]
Soong, Y., Goodman, A.L., McCarthy-Jones, J.R. and Baltrus, J.P., 2004. Experimental and simulation studies on mineral trapping of CO_2 with brine. *Energy Conversion and Management*, 45, pp.1845–1859. [DOI]
Spinti, J.P., Smith, P.J. and Smith, S.T., 2022. Atikokan Digital Twin: machine learning in a biomass energy system. *Applied Energy*, 310, pp.118436. [DOI]
Takht Ravanchi, M. and Sahebdelfar, S., 2014. Carbon dioxide capture and utilization in petrochemical industry: potentials and challenges. *Applied Petrochemical Research*, 4, pp.63–77. [DOI]
Tang, J., Lu, J., Li, J. and Wang, S., 2022. Study on adsorption characteristics of CO_2/H_2O. *Proceedings of the CSEE*, 42, pp.2216–2227.
Tantikhajorngosol, P., Laosiripojana, N., Jiraratananon, R. and Assabumrungrat, S., 2019. Physical absorption of CO_2 and H_2S from synthetic biogas at elevated pressures using hollow fiber membrane contactors: the effects of Henry's constants and gas diffusivities. *International Journal of Heat and Mass Transfer*, 128, pp.1136–1148. [DOI]
Wen, G., Li, Z., Azizzadenesheli, K., Anandkumar, A. and Benson, S.M., 2022. U-FNO—An enhanced Fourier neural operator-based deep-learning model for multiphase flow. *Advances in Water Resources*, 163, pp.104180. [DOI]
Wu, X., Shen, J., Wang, M. and Lee, K.Y., 2020. Intelligent predictive control of large-scale solvent-based CO_2 capture plant using artificial neural network and particle swarm optimization. *Energy*, 196, pp.117070. [DOI]
Yamada, H., 2021. Amine-based capture of CO_2 for utilization and storage. *Polymer Journal*, 53, pp.93–102. [DOI]
Yan, S., Chen, J., Ai, P., Wang, Y. and Zhang, Y., 2012. CO_2 removal from biogas by using membrane absorption technology. *Transactions of the Chinese Society of Agricultural Engineering*, 28, pp.196–204.
Zhang, H., Xue, K., Cheng, C., Gao, D. and Chen, H., 2021. Study on the performance of CO_2 capture from flue gas with ceramic membrane contactor. *Separation and Purification Technology*, 265, pp.118521. [DOI]
Zhang, X., Li, Y., Ma, Q. and Liu, L., 2021. Development of carbon capture, utilization and storage technology in China. *Strategic Study CAE*, 23, pp.70–80. [DOI]
Zhou, Q., Chan, C.W., Tontiwachiwuthikul, P., Idem, R. and Gelowitz, D., 2009. A statistical analysis of the carbon dioxide capture process. *International Journal of Greenhouse Gas Control*, 3, pp.535–544. [DOI]