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Review Research Paper

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 the industrial sector decarbonizing since it still contributes most to world greenhouse gas emissions and energy consumption. Reducing emissions from fossil fuel-based energy systems depends critically on carbon capture—especially post-combustion carbon capture (PCC). Absorption-based carbon capture (ACC) is the most developed and extensively applied of the PCC systems. But ACC systems are quite energy-intensive and need for major heating and cooling utilities, which increases running costs and makes large-scale adoption difficult. This paper investigates current developments in carbon capture technology and emphasizes artificial intelligence (AI) integration to handle optimization difficulties. More especially, it suggests an artificial intelligence-based approach for improving ACC system design and operation and utility consumption forecast. AI-driven solutions can promote scalable, reasonably priced carbon capture technologies by allowing accurate, fast assessments of technical and financial viability. This research emphasizes how artificial intelligence might hasten the shift toward more environmentally friendly industrial methods and significantly support world 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) projected that severe weather events had caused over 2 million fatalities and US$4.3 trillion in economic damages from 1970 to 202. Global warming and anthropogenic carbon emissions are widely acknowledged as the causes of the escalating frequency and severity of extreme weather events, even though 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, industry is the sector with the highest carbon emissions. Consequently, it is imperative and crucial to implement industry decarbonization to mitigate extreme weather events. Energy efficiency improvement, carbon capture, and hydrogen energy are some of the primary techniques for industrial decarbonization (Baker et al., 2018; Ritchie and Roser, 2024; Schiermeier, 2018).

Carbon emissions can be reduced by implementing strategies such as improving energy structure, electrification, decreasing excessive energy usage, and carbon sequestration. Carbon dioxide capture and storage (CCS) is a method that utilises pipeline transportation to extract carbon dioxide (CO_2) from the atmosphere or industrial waste gas and store 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 (X. Zhang et al., 2021). Nevertheless, its development is constrained by the high cost and the potential long-term environmental impact. In recent years, the field of CO_2 capture and utilisation (CCU) has garnered a growing interest as a result 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 summarises the relevant carbon dioxide capture and utilisation technologies concerning their features, benefits, and drawbacks. By capturing and using CO_2 gas on-site, the integrated carbon dioxide capture and utilisation (ICCU) system makes CO_2 use efficient and economical by lowering transportation and compression costs (Guo et al., 2023).

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	By combusting fuel with either pure oxygen or a combination of oxygen, the 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 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)

An essential part of carbon capture, use, and storage (CCUS) to reduce greenhouse gas emissions and meet climate objectives is geological carbon storage (GCS) (Ringrose and 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 operational globally by 2030, according to the International Energy Agency (IEA) (Lin et al., 2022). Because one of the biggest 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. This quantity of CO_2 increases as the global energy consumption increases to support our energy-intensive activities (Seabra et al., 2024). For the foreseeable future, fossil fuels will remain the primary source of energy in the globe, despite the grave environmental problems that are 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 the emission of carbon dioxide into the atmosphere.

Most carbon capture and storage methods involve either post-combustion carbon capture, oxyfuel combustion carbon capture, or pre-combustion carbon capture. The development and deployment of combustion systems that are suitable for their intended purpose are necessary for both pre-combustion and oxyfuel carbon capture (Al-Hamed and Dincer, 2022; Park et al., 2015). Alternatively, post-combustion carbon capture technology may be used to upgrade and modify already existing fossil-fuel burning facilities (Khalilpour, 2014). Thus, it may reduce emissions without replacing 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; H. Zhang et al., 2021).

This work develops 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 engineering models in a number of 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 work uses 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. Due to the tendency of fresh dual function material samples to absorb carbon dioxide and water from the surrounding air, it is often necessary to perform a pre-reduction step prior to the reaction (Bermejo-López et al., 2022). Initially, CO_2 is drawn in at a particular temperature until the adsorbent is fully absorbed. Second, the adsorbed CO_2 in the saturated materials interacts with hydrogen to form CH_4 when they are placed in a reducing environment. The integrated carbon dioxide capture and methanation procedure is primarily composed of this two-step process (Dongbo and Xiangwei, 2022). Carbon dioxide can be consistently captured and transformed in a single reactor throughout multiple cycles. The reaction exhibits favorable cyclic performance and can be conducted at a moderate temperature of approximately 300°C. This streamlines the procedure and improves energy efficiency. The integrated carbon dioxide capture and utilization (ICCU) technology has gained significant attention due to its ability to efficiently convert carbon dioxide into fuels, such as carbon, using dual-function materials. This approach delivers high efficiency with little energy usage by combining carbon dioxide adsorption and in-situ conversion (Guo et al., 2023). Table 2 represents the various reviews that have used ML within the ACC.

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 CO2; 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 CO2; 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	Forecasting the efficiency of CO2 capture	Flow rate of flue gas, pressure, temperature, and concentration of CO_2; flow rate and temperature of lean fluid; concentration	Efficiency in CO_2 capture	gPROMS	(Li et al., 2017)

combined neural network with a single layer neural network.		of MEA; and temperature of the reboiler			
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)

Carbon capture research is primarily focused on developing new methods to reduce the cost of CO_2 collection. Some of the methods used are coming up with new solvents, using catalysts to make old solvents stronger, applying artificial intelligence to the CO_2 capture process, and coming up with new ways to repair things. This session will thoroughly examine several approaches to determine the column height of the CO2 absorbent. Some of the methods that are used are empirical design, theoretical design, laboratory and pilot plant processes, and so on. This review is based on the idea of using AI to help catch CO_2. The coming together of many AI programs. The potential for AI-assisted CO_2 collecting is examined, along with the difficulties involved.

2. MATERIALS AND METHODS

2.1. A summary of the process of capturing carbon dioxide

Extensive research has been conducted on CO_2 capture systems, which are crucial in reducing industrial carbon emissions. Among the most significant contributors to carbon monoxide emissions are high-temperature industrial activities, which include 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 that has the greatest documented track record and is potentially economically viable. This technique involves the utilization of amine solvents that are aqueous in order to selectively absorb carbon monoxide from exhaust gasses (Raganati et al., 2021). In real time, intelligent control systems that make use of artificial intelligence are able to monitor membrane performance, identify fouling or degradation, and dynamically alter operating settings. Models that are driven by data also provide support for the selection of materials and the creation of hybrid systems (for example, coupling membranes with adsorption or absorption).

The procedure involves absorbing CO_2 from flue gas with an amine solvent and then separating the 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 it has been extracted (Yamada, 2021). The capture of CO_2 is essential in petrochemical activities, particularly in the production of ammonia, due to the significant volume of CO_2 emissions produced during the process (Takht Ravanchi and Sahebdelfar, 2014). It is common practice to implement this cycle process in large-scale industrial processes, such as the processing of natural gas and the manufacturing of ammonia, when the amount of carbon dioxide produced is significant. The solvent-based approach is frequently followed by the sorbent method. At present, fewer than a third of the processes are implemented 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 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 conduct a comprehensive selection and optimisation of these parameters to achieve the desired results. The subsequent discourse will provide a comprehensive examination of the diverse techniques for CO_2 capture, including membrane-based, adsorption, and absorption (Priya et al., 2023).

Adsorption is a relatively new alternative to absorption that offers a number of benefits similar to those of absorption, including reduced energy usage and simpler regeneration. Carbon monoxide molecules are able to attach themselves to the surface of a solid porous substance, which is referred to as an adsorbent, in this approach. Temperature, pressure, pore size, surface area, and adsorption kinetics are some of the key operating parameters that have a significant impact on performance. High CO_2 selectivity, rapid adsorption and desorption rates, mechanical durability, and economic viability for regeneration are only few of the characteristics that should be present in effective adsorbents (Abd et al., 2020). Systems that are based on absorption consume a significant amount of energy, particularly because of 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. It is possible to considerably improve the design and control of absorption systems in terms of energy efficiency and economic feasibility by utilizing AI-driven predictive modeling.

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 lets CO_2 flow over the system unhindered. The adsorbent grabs CO_2 through its surface. Once the balancing condition is reached, the duplicated adsorbent can be employed for the following one in CO_2 intake. Pressure swing adsorption is a technique that includes controlling pressure to improve both the absorption and desorption of CO_2 by the adsorbent, to separate CO_2 from a gas mixture. The technique will occur until the necessary amount of CO_2 removal is accomplished, at which point the gas mixture will exit the adsorbent bed with a decreased concentration of CO_2 (Siqueira et al., 2017). When optimizing adsorption processes, it is necessary to solve difficult problems that involve multiple variables. Modeling non-linear interactions among parameters, predicting breakthrough curves, and optimizing PSA cycle times and operating conditions are all possible with the help of artificial intelligence and machine learning techniques.

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

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

To optimize these variables, techniques based on artificial intelligence play a crucial role. This study highlights a growing corpus of work that employs artificial intelligence to enhance the scalability, responsiveness, and sustainability of carbon capture systems.

3. RESULTS AND DISCUSSIONS

3.1. Technologies for sequestering carbon

Deep-ground injection, ocean storage, and improved oil recovery (EOR) are main approaches of carbon sequestration (Alvarado and Manrique, 2010; Lemieux, 2011). Deep-ground injection involves using geological formations to store CO2, while ocean storage takes advantage of the vast carbon-absorbing capacity of the oceans. Enhanced oil recovery (EOR) combines CO_2 storage with the practical generation of energy. These several 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 located beneath the surface of the Earth. As a result of the intense pressure and temperature at extreme depths, the CO_2 frequently becomes supercritical, leading to improved storage efficiency because of its higher density (Bloom Energy, 2024). Trapping by structural means 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 the pore spaces, even if the structural trap is compromised (El-Maghraby and Blunt, 2013). Carbonic acid is produced when CO_2 dissolves in formation water during solubility trapping. This process also reduces buoyancy and leakage potential by re-acting 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 and forms stable carbonate minerals. This reaction occurs over a long period and helps to improve the long-term security of CO_2 storage (Soong et al., 2004). The longevity of this method's ability to store huge volumes of CO_2 is heavily contingent upon geological and technical conditions. The fissures in the rock, which might 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 stored CO_2.

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, 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	Robust to noise; handles missing data well	Less interpretable; can be slow for large datasets	(Chen et al., 2021)

	importance ranking			
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 benefits of multiple techniques for improved optimization	Complex to implement and validate	(Ehteram et al., 2021)

3.2. AI-based carbon capture applications

As computer technology has improved significantly over the last two decades, numerical simulation of processes has grown in importance and popularity across a wide range of engineering and academic disciplines. Many researchers are presently investigating artificial intelligence (AI) technologies, namely machine learning approaches, because of their potential as attractive alternative solutions (Alabdraba et al., 2017). Significant post-combustion CO_2 collecting 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 meant to enhance the CO_2 capture mechanism (Chan and Chan, 2017). Artificial neural networks or ANN are one of the widely utilized and popular techniques of artificial intelligence applied for mass transfer and property prediction in the CO_2 capture process; this can be due to several factors. Quick formulation of the ANN predictive models including several parameters is possible. They possess a great degree of adaptability and often yield more accurate outcomes compared to numerical simulations and correlations (Li et al., 2015). The ANN method is briefly introduced as follows. Fig. 1 shows the smart carbon capture technologies and its utilization.

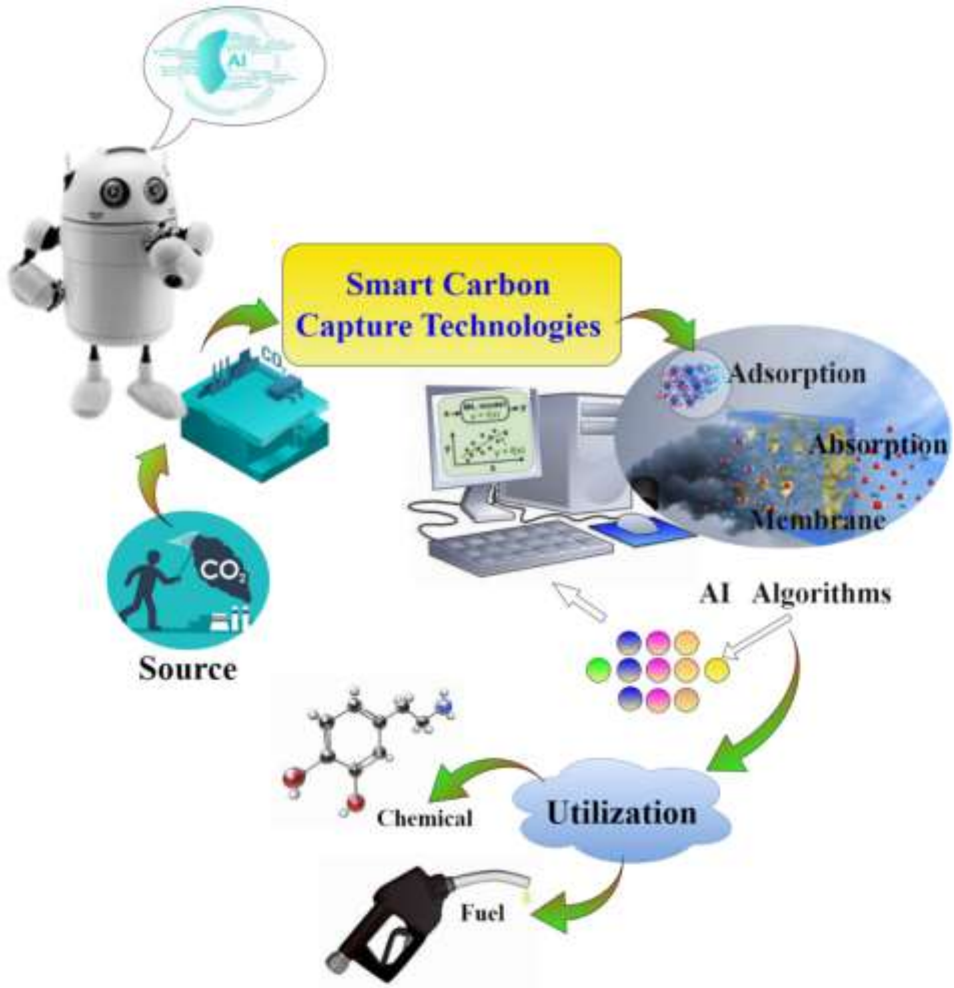

Fig. 1: Smart carbon capture technologies and utilisation

In its input and output data, an Artificial Neural Network (ANN) model can display both linear and non-linear relationships (Fu et al., 2014). The network has many processing units that work at the same time 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 are fully coupled to every neuron in the hidden layer. The following formula can be used to determine each neuron's output (yj). Functions such as sigmoid, piecework linear, radial basis, and Gaussian are among the many activation or transfer functions. (Adeyemi et al., 2018). Utilising either the sigmoid or hyperbolic functions as the concealed activation mechanism, the multilayer perceptron is the most frequently employed feedforward neural network (Chan and Chan, 2017). AI applications in CO_2 capture now encounter a number of significant constraints:

- For CO_2 capture procedures at the plant size, 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.

3.3. AI's application to physical attributes and solubility

The physical and chemical properties of CO_2 and amines, such as their viscosity, density, heat capacity, rate of reaction, diffusivity, and conductivity, can substantially influence the efficiency and effectiveness of the carbon capture process in CCS (Tantikhajorngosol et al., 2019). The properties are frequently utilized in the process simulations of the CO_2 capture process and are necessary for the calculation of heat duty. The properties' values are frequently determined by measuring them in a laboratory environment with costly instruments (Pouryousefi et al., 2016). However, the experiments and the collection of experimental sample data require a high level of expertise and a comprehensive understanding of the process. The process of capturing data 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 a simpler way to find the values of the features than the experimental technique (Fu et al., 2014; Mohagheghian et al., 2015). However, there are several downsides to the modeling technique, including: (i) The correlations can't capture the non-linear 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 the models and numerical simulations are correct, (iv) it might take a lot of computing power to come up with the solutions, (v) there's a chance that the models and simulations made for certain conditions won't work outside of those parameters, and (vi) The unfavorable characteristics of gases and amines might complicate computations relying on correlations (Bahadori and Mokhatab, 2008; Zhou et al., 2009). Many studies have proposed using 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 and 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 are capable of giving 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 solutions of TBAB was predicted using RBFNN and ANFIS (Hoseinpour et al., 2018). The CO_2 solubility served as the end parameter; mass, mole percent of TBAB, temperature, and pressure were the study's inputs. Accuracy of the AI models' predictions was confirmed using statistical and graphical analytic 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 genetic algorithm with least square support vector machine (GA-LSSVM) enabled precise predictions of hydrocarbon solubility in water (Helei et al., 2021).

3.4. AI application for CO_2 mass transfer

For designing, simulating, and improving the CO_2 collection process, it is especially important to get accurate measurements of the rate of mass transfer. Over the past fifteen years, experts have looked into how artificial intelligence (AI) can be used to copy the process of moving mass and test how well CO_2 can be captured. The purpose of this study is to come up with accurate and reliable estimates of how fast mass moves (Meesattham et al., 2020). Predicting properties like CO_2 concentration, temperature, heat duty, and removal efficiency is a common focus in these applications. In contrast, the CO_2 collection process's conditions are the input predictors (Afkhamipour and Mofarahi, 2016; Fu et al., 2014). The research comprised of 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 handle weird data that doesn't fit in with the training samples. Moreover, the tests produced a limited sample of data that accurately represents the population. Here are some instances of sample investigations. The current research states that hybrid models integrating experimental and simulation datasets have improved the prediction of CO_2 transfer coefficients. To illustrate the point, accurate estimates of total mass transfer rates in absorber columns have been achieved by estimating Sherwood and Reynolds numbers using ANN+PSO models (Hoseinpour et al., 2018).

3.5. The potential and difficulties of AI-assisted carbon capture

An estimated 53 gigatonnes of CO_2 equivalent of 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 temperatures to 1.5 °C. By the conclusion of this decade, emissions must be diminished by 50% in order 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 giga tonnes of CO_2 equivalent (Degot et al., 2021). An important advantage of AI-assisted carbon capture is its ability to significantly decrease the expense 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 while being efficient and cost-effective. AI-assisted CO_2 capture enhances the reliability and accuracy of the CO_2 capture system. Artificial intelligence algorithms are capable of observing and evaluating the operation of CO_2 extraction devices, and they can make immediate adjustments to enhance efficiency. This can reduce the likelihood of costly malfunctions and guarantee the system's ongoing functionality. A novel AI-based instrument has been 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. The Fourier neural operator-based deep-learning model, a unique neural operator architecture, was employed to efficiently mimic 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 lab, but practical implementations have been slow to materialize. Compact carbon capture systems assisted by artificial intelligence have been created 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, have invested in direct air capture (DAC) systems that are powered by artificial intelligence (AI). The shift from AI models in labs to real-world control systems in manufacturing is illustrated by these examples (Allam et al., 2017).

3.6. 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. In their study, 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 the training and validation of the ANN. 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 may be used as predictors. The anticipated or resulting parameters were: (i) the pace at which CO_2 was caught, (ii) the amount of CO_2 absorbed, and (iii) the amount of heat required for the operation. The investigation used the LM and Scaled Conjugate Gradient (CG) algorithms to improve the accuracy of the predictions. The study found that the LM approach produced the most accurate forecasts for all three parameters. Pre-designing a power plant that could capture CO_2 relied on these anticipated values (Aliyon et al., 2023). Figure 1 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 CO_2 capture strategies in a comprehensive manner.
- Artificial intelligence for multi-objective optimization: little is known about how to optimise cost, energy, emissions, and operability all at once.

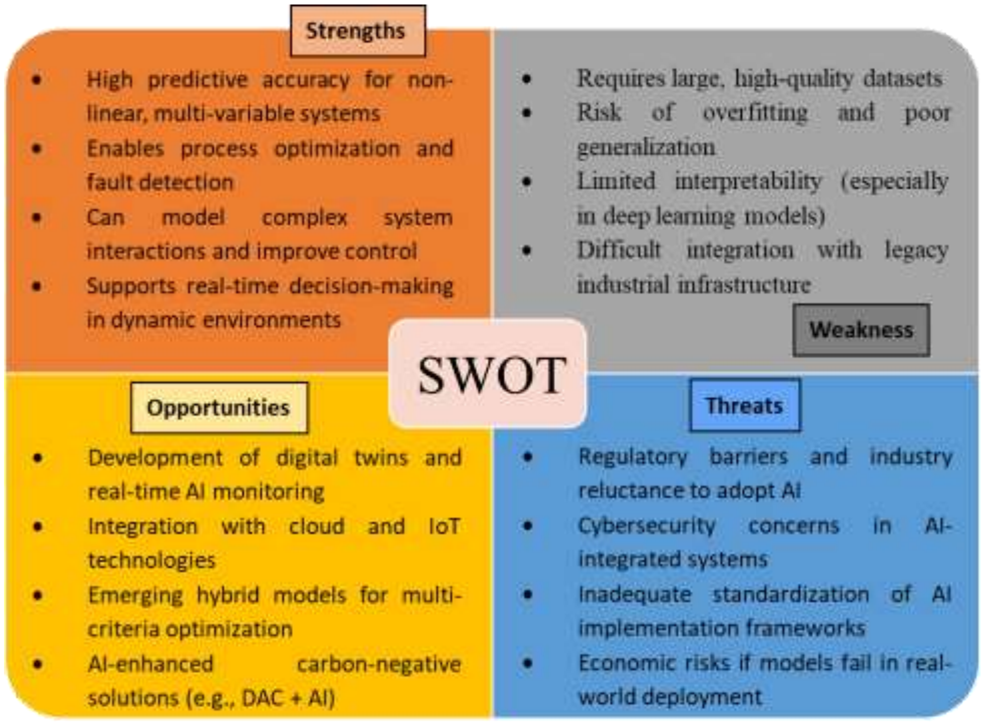

Fig. 2: SWOT Analysis: AI Applications in CO_2 Capture Technologies

4. Conclusion

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, helping with design and PCC technology optimization is the artificial intelligence technology. There is a substantial need for additional study in the area of using artificial intelligence to PCC. Hence, it is imperative to foster collaboration between PCC specialists and AI researchers to advance research in this field. This study utilizes 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 operations. Furthermore, studies suggest that specific models exhibit superior performance when provided with a limited number of data points, while other models outperform others when given a reduced number of input sets. Based on the data that is now accessible, one model may exhibit more superiority compared to the other. The economic viability of carbon capture technologies is on the rise. It is imperative to evaluate the most efficient and viable technology to minimize CO_2 emissions and achieve optimal CO_2 removal, taking into account economic and energy considerations. Furthermore, optimal outcomes can be attained by integrating a diverse range of machine and deep learning models with hybrid models. As technological advancements progress, artificial intelligence techniques are likely to offer advantages in the field of CO_2 capture. Artificial intelligence models possess the capacity to produce accurate outcomes by leveraging their capability to estimate variables and acquire knowledge from data. Despite the growing use of these algorithms in current research, further work is needed 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 example of such a system. 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, thus maximizing efficiency.

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

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Conflicts of Interest

The authors declare no conflict of interest.

REFERENCES

Abd, A.A., Naji, S.Z., Hashim, A.S., Othman, M.R., 2020. Carbon dioxide removal through physical adsorption using carbonaceous and non-carbonaceous adsorbents: a review. J. Environ. Chem. Eng. 8, 104142. https://doi.org/10.1016/j.jece.2020.104142

Adamczyk, K., Prémont-Schwarz, M., Pines, D., Pines, E., Nibbering, E.T.J., 2009. Real-time observation of carbonic acid formation in aqueous solution. Science (80-.). 326, 1690–1694. https://doi.org/10.1126/science.1180060

Adeyemi, I., Abu-Zahra, M.R.M., AlNashef, I.M., 2018. Physicochemical properties of alkanolaminecholine chloride deep eutectic solvents: Measurements, group contribution and artificial intelligence prediction techniques. J. Mol. Liq. 256, 581–590. https://doi.org/10.1016/j.molliq.2018.02.085

Afkhamipour, M., Mofarahi, M., 2016. Modeling and optimization of CO2 capture using 4-diethylamino-2-butanol (DEAB) solution. Int. J. Greenh. gas Control 49, 24–33. https://doi.org/10.1016/j.ijggc.2016.02.019

Akinola, T.E., Prado, P.L.B., 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. Appl. Energy 317, 119156. https://doi.org/10.1016/j.apenergy.2022.119156

Al-Hamed, K.H.M., 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, 123814. https://doi.org/10.1016/j.energy.2022.123814

Alabdraba, W.M.S., Arslan, C.A., 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. Trans. Mach. Learn. Artif. Intell. 5, 47. https://doi.org/10.14738/tmlai.55.3511

Aliyon, K., Mehrpooya, M., Hajinezhad, A., 2020. Comparison of different CO2 liquefaction processes and exergoeconomic evaluation of integrated CO2 liquefaction and absorption refrigeration system. Energy Convers. Manag. 211, 112752. https://doi.org/10.1016/j.enconman.2020.112752

Aliyon, K., Rajaee, F., Ritvanen, J., 2023. Use of artificial intelligence in reducing energy costs of a post-combustion carbon capture plant. Energy 278, 127834. https://doi.org/10.1016/j.energy.2023.127834

Alvarado, V., Manrique, E., 2010. Enhanced oil recovery: an update review. Energies 3, 1529–1575. https://doi.org/10.3390/en3091529

Arif, M., Barifcani, A., Lebedev, M., Iglauer, S., 2016. Structural trapping capacity of oil-wet caprock as a function of pressure, temperature and salinity. Int. J. Greenh. Gas Control 50, 112–120. https://doi.org/10.1016/j.ijggc.2016.04.024

Baghban, A., Ahmadi, M.A., Shahraki, B.H., 2015. Prediction carbon dioxide solubility in presence of various ionic liquids using computational intelligence approaches. J. Supercrit. Fluids 98, 50–64. https://doi.org/10.1016/j.supflu.2015.01.002

Bahadori, A., Mokhatab, S., 2008. Estimating Thermal Conductivity of Hydrocarbons. Chem. Eng. 115.

Baker, H.S., Millar, R.J., Karoly, D.J., Beyerle, U., Guillod, B.P., Mitchell, D., Shiogama, H., Sparrow, S., Woollings, T., Allen, M.R., 2018. Higher CO2 concentrations increase extreme event risk in a 1.5 C world. Nat. Clim. Chang. 8, 604–608. https://doi.org/10.1038/s41558-018-0190-1

Bellprat, O., Guemas, V., Doblas-Reyes, F., Donat, M.G., 2019. Towards reliable extreme weather and climate event attribution. Nat. Commun. 10, 1732. https://doi.org/10.1038/s41467-019-09729-2

Bermejo-López, A., Pereda-Ayo, B., Onrubia-Calvo, J.A., González-Marcos, J.A., González-Velasco, J.R., 2022. Tuning basicity of dual function materials widens operation temperature window for efficient CO2 adsorption and hydrogenation to CH4. J. CO2 Util. 58, 101922.https://doi.org/10.1016/j.jcou.2022.101922

Blake, O.O., Faulkner, D.R., Worden, R.H., Armitage, P.J., Espie, A.A., 2022. Effect of thermal shock on the permeability and seismic wave velocity of the caprock and reservoir during CO2 injection. Int. J. Greenh. Gas Control 118, 103691. https://doi.org/10.1016/j.ijggc.2022.103691

Bloom Energy, 2024. Carbon Capture Technology for Carbon Capture and Sequestration 13. https://doi.org/10.1016/j.ccst.2024.100257

Chan, V., Chan, C., 2017. Learning from a carbon dioxide capture system dataset: Application of the piecewise neural network algorithm. Petroleum 3, 56–67. https://doi.org/10.1016/j.petlm.2016.11.004

Chao, C., Deng, Y., Dewil, R., Baeyens, J., Fan, X., 2021. Post-combustion carbon capture. Renew. Sustain. Energy Rev. 138, 110490. https://doi.org/10.1016/j.rser.2020.110490

Chegari, B., Tabaa, M., Simeu, E., Moutaouakkil, F., Medromi, H., 2022. An optimal surrogate-model-based approach to support comfortable and nearly zero energy buildings design. Energy 248, 123584.https://www.sciencedirect.com/science/article/pii/S036054422200487X

Cotterill, D., Stott, P., Christidis, N., Kendon, E., 2021. Increase in the frequency of extreme daily precipitation in the United Kingdom in autumn. Weather Clim. Extrem. 33, 100340.https://doi.org/10.1016/j.wace.2021.100340

Degot, C., Duranton, S., Frédeau, M., Hutchinson, R., 2021. Reduce Carbon and Costs with the Power of AI. Bost. Consult. Gr.https://www.bcg.com/publications/2021/ai-to-reduce-carbon-emissions

Dongbo, Z.H.U., Xiangwei, Z., 2022. Research on the environmental effect of digital finance development in China and its influence mechanism. Collect. Essays Financ. Econ. 38, 37.

El-Maghraby, R.M., Blunt, M.J., 2013. Residual CO2 trapping in Indiana limestone. Environ. Sci. Technol. 47, 227–233. https://pubs.acs.org/doi/10.1021/es304166u

Fu, K., Chen, G., Liang, Z., Sema, T., Idem, R., Tontiwachwuthikul, P., 2014. Analysis of mass transfer performance of monoethanolamine-based CO2 absorption in a packed column using artificial neural networks. Ind. Eng. Chem. Res. 53, 4413–4423. https://pubs.acs.org/doi/abs/10.1021/ie403259g

Garg, S., Shariff, A.M., Shaikh, M.S., Lal, B., Suleman, H., Faiqa, N., 2017. Experimental data, thermodynamic and neural network modeling of CO2 solubility in aqueous sodium salt of l-phenylalanine. J. CO2 Util. 19, 146–156. https://doi.org/10.1016/j.jcou.2017.03.011

Gu, M., Zhang, B., Qi, Z., Liu, Z., Duan, S., Du, X., Xian, X., 2015. Effects of pore structure of granular activated carbons on CH4 enrichment from CH4/N2 by vacuum pressure swing adsorption. Sep. Purif. Technol. 146, 213–218. https://doi.org/10.1016/j.seppur.2015.03.051

GUO, Z., BIAN, X., DU, Y., ZHANG, W., YAO, D., YANG, H., 2023. Recent advances in integrated carbon dioxide capture and methanation technology. J. Fuel Chem. Technol. 51, 293–302. https://doi.org/10.1016/S1872-5813(22)60048-3

Guo, Z.L., Bian, X.L., Du, Y.B., Zhang, W.C., Yao, D.D., Yang, H.P., 2023. Recent advances in integrated carbon dioxide capture and methanation technology. Ranliao Huaxue Xuebao/Journal Fuel Chem. Technol. 51, 293–303. https://doi.org/10.1016/S1872-5813(22)60048-3

Helei, L., Tantikhajorngosol, P., Chan, C., Tontiwachwuthikul, P., 2021. Technology development and applications of artificial intelligence for post-combustion carbon dioxide capture: Critical literature review and perspectives. Int. J. Greenh. Gas Control 108, 103307. https://doi.org/10.1016/j.ijggc.2021.103307

Hoseinpour, S., Barati-Harooni, A., Nadali, P., Mohebbi, A., Najafi-Marghmaleki, A., Tatar, A., Bahadori, A., 2018. Accurate model based on artificial intelligence for prediction of carbon dioxide solubility in aqueous tetra-n-butylammonium bromide solutions. J. Chemom. 32, e2956. https://doi.org/10.1002/cem.2956

Ishaq, H., Siddiqui, O., Chehade, G., Dincer, I., 2021. A solar and wind driven energy system for hydrogen and urea production with CO2 capturing. Int. J. Hydrogen Energy 46, 4749–4760.https://doi.org/10.1016/j.ijhydene.2020.01.208

Jain, P., Castellanos-Acuna, D., Coogan, S.C.P., Abatzoglou, J.T., Flannigan, M.D., 2022. Observed increases in extreme fire weather driven by atmospheric humidity and temperature. Nat. Clim. Chang. 12, 63–70.https://doi.org/10.1038/s41558-021-01224-1

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, 172–186.https://doi.org/10.1016/j.energy.2013.10.086

Lemieux, J.-M., 2011. The potential impact of underground geological storage of carbon dioxide in deep saline aquifers on shallow groundwater resources. Hydrogeol. J. 19, 757.https://doi.org/10.1007/s10040-011-0715-4

Li, A.G., West, A.C., Preindl, M., 2022. Towards unified machine learning characterization of lithium-ion battery degradation across multiple levels: A critical review. Appl. Energy 316, 119030. https://doi.org/10.1016/j.apenergy.2022.119030

Li, F., Zhang, J., Oko, E., Wang, M., 2017. Modelling of a post-combustion CO 2 capture process using extreme learning machine. Int. J. Coal Sci. Technol. 4, 33–40.https://doi.org/10.1007/s40789-017-0158-1

Li, F., Zhang, J., Oko, E., Wang, M., 2015. Modelling of a post-combustion CO2 capture process using neural networks. Fuel 151, 156–163.https://doi.org/10.1016/j.fuel.2015.02.038

Li, F., Zhang, J., Shang, C., Huang, D., Oko, E., Wang, M., 2018. Modelling of a post-combustion CO2 capture process using deep belief network. Appl. Therm. Eng. 130, 997–1003.https://doi.org/10.1016/j.applthermaleng.2017.11.078

Liang, J., Wu, Q., Cao, R., 2021. Reticular frameworks and their derived materials for CO2 conversion by thermo− catalysis. EnergyChem 3, 100064.https://doi.org/10.1016/j.enchem.2021.100064

Lin, Q., Zhang, X., Wang, T., Zheng, C., Gao, X., 2022. Technical perspective of carbon capture, utilization, and storage. Engineering 14, 27–32.https://doi.org/10.1016/j.eng.2021.12.013

March, R., Doster, F., Geiger, S., 2018. Assessment of CO2 storage potential in naturally fractured reservoirs with dual-porosity models. Water Resour. Res. 54, 1650–1668. http://dx.doi.org/10.1002/2017WR022159

Martin, C.F., Garcia, S., Pis, J.J., Rubiera, F., Pevida, C., 2011. Doped phenol-formaldehyde resins as precursors for precombustion CO2 capture adsorbents. Energy Procedia 4, 1222–1227.https://doi.org/10.1016/j.egypro.2011.01.177

Meesattham, S., Charoensiritanasin, P., Ongwattanakul, S., Liang, Z., Tontiwachwuthikul, P., Sema, T., 2020. Predictions of equilibrium solubility and mass transfer coefficient for CO2 absorption into aqueous solutions of 4-diethylamino-2-butanol using artificial neural networks. Petroleum 6, 385–391.https://doi.org/10.1016/j.petlm.2018.09.005

Meng, Y., Kuang, S., Liu, H., Fan, Q., Ma, X.B., Zhang, S., 2021. Recent advances in electrochemical CO2 reduction using copper-based catalysts. Acta Phys.-Chim. Sin. 37.https://doi.org/10.3866/PKU.WHXB202006034

Mohagheghian, E., Zafarian-Rigaki, H., Motamedi-Ghahfarrokhi, Y., Hemmati-Sarapardeh, A., 2015. Using an artificial neural network to predict carbon dioxide compressibility factor at high pressure and temperature. Korean J. Chem. Eng. 32, 2087–2096.https://doi.org/10.1007/s11814-015-0025-y

Moss, M., Reed, D.G., Allen, R.W.K., Styring, P., 2017. Integrated CO2 capture and utilization using non-thermal plasmolysis. Front. Energy Res. 5, 20.https://doi.org/10.3389/fenrg.2017.00020

Park, S.H., Lee, S.J., Lee, J.W., Chun, S.N., Lee, J. Bin, 2015. The quantitative evaluation of two-stage pre-combustion CO2 capture processes using the physical solvents with various design parameters. Energy 81, 47–55.https://doi.org/10.1016/j.energy.2014.10.055

Pouryousefi, F., Idem, R., Supap, T., Tontiwachwuthikul, P., 2016. Artificial neural networks for accurate prediction of physical properties of aqueous quaternary systems of carbon dioxide (CO2)-loaded 4-(Diethylamino)-2-butanol and Methyldiethanolamine blended with Monoethanolamine. Ind. Eng. Chem. Res. 55, 11614–11621.https://pubs.acs.org/doi/abs/10.1021/acs.iecr.6b03018

Priya, A.K., Devarajan, B., Alagumalai, A., Song, H., 2023. Artificial intelligence enabled carbon capture: A review. Sci. Total Environ. 886, 163913. https://doi.org/10.1016/j.scitotenv.2023.163913

Raganati, F., Miccio, F., Ammendola, P., 2021. Adsorption of carbon dioxide for post-combustion capture: a review. energy & fuels 35, 12845–12868.https://pubs.acs.org/doi/10.1021/acs.energyfuels.1c01618

Rahimi, N., Moradi, D., Sheibak, M., Moosavi, E., Karimzadeh, R., 2016. The influence of modification methods on the catalytic cracking of LPG over lanthanum and phosphorus modified HZSM-5 catalysts. Microporous Mesoporous Mater. 234, 215–223.https://doi.org/10.1016/j.micromeso.2016.07.010

Ringrose, P.S., Meckel, T.A., 2019. Maturing global CO2 storage resources on offshore continental margins to achieve 2DS emissions reductions. Sci. Rep. 9, 1–10.https://doi.org/10.1038/s41598-019-54363-z

Ritchie, H., Roser, M., 2024. Sector by sector: where do global greenhouse gas emissions come from? Our world data. https://ourworldindata.org/ghg-emissions-by-sector

Schiermeier, Q., 2018. Climate as culprit. Nature 560, 20–22.

Seabra, G.S., Mücke, N.T., Silva, V.L.S., Voskov, D., Vossepoel, F., 2024. AI enhanced data assimilation and uncertainty quantification applied to Geological Carbon Storage. Int. J. Greenh. Gas Control 136, 104190. https://doi.org/10.1016/j.ijggc.2024.104190

Shalaby, A., Elkamel, A., Douglas, P.L., Zhu, Q., Zheng, Q.P., 2021. A machine learning approach for modeling and optimization of a CO2 post-combustion capture unit. Energy 215, 119113. https://doi.org/10.1016/j.energy.2020.119113

Sipöcz, N., Tobiesen, F.A., Assadi, M., 2011. The use of artificial neural network models for CO2 capture plants. Appl. Energy 88, 2368–2376. https://doi.org/10.1016/j.apenergy.2011.01.013

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., Bastos-Neto, M., 2017. Carbon dioxide capture by pressure swing adsorption. Energy Procedia 114, 2182–2192. https://doi.org/10.1016/j.egypro.2017.03.1355

Soong, Y., Goodman, A.L., McCarthy-Jones, J.R., Baltrus, J.P., 2004. Experimental and simulation studies on mineral trapping of CO2 with brine. Energy Convers. Manag. 45, 1845–1859. https://doi.org/10.1016/j.enconman.2003.09.029

Spinti, J.P., Smith, P.J., Smith, S.T., 2022. Atikokan Digital Twin: Machine learning in a biomass energy system. Appl. Energy 310, 118436. https://doi.org/10.1016/j.apenergy.2021.118436

Takht Ravanchi, M., Sahebdelfar, S., 2014. Carbon dioxide capture and utilization in petrochemical industry: potentials and challenges. Appl. Petrochemical Res. 4, 63–77. https://doi.org/10.1007/s13203-014-0050-5

Tang, J., Lu, J., Li, J., Wang, S., 2022. Study on adsorption characteristics of CO2/H2O. Proc CSEE 42, 2216–2227.

Tantikhajorngosol, P., Laosiripojana, N., Jiraratananon, R., Assabumrungrat, S., 2019. Physical absorption of CO2 and H2S from synthetic biogas at elevated pressures using hollow fiber membrane contactors: The effects of Henry's constants and gas diffusivities. Int. J. Heat Mass Transf. 128, 1136–1148.https://doi.org/10.1016/j.ijheatmasstransfer.2018.09.076

Wen, G., Li, Z., Azizzadenesheli, K., Anandkumar, A., Benson, S.M., 2022. U-FNO—An enhanced Fourier neural operator-based deep-learning model for multiphase flow. Adv. Water Resour. 163, 104180.

https://doi.org/10.1016/j.advwatres.2022.104180

Wu, X., Shen, J., Wang, M., Lee, K.Y., 2020. Intelligent predictive control of large-scale solvent-based CO2 capture plant using artificial neural network and particle swarm optimization. Energy 196, 117070. https://doi.org/10.1016/j.energy.2020.117070

Yamada, H., 2021. Amine-based capture of CO2 for utilization and storage. Polym. J. 53, 93–102.https://doi.org/10.1038/s41428-020-00400-y

Yan, S., Chen, J., Ai, P., Wang, Y., Zhang, Y., 2012. CO2 removal from biogas by using membrane absorption technology. Trans. Chinese Soc. Agric. Eng. 28, 196–204.

Zhang, H., Xue, K., Cheng, C., Gao, D., Chen, H., 2021. Study on the performance of CO2 capture from flue gas with ceramic membrane contactor. Sep. Purif. Technol. 265, 118521.https://doi.org/10.1016/j.seppur.2021.118521

Zhang, X., Li, Y., Ma, Q., Liu, L., 2021. Development of carbon capture, utilization and storage technology in China. Strateg. Study CAE 23, 70–80. https://doi.org/10.15302/J-SSCAE-2021.06.004

Zhou, Q., Chan, C.W., Tontiwachiwuthikul, P., Idem, R., Gelowitz, D., 2009. A statistical analysis of the carbon dioxide capture process. Int. J. Greenh. Gas Control 3, 535–544.https://doi.org/10.1016/j.ijggc.2009.02.007