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Status and Prospects of Carbon Capture Strategy in fossil Power Plants: An updated Review (2010-2020)

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Abstract
Minimizing carbon dioxide emissions from fossil fuel power plants has been a key environmental issue for decades. To avoid the negative impact of greenhouse gases on the environment, many parts of the world are gradually turning to low-carbon energy systems, which makes it necessary to meet the increasing energy demand, upgrade existing power plants and avoid high construction costs of new power generation facilities. The use of carbon capture and storage (CCS) technology to retrofit existing coal-fired power plants is seen as a promising and cost-effective solution to alleviate global warming. However, the effective use of CCS requires extensive modeling, optimization, and cost-benefit evaluation of the outputs of retrofitting plants. Machine learning models have been widely used to accurately estimate and optimize key performance outputs that are difficult to obtain from physical measurements. From an implementation point of view, applying these models to power plant retrofits is still a challenging task. This article systematically reviews the latest knowledge of machine learning tools, their application progress and limitations in CCS simulation.

Keywords. *Carbon capture and storage, fossil power plant retrofitting, machine learning, energy generating facilities*

1. INTRODUCTION

Despite rapid development in renewable energy, fossil fuel power plants (FFPPs) have occupied as large as 64.1% of global electricity consumption in 2018 (IEA, 2021). This trend will increase as new FFPPs are been constructed and may continue to serve for another three to four decades (IEA, 2021). High energy demands for a relatively cheap, affordable and flexible energy source, lead to heavy reliance on fossil-fuel fired power plants (See Figure 1). Moreover, the proven economically recoverable global coal reserves are estimated to last for about 150 years, indicates that coal will remain a major energy source now and in the foreseeable future (Wu et al., 2010; Osei et al., 2017; EIA, 2021). However, the combustion of fossil fuel in power generation plants and various industrial processes has produced a huge amount of greenhouse gases, particularly CO_2 which accounted for approximately 70% of global warming (Manaf et al., 2016; Wu et al., 2010). According to IEA (2018), coal-fired power plants emit twice as much carbon dioxide per unit of electricity as natural gas.

With increasing environmental concerns, the reduction of greenhouse gas emissions for coal-fired power plants has become a major concern threatening global industrialization and urbanization (Wu et al., 2010; Sharma et al., 2019). Although coal-fired power plants have a greater impact on climatic change than any other fossil fuel, shutting the facilities down would not be a practical solution (Osei et al., 2017). In this sense, carbon capture and storage (CCS) can be utilized as a practical and sustainable solution in reducing carbon dioxide emissions. The main approaches employed to capture CO_2 include pre-combustion, post-combustion capture (PCC), and oxy-combustion (Mores et al., 2012; Kenarsar et al., 2013). In post-combustion carbon dioxide capture, the carbon dioxide is absorbed and separated from other flue gas components. While the carbon in the fuel is separated before combustion in the case of pre-combustion carbon dioxide capture (Baghban et al., 2015).

Among these technologies, post-combustion carbon capture (PCC) with amine-based chemical absorption is the most commercially available technology in retrofitting traditional fossil-fired power plants. Post-Combustion Carbon Capture is easier to integrate into the existing plant without substantially changing the configuration technology of the plant. Again, it is flexible as its maintenance does not stop the operation of the power plant and it can be controlled. Conversely, thermal energy for regeneration involved is usually obtained from extracted steam from the low-pressure steam turbines, which in turn reduces the efficiency of the coal-fired power plant. Therefore, it is necessary to compromise between CO_2 capture level and energy consumption through process optimization while improving efficiency and reducing the cost of CO_2 capture. To perform optimization, it is required to develop an accurate model for the post-combustion carbon capture process through mechanistic and statistical models, or machine learning (ML) based model techniques. Many studies (Chen et al., 2021; Wu et al., 2010; Ben-Mansour et al., 2016; Liang et al., 2015; Li et al., 2015; Zhou et al., 2010) have recognized ML techniques as the most powerful tool in complex process modelling to coordinate the couplings between carbon and electricity for achieving low-carbon energy systems.

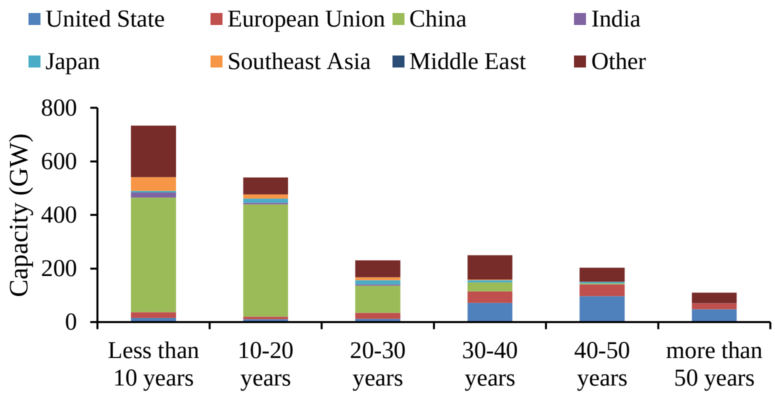

Figure 1 Age structure of existing power capacity by region (EIA, 2018)

Over the past 10 years, there has been significant progress in the development of ML simulation for the post-combustion carbon capture (PCC) technology. A systematic Literature Review (SLR) approach was chosen for its ability to offer high quality and well-defined transparent approach for identifying, evaluating, and summarizing the findings from large quantities of resources. Thus, this review aims to systematically extract relevant contributions of machine learning modeling techniques of CCS in FFPPs in the form of research questions:

(i) What are the current ML models used in CCS simulation and optimization?
(ii) What are the performance measures for rating the effectiveness of ML techniques in CCS ML?
(iii) What are the ML limitations identified in the last decades?

2. METHODOLOGY

A systematic review was conducted based on Xiao and Watson (2019) framework shown in Figure 2. The framework involves sequential steps of literature search, analyzing and synthesizing the findings. A deep search of the major electronic databases (Google Scholar, Sage, Science Direct, Scopus, and Web of Science) was conducted to identify studies reporting on the application of machine learning in simulation and optimization of carbon capture processes of FFPPs. Then, the search of these keywords (Carbon capture and storage, fossil power plant, machine learning, retrofitting, artificial intelligence, Artificial Intelligence, AI, Machine Learning, ML, deep learning, DL) either in the title, abstract, or keywords only in peer-reviewed journals were selected for this systematic review (See Figure 3). Articles published over the past decade were selected using keywords 396 records relevant articles were further identified from the database via repeated search processes.

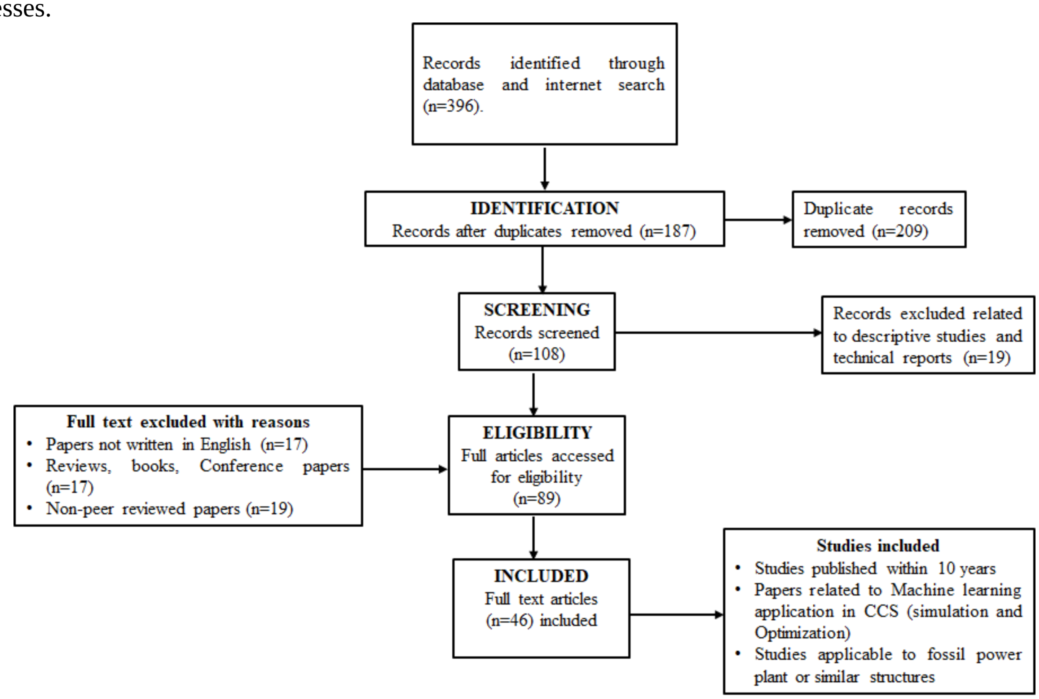

Figure 2 Systematic Review Flowchart

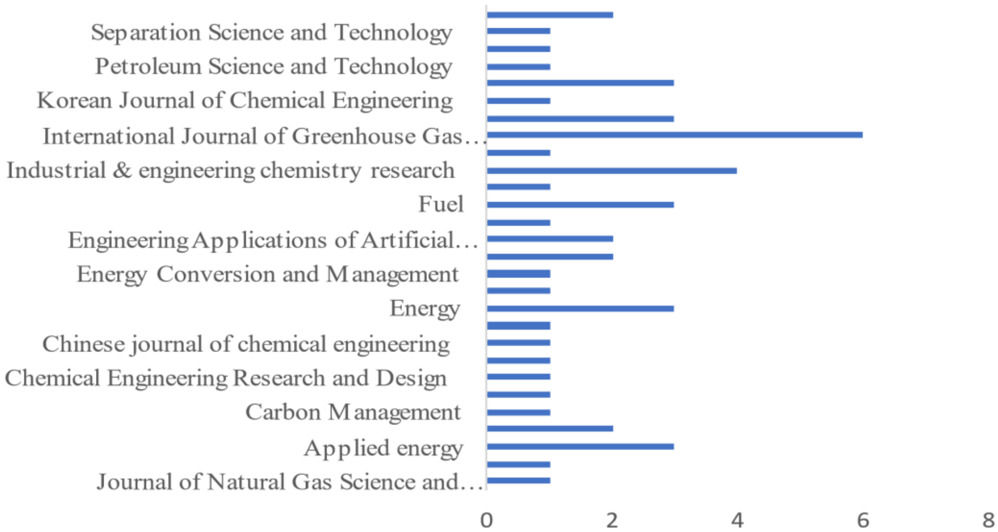

Figure 3 Frequency of Publications in Top Journals

In total, 187 articles were extracted and exported to EndNote software according to exclusion criteria. These articles were screened twice by authors independently. First, 209 duplicate articles were removed. After screening, 53 articles were discarded, the full-text of the refined list (46 articles) was screened to finalize eligible articles that complied with the specified inclusion criteria (see Fig 2). Data extracted from the selected studies were summarized in the form tables. The tabulated information included authors, year of publication, ML models adopted, and key findings were presented in the next section.

Table 1 Typical Literature matrix adopted for the SLR

Refs	ML techniques	Input(s)	Output(s)	CCS Method	Performance/ Strength
Sipöcz et al. (2011)	ANN with sensitivity analysis	Temperature, mass flow, mass fraction, solvent lead load, solvent circulation rate, removal efficiency	Mass flow CO_2 captured, rich load, specific duty	PCC	Prediction of solvent rich load and amount CO2 captured have maximum error below 2.8% and 0.17% respectively
Sharma et al. (2019)	Adaptive network-based fuzzy inference system (ANFIS) and multi-gene genetic programming (MGGP)	load and the CO2 emission	COE, annual CO_2 emissions	PCC	R^2 for MGGP and ANFIS is 0.99 and 0.96 respectively. Also, ANFIS model fails to replicate the expected sensitivity analysis.
Hoseinpour et al. (2018)	GA-RBF(genetic algorithm- radial basis function neural networks, Hybrid-ANFIS, and GEP (gene expression programming)	Temperature, pressure, mass fraction of TBAB in feed aqueous solution (wTBAB)	solubility of CO_2 (xCO_2)	PCC	R^2 for GA-RBF and Hybrid-ANFIS models was 0.9994 and 0.9927 respectively.
Mohagheghian et. al. (2015)	Feedforward artificial neural networks (FFANN)	Reduced temperature and pressure	CO_2 capture rate	PCC	Accurate prediction with 0.00175% RMSE
Mirarab et al. (2015)	ANN (artificial neural networks)	Water content, ionic liquid content, temperature, pressure	CO_2 capture rate	PCC	Small difference between the estimated results of ANN approach and experimental data of CO_2 capture rate for the training, validation, and test data sets
Zhou et al. (2010)	Adaptive-network-based fuzzy inference system(ANFIS)	Steam flow rate,CO_2 concentration in flue gas, Ratio between amine and flue gas flow rate	CO_2 production rate, CO_2 absorption efficiency, Heat duty, Lean loading	PCC	High accuracy, can model irregular non-linear function enable interpretation of the interrelationships among the parameter

3. RESULTS AND ANALYSIS

In this contribution, out of the total 94 articles identified shown in Figure 3, 49 met the criteria for full-text review but only 40 were eligible for inclusion. Analysis of the 40 articles is presented in terms of CCS Machine learning approaches, inputs and output variables as well as accuracy performance measures. It is worth noting in Figure 4, during the Covid -19 pandemic there is a decline in the number of research papers, which could be attributed to the subsequent coal consumption downturn recovery in the power sector due to the Covid-19 pandemic. At the end of 2019, increasing power consumption is observed due to a recovering demand for coal-fired electricity generation.

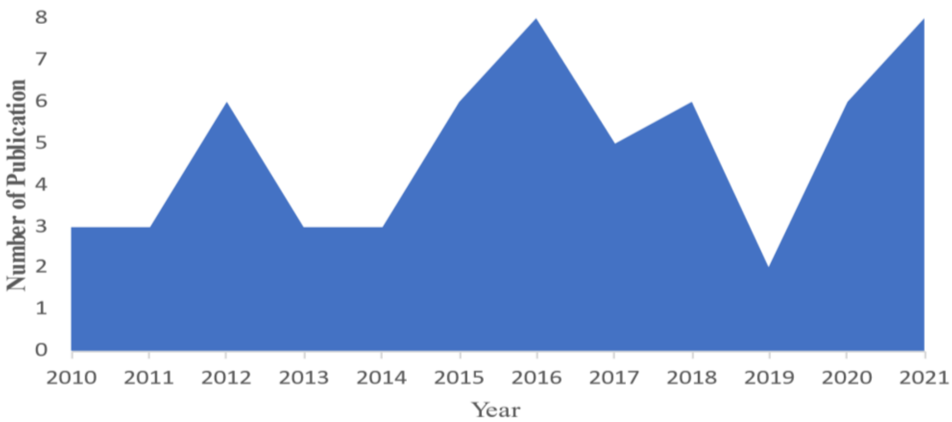

Figure 4: Trend of CCS-Machine Learning research evolution (2010 to 2021)

The most frequently used machine learning often used interchangeably with the term machine learning is the artificial neural network (ANN). ANN provides good correlations between the inputs and outputs, unfortunately, it cannot explain the relationships among the parameters (Helei et al., 2021). Another study reported that deep learning models have better model, accuracy and generalization ability, especially for multi-step ahead predictions (Li et al., 2018). Therefore, various deep multi-layer neural networks techniques have been developed in the solvent-based PCC process to address difficulties typically related to traditional ANN such as overfitting, local minima at the unsupervised stage, optimal number of layers and neurons per layer, and choice of the activation function. These strategies are aimed at (i) reducing fossil fuel burning (ii) improving coal-fired plant efficiency (iii) capture and storage of carbon dioxide (iv) enhancement of CO_2 partial pressure in the exhaust gas (28 studies). Moreover, 14 studies proposed Particle Swarm Optimization (PSO) to improve the optimization efficiency of the ANN model is consider and thus alleviate the effect of unavoidable modelling mismatches (e.g Baghban et al., 2015; Ahmadi, 2016; Wu et al.,2020; Xi et al.,2021; Sipöcz et al., 2011; Zhou et al., 2010, etc.). Satisfactory validation results proved that the accuracy of the PSO was 10 times higher than the conventional single-hidden layer (Wu et al., 2010). This technique allows one to find the best future control sequence for the PCC process.

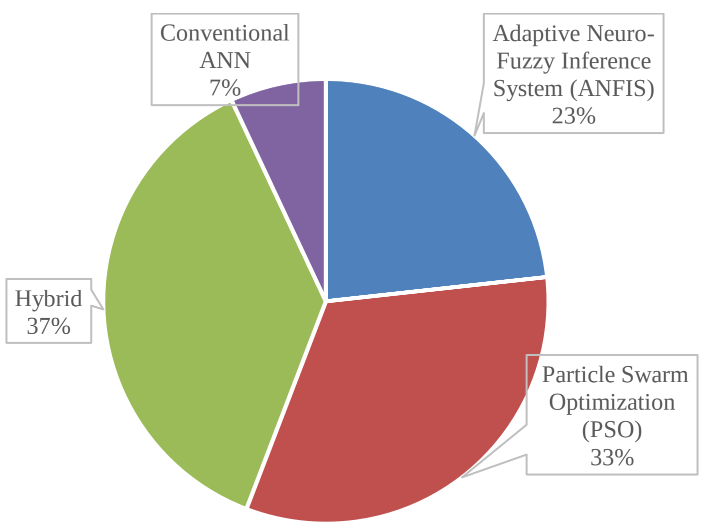

Figure 5 Break-down of the Common ML techniques

Another common approach is Adaptive Neuro-Fuzzy Inference System (ANFIS) implemented in 10 studies. The Neuro-fuzzy approach model is typically attractive for modeling the CO_2 capture process due to the following advantages: (i) It can model irregular non-linear functions among the data (ii) it is knowledge base capacity enables interpretation of the interrelationships among input-output parameters (ii)High accuracy of modeling (Zhou et al., 2010). Zhou et al. (2010) developed single-hidden layer feed-forward back-propagation neural network (FFBNN) models and adaptive network-based fuzzy inference system (ANFIS) models for the PCC process to predict the steady-state values of re-boiler heat duty, absorption efficiency, lean solvent loading and CO_2 production rate. Another comparative by Sharma et al. (2019) used an adaptive network-based fuzzy inference system (ANFIS) and multi-gene genetic programming (MGGP) to model Indian coal-fired power plants with CO_2 capture. MGGP model is better in predicting the cost and emission of the resulting plants with CO_2 capture. Due to its higher degree of correlation, ANFIS model fails to replicate the expected sensitivity analysis results. Precisely, MGGP has R^2 value of more than 99% between the predicted and actual values, as against the 96% correlation for the ANFIS approach.

Many studies have now focused on hybrid simulation approaches using multiple performance error measures can determine the accuracy of prediction to experimental data. In total, 23 studies have applied this approach (e.g., Zhou et al.,2010; Zhou et al.,2016; Baghban et al.,2015; Hoseinpour et al., 2018; Zarei et al.,2018; Sharma et al.,2019). For example, Chan et al. (2017) proposed a PWL-ANN algorithm to explore the relationships among key operational parameters of the CO_2 capture process system. In another study, Ahmadi (2016) compared the PSO-ANN and Genetic algorithm (GA)- least squares support vector machine models in terms of MAE and R^2. The PSO-ANN and GA-LSSVM methods yielded the mean absolute error (MAE) and coefficient of determination (R^2) values of 1.736 and 0.995 as well as 0.51930 and 0.99934, respectively.

Thus, the respective choice of the appropriate machine learning approach depends on the proper selection of operational parameters (inputs and outputs). To this end, physical parameters are incorporated in the formulation of the ANN inputs and output. Different outputs reviewed to reflect the performance of the PCC process include CO_2 production rate, solubility of CO_2, annual CO_2 emissions and Mass flow CO2 captured among others (Chu et al., 2016). The process parameters enable prediction and optimization and improving the efficiency of the CO_2 capture process (Zhou et al., 2016). Amongst the various inputs of CCS, reduced temperature and pressure are commonly utilized to obtained carbon capture rates. This is because retrofitting the existing coal-fired power plant easily and treat flue gas stream with low CO_2 partial pressure. Moreover, reducing lean solvent flow rate to the barest minimum will minimize the energy consumption in the regenerator of the coal-fired power plant. Altogether, it is shown multiple inputs and outputs are used for design, process prediction and performance estimation

The error is determined by comparing the current network output to the correct output (which is available in a supervised learning scenario). To evaluate the performance and accuracy of the optimal ML model, coefficient of determination (R^2), mean absolute percentage error (MAPE), and root mean square error (RMSE) were calculated using the following Eqns. (1) - (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{Act,i} - Y_{Pred,i}\right)^2}{\sum_{i=1}^{n}\left(Y_{Act,i} - \bar{Y}_{Pred,i}\right)^2} \quad (1)$$

$$MAPE = \left[\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{Act,i} - Y_{Pred,i}}{Y_{Act,i}}\right|\right] \times 100 \quad (2)$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(Y_{Act,i} - Y_{Pred,i}\right)^2\right]^{0.5} \quad (3)$$

The coefficient of determination (R^2) is a number that specifies how well data fit into a statistical model such as a regression line or curve. It provides a measure of how well-observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model. It is used to measure the error rate of a regression model and it represents the standard deviation of the model prediction error. A smaller value indicates better model performance Similarly, MAPE provides a useful measure of prediction accuracy in a forecasting method, it usually expresses accuracy as a percentage. RMSE of a model prediction for the estimated variable Y_{Pred} is defined as the square root of the mean squared error. Mean Squared Error (MSE) is the average squared difference between outputs and targets, lower MSE values are better, while zero means no error. Regression R Values measure the correlation between outputs and targets. An R-value of 1 means a close relationship, 0 a random relationship.

To enhance the control performance PCC process, PSO algorithm is applied in the IPC design to solve the receding horizon optimization problem and search for the best control actions. Interestingly, Mac Dowell et al. (2013) identified that more than 50% of energy cost in the PCC plant is associated with the cost of solvent regeneration, which accounts for most parts of the total annualized cost. Therefore, seeking for optimal operation conditions with minimum energy consumption and a satisfied capture degree appears most important consideration in designing a PCC plant. This motivated Manaf et al. (2021) to analyze the trade-offs mainly between the cost of CO_2 emission and the cost of PPCCS. The model is based on mixed-integer non-linear programming (MINLP) formulation for predicting the practicality and feasibility of CCS at large-scale commercialization. The key contribution here is determining the most feasible time for the realization of CCS commercialization considering both present and forecast trends and to estimate profit/loss of the PP-CCS.

4. CONCLUSIONS AND FUTURE PERSPECTIVE

The Systematic Literature Review (SLR) summarizes current machine learning applications and considers future potential in fossil fuel power plant CCS potentials. It does this by synthesizing 40 relevant studies out of 396 studies developed in 10 years (2010 to 2020) indicated in Figure 2. These studies are analyzed in terms of the number of publications by year, publication channels, type of ML simulation and optimization models and limitations. Machine learning based Carbon Capture and Storage (CCS) research is a rapidly evolving technology, most deep learning models require further improvements in terms of reduction in expensive computational costs. Future work will include two limitations identified in the current review. First, optimization of large energy requirement for regeneration of cheaper potential absorbents (apart from amine solution). Secondly, harnessing simulation optimization of green gas and carbon capture processes to cope with complex evolving hybrid ML models. Finally, development of a feasible optimization model on integrated design, scheduling and control of large-scale PCC plant to optimize the design and operating conditions base on a machine learning model could be future research direction.

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