Solvent-based post-combustion CO_2 capture for power plants: a critical review and perspective on dynamic modelling, system identification, process control and flexible operation

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Highlights

- Critical review on dynamic modelling, system identification and control of the PCC process
- Classification of the existing studies according to the approaches used
- Comprehensive analysis of the advantages and limitations of current studies
- Summary of research achievements and challenges for flexible operation of solvent-based PCC
- Prediction of the future research opportunities in solvent-based PCC process

Abstract:

Solvent-based post-combustion CO_2 capture (PCC) appears to be the most effective choice to overcome the CO_2 emission issue of fossil fuel fired power plants. To make the PCC better suited for power plants, growing interest has been directed to the flexible operation of PCC in the past ten years. The flexible operation requires the PCC system to adapt to the strong flue gas flow rate change and to adjust the carbon capture level rapidly in wide operating range. In-depth study of the dynamic characteristics of the PCC process and developing a suitable control approach are the keys to meet this challenge. This paper provides a critical review for the dynamic research of the solvent–based PCC process including first-principle modelling, data-driven system/process identification and the control design studies, with their main features being listed and discussed. The existent studies have been classified according to the approaches used and their advantages and limitations have been summarized. Potential future research opportunities for the flexible operation of solvent-based PCC are also given in this review.

Keywords: Solvent-based post-combustion CO_2 capture; Flexible operation; First principle modelling; System identification; Dynamic control; Review

1. Introduction

Greenhouse gas emissions represented by CO_2 and the resulting global climate change have become the most serious environmental problem facing humanity in this century [1]. Fossil fuel fired power plant is the largest stationary source of CO_2 emission since the majority of electricity around the world is generated there [2] and this trend will not change in a foreseeable future [3]. In this context, the technology of Carbon Capture and Storage (CCS) remains a critical solution to make deep and rapid reductions in CO_2 emissions. According to the prediction of Global CCS Institute in 2018 [4], 14% of cumulative CO_2 emissions reduction must be achieved through CCS by 2050 to reach the Paris 2℃ target [5]. This means, in the year 2050, over 5Gt of CO_2 must be captured using CCS technologies (equivalent to present-day annual CO_2 emissions in the US). Many thousands of CCS facilities must be deployed in the coming decades if the target are to be achieved [4].

Compared with other CO_2 capture technologies, the use of amine-based solvent for post-combustion CO_2 capture (PCC) can directly remove the low concentration CO_2 from flue gas, which is mature in technology, relatively low in cost and easily retrofitted to existing power plants. Therefore, it has been regarded as the most promising technology for power plant CO_2 capture [6-10]. A typical monoethanolamine (MEA) solvent-based PCC process is shown in Fig.1.

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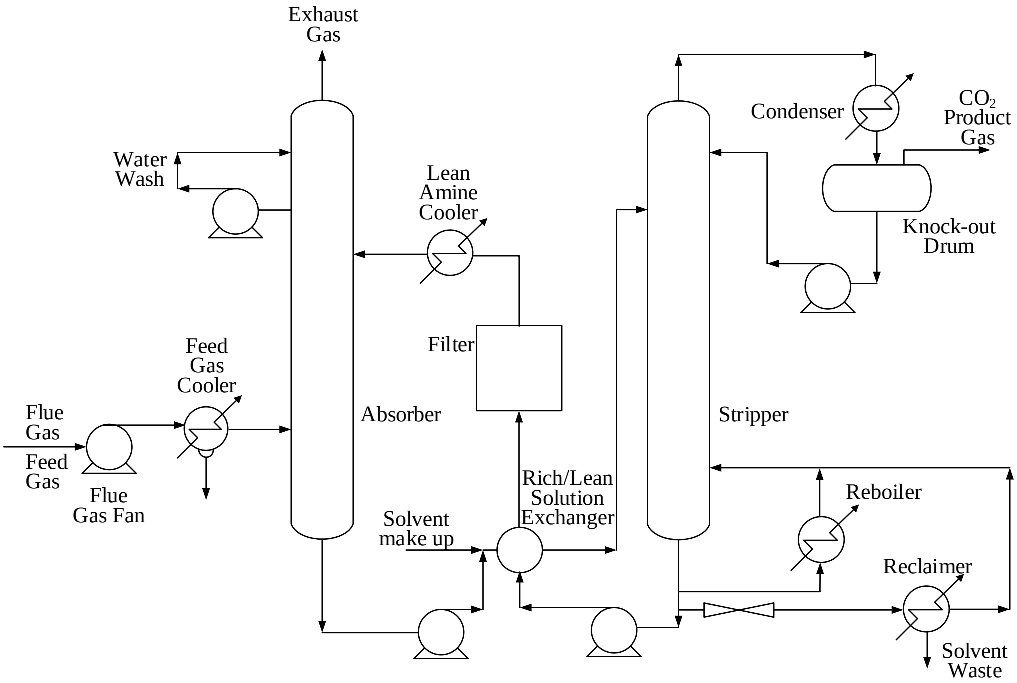

Fig.1 Process topology of solvent based-PCC system [7].

Prior to CO_2 absorption, the flue gas must go through desulfurization, denitrification, dust removal and cooling processes as they will degrade the solvent, therefore reduce the CO_2 absorption capacity and efficiency of the PCC process. The flue gas mainly containing CO_2, H_2O and N_2 is then fed into the bottom side of the absorber and contacts with the lean solvent (about 0.1–0.2 mol CO_2/mol MEA loading) counter currently. CO_2 is chemically absorbed by the solvent from the flue gas, yielding rich solvent of about 0.4–0.5 mol CO_2/mol MEA loading. The scrubbed gas is then water washed of solvent and vented into the atmosphere from the top side of the absorber. Next, the CO_2 rich solvent is heated by the regenerated lean-solvent in a cross heat exchanger and then pumped into the stripper, where it is heated by the steam drawn-off from the medium/low-pressure turbine of power plant to release CO_2. During heating, part of the water and MEA vapor is mixed with the removed CO_2, thus a condenser is used to recollect the fugitive steam and MEA, the separated high purity CO_2 is then compressed and transported to storage. The resulting lean solvent is then resent to the absorber via the cross heat exchanger and cooler to reduce the temperature and starts the next cycle [11].

Because CO_2 is chemically stable and the flue gas to be treated is large in flow rate but low in CO_2 concentration, the operation of solvent-based PCC process requires a large amount of heat for solvent regeneration, which is the major drawback hinders the large scale application. The heat is typically provided by the steam drawn-off from the crossover of medium/low-pressure turbine of power plant. Taking the current pulverized coal-fired supercritical power plant as an example, when the CO_2 capture rate is 90%, the net power generation efficiency of the plant will be reduced from 41-45% to 30-35% [12-14]. For this reason, considerable studies have been carried out for reducing the energy efficiency penalty of CO_2 capture. The studies can be divided into four categories: 1) developing new solvents with desired operation performance, including high CO_2 absorption capacity, absorption rate, lower regeneration heat and etc. [15]; 2) process configuration modifications, including: intercooling in absorber, stripper vapor recompression, rich amine split-stream, etc. [16, 17]; 3) process parameter optimization, including: absorber/stripper sizes, solvent flow rate and re-boiler temperature/pressure etc. [18, 19]; and 4) effective integration between the PCC plant and power plant [20-22].

These efforts in solvent-based PCC provide critical foundation for operating cost reduction. Nevertheless, they have only focused on the steady state performance of the process under given operating conditions, the flue gas flow rate/composition and the CO_2 capture level are fixed at certain values. However, the following two features have made the dynamic flexible operation of PCC imperative towards the large scale commercialization.

1) The fossil fuel-fired power plants are required to participate in the grid power regulation frequently to balance the difference between the power supply side and the demand side. With the growth of electric power demand and extensive use of the renewable sources such as wind and solar, this requirement has become tighter. The fossil fuel-fired power plants

have to respond to the load demand variation quickly within a wide operation range. As a result, the flue gas flow rate will have significant variations and the downstream PCC plants are forced to operate in a flexible manner to follow these changes [23];

2) As the high operating cost limits the PCC technology's deployment in power plant, operation of the PCC plant at full load condition all the time is not a viable option. Flexible adjustment of the PCC process according to the electricity price offers an alternative approach to overcome this issue. During periods of high electricity prices, the PCC system can decrease the steam consumption and allow more steam for power generation; while during the periods of low electricity prices, more steam can be drawn off from the turbine and used for CO_2 capture [24].

It has been reported in many studies that implementing a flexible operating scheme can greatly improve the economic performance of the integrated power plant-PCC system and enhance the load ramping ability of power plants. However, the flexible operation also increases the challenges for the PCC control because the frequent fluctuations in flue gas flow rate, solvent circulation flow rate and steam flow rate to re-boiler will bring strong disturbances into the process [25].

Various operating modes and process configuration modifications have been proposed for the flexible operation of PCC process such as flue gas venting, varying degree of solvent regeneration and lean/rich solvent storage [26]. However, no matter which mode or configuration is employed, how to achieve a smooth and rapid transition between different working conditions is still the key issue to be faced. Fundamentally, achieving a satisfactory flexible operation depends on in-depth understanding of the dynamic behavior of the PCC process and developing a proper control system for it. Therefore, much attention has been paid in these areas to meet the growing demand for flexible operation.

Two methods are commonly used in the past decade to investigate the dynamic behavior of the PCC process. The first is to directly carry out dynamic experimental studies on the pilot plants [27, 28]. The second, and more frequently used, is to build a dynamic PCC model, validate the model under different conditions and conduct simulations considering various disturbances. In addition to the first-principle models [29], [30], data-driven identification models were also presented [31, 32], since they are simple to develop, efficient in calculation, and suitable for advanced controller design. Based on a comprehensive understanding of the PCC dynamics, different control approaches are then developed for the PCC process with different purposes such as fast regulation, optimization or system stability [33-35].

The primary purpose of this paper is to present a comprehensive and critical review of the recent contributions to first principle modelling, system identification, dynamic behavior investigation and control of the PCC process, in order to discover how they can help in improving the quality and performance of PCC flexible operation.

The differences between this paper and previous reviews such as [7, 8] are: i) first principle dynamic modelling of the advanced PCC processes with configuration modifications have been reviewed; ii) the latest PCC dynamic models, which have been validated through pilot-scale dynamic experimental data have been reported in this review; iii) this paper provides the first review for the research activities in system identification and control design of the solvent-based PCC process; and iv) the limitations of current studies on dynamic modelling, system identification and control of the PCC process are summarized and the future research directions are predicted in this review.

The remainder of this paper is organized as follows. A review of the first principle modeling of solvent-based PCC process will be presented in Section 2. The PCC model developed through system identification will then be reviewed in Section 3, followed by a summary of the PCC system dynamics and resulting control challenges in Section 4. The main focus is to summarize different control strategies for the PCC process with their significant features outlined and discussed. Achievements so far, challenges ahead and future perspectives are presented in Section 5. Conclusions will be drawn in the end.

2. First principle dynamic modelling of solvent-based PCC

2.1. Overview of PCC modelling studies

Carrying out the dynamic experimental tests at pilot PCC plant is a time-consuming, laborious and costly work. Moreover, it is often subject to various limitations and cannot be fully conducted according to the designed cases. For these reasons, developing an accurate PCC dynamic model and performing simulation studies on the model has become necessary to gain insights into the dynamic behavior of the PCC process, providing guidance for the operation and control design of the process. The first principle models, which are developed through the mechanism of mass transfer, heat transfer and chemical reaction of the PCC process has received the most attention in the past two decades.

The key to PCC process modelling is to develop models for the absorber and stripper, which are two primary components within the process. In order to properly reflect the dynamics of absorber and stripper, mass transfer from vapour side to liquid side and the chemical reaction between CO_2 and solvent are two main phenomena to be properly described [36]. A critical analysis in [37] suggested that mass transfer is the dominant factor limiting the performance of CO_2 absorption and desorption. According to the complexity levels of mass transfer description, the PCC modelling can be roughly divided into two major categories: equilibrium-based approach and rate-based approach. The former approach assumes a theoretical stage in which liquid and gas are well-mixed and attain an equilibrium, and the performance of each stage is changed by adjusting an efficiency correlation factor [38]; while for the rate-based approach, actual mass and heat transfer rate are considered directly [39]. Further considering the description of the chemical reactions, the PCC model development can be subdivided into five categories [7, 36, 40], as illustrated in Fig.2.

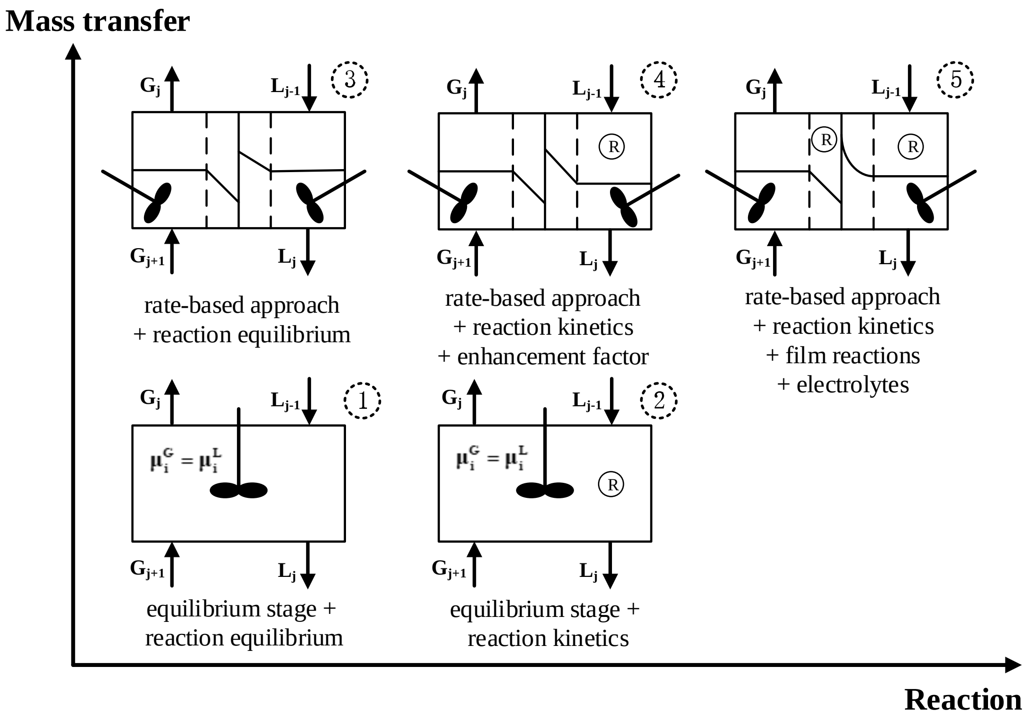

Fig. 2 Different categories of the PCC first principle models [7, 36, 40]

Starting from the bottom left, Model 1 is the simplest, which assumes both the liquid and gas phases achieve a thermodynamic equilibrium stage and the chemical reaction is very fast to achieve the equilibrium. The performance of each stage is adjusted using an efficiency correction factor, so that the non-equilibrium processes can be described. PCC models presented in [36], [41]- [43] belongs to this category. Moving right, Model 2 is more rigorous which considers the chemical reaction kinetics in the liquid film. PCC models presented in [44], [45] belongs to this category. In practice, it is difficult to attain equilibrium since the mass and heat transfer are driven by gradients of chemical potential and temperature [46]. Therefore, actual mass transfer rate is considered in Models 3, 4, 5 in the upper layer of Fig. 2. The so-called rate-based approach is more appropriate in reflecting the active CO_2 absorption and desorption processes, thus has been used in most of the PCC modelling. Among them, Model 3 assumes that the reaction rate between CO_2 and solvent is very fast and the chemical reaction between them is thus in an equilibrium stage [7]. This approach has been adopted in [36], [37], [47]- [53]. The complexity of modelling is then greatly increased in Model 4 by further considering the chemical reaction kinetically and using an enhancement factor to reflect the effect of chemical reaction on mass transfer. The enhancement factor is generally calculated based on the estimated reaction rates and is best suited for processes involving single irreversible reactions. Kucka et al. [54] has pointed out that the enhancement factor used is strictly valid for the pseudo first-order reaction regime. PCC models presented in [55]- [69] all belongs to this category. Model 5 can give the most realistic and accurate descriptions for the PCC dynamics among the five categories, in which the additional influences of electrolytes, mass transfer resistances, reaction systems as well as the configurations are taken into account [46]. PCC models presented in [70]- [74] belongs to this category. The improvement of model accuracy is achieved at the expense of model complexity increase. Therefore, both the accuracy and computational effort of the simulation need to be considered to select a suitable model. Peng et al. [75] found that the transient performance of rate based model and equilibrium based model is similar, but the steady state deviation between the two models are large [36, 37]. Most of the PCC modelling studies select the rate-based approach.

From the perspective of PCC system, early studies of PCC modelling started from dynamic modelling of the standalone absorber [36], [50], [56], [58], [62], [63], [71] and stripper [48], [50], [57], [65]. The independent absorber/ stripper models cannot represent the dynamic behavior of the entire PCC process since these two sections are highly coupled. Thus current major studies were progressed on to the dynamic modelling of integrated PCC plant [37], [47], [51], [52], [55], [60], [64], [68]. The methods and simulation results of these studies have been summarized and analyzed in the review papers [7], [8], [76], [77], thus they are not introduced in detail here.

2.2. Dynamic models for advanced PCC process

Besides the conventional PCC process, dynamic modelling of the advanced PCC processes with configuration modifications has also received much attention, because the modified processes are shown to have better economic performance or flexibility in operation.

Waters et al. [73] developed a rate-based dynamic model in gPROMS for an intercooled absorber with piperazine (PZ) solvent. Absorber intercooling can effectively improve the solvent capture capacity within the absorber, thus decreasing the energy consumption in solvent regeneration. A regressed electrolyte non-random two-liquid (eNRTL) thermaldynamic physical property method was used in the model development; and the liquid film mass transfer coefficient was estimated by experimental method according to different CO_2 loading. Predictions of CO_2 capture level and absorber temperature profile show high agreement with a rigorous steady state model developed in Aspen Plus®.

Biliyok et al. [37] presented a dynamic model for the PCC process with intercooled absorber in gPROMS®. The model in this study was modified from Lawal et al. [47] using the two-film approach with rate-based formulation. The chemical reaction was assumed to be in equilibrium for simplification. The study highlighted that three groups of experimental data collected from the SRP pilot plant in the University of Texas at Austin were used for dynamic validation of the model, one for the conventional PCC process and the other two for the advanced process considering the absorber intercooling. The experimental data was collected in a closed-loop condition under the simultaneous changes of various input variables such as lean solvent flow rate/ temperature, flue gas flow rate/ CO_2 concentration/ temperature and intercooled solvent flow rate/ temperature. It was observed from the comparison results that the developed model can satisfactorily predict the behavior of the plant, especially for the trend of dynamic change. The validated model was then used to analyze the impact of flue gas moisture content increase and intercooled solvent temperature decrease. The simulation results showed that the moisture content in flue gas could strongly influence the temperature profile of the absorber but only had a trivial influence on the capture level. On the other hand, it was discovered that the intercooling can modestly improve the absorber performance when the temperature bulge is located around it.

Waters et al. [74] established a lumped parameter model for the PCC process using MATLAB®. Aqueous PZ solvent is selected as the chemical absorbent. An intercooled absorber and flash stripper configuration are considered to improve the operation efficiency. The model used semi-empirical thermodynamics and rate based mass transfer, the reaction kinetics was considered in a constant overall transfer coefficient for model simplification. Key parameters of the model were adjusted to make the model output better match that of a rigorous model in the design conditions. The dynamic performance of the model was then validated against the SRP pilot plant experimental data with a stepwise increase of stripper pressure control valve. The dynamic variation of rich and lean solvent density showed that the model can correctly predict the dynamic behavior of the capture process and was capable to be used in PCC control design.

Karimi et al [17, 78] developed rate-based dynamic models for five different stripper configurations of the PCC process, which are: conventional configuration, split-stream, multi-pressure stripper, vapor recompression and compressor integration. The capital cost and CO_2 avoidance cost are calculated to evaluate the steady state performance of the processes [17]. In addition, PI control loops were designed for the PCC processes following the method given by Panihi et al. in [79]. The dynamic performance of PCC processes with conventional configuration, split-stream and vapor recompression configurations were then investigated. Four types of dynamic tests including 10% re-boiler duty step reduction, ±10% flue gas flow rate/ composition change in a ramp type function and flue gas flow rate change with constant re-boiler duty were carried out in a closed loop condition [78]. The simulation results showed that the conventional configuration has the best dynamic behavior and is the most stable one. For the other two configurations, the vapor recompression configuration can handle disturbances better than the split-stream configuration.

Flø et al. [26] tested the dynamic performance of four flexible operating modes for the PCC process through simulations on a model developed for Brindisi CO_2 capture pilot plant [68]. The flexible operation modes including: load following, exhaust gas venting, varying solvent regeneration and solvent storage were considered and compared in the study. Dynamic simulations in case of varying power plant load and electricity price show that solvent storage mode had the best performance in terms of CO_2 capture and energy consumption. However, large investments are required for the construction of solvent storage tanks and the use of additional solvent. In contrast, the exhaust gas venting and varying solvent regeneration modes can be implemented without complex process modifications. The dynamic simulations showed that under these two operation modes, satisfactory performance could also be achieved for the PCC process. Nevertheless, in order to maintain a desired daily-average CO_2 capture rate, the PCC plant may be required to operate at high capture level condition during the periods with higher electricity prices. The economic performance of the integrated power generation and CO_2 capture system will therefore decrease.

2.3. Dynamic models for the integrated power plant and PCC system

There are strong interactions between the fossil-fuel fired power plant and the PCC system: the large variation of flue gas flow rate due to power plant load change will significantly influence the operation of the PCC system; and the steam drawn-off from turbine in power plant to re-boiler in stripper will quickly affect the electricity generation of power plant. For these reasons, investigating the dynamic behavior of the entire power generation- carbon capture system is critical to improve the operation performance of the integrated system.

Lawal et al. [51] developed a dynamic model for the 500MWe sub-critical coal fired power plant (CFPP) using gPROMS® and linked it with an industrial size PCC model. Simplified decentralized PI controllers were designed to control the CFPP and PCC systems respectively. The dynamic performance of the integrated CFPP-PCC system was then evaluated in cases of target power output reduction and target CO_2 capture level increase. The simulation results illustrated that the response of the PCC process was much slower compared to that of the CFPP and showed that poor control scheme can have negative effect on the operation of the integrated CFPP-PCC system.

Olaleye et al. [53] developed a 600MWe super-critical CFPP-PCC model and investigated the dynamic responses of main variables within the integrated system to ramp change of power load. Authors then further tested the performance of steam reduction/stop strategy in improving the power output adjustment speed of CFPP. The steam drawn-off from the turbine to re-boiler was decreased or stopped temporarily to quickly generate more power to meet the urgent power demand of the electricity grid. The simulation results showed that about 4.67% the maximum power of the CFPP can be quickly produced by the stripper stop mechanism, which has potential benefit for the wide-range load varying operation of the power plant.

2.4. Dynamic validation of the PCC model

The dynamic modelling of PCC process has gone through many years of development and improvement, and has now become mature in methods and theory. Many scholars have also developed corresponding PCC models on various simulation platforms, such as gPROMS® [36], [37], [47], [73], Aspen Dynamics® [25], Modelica® [49], [52], [61], Matlab® [55], [68], [74], and gCCS® [29], [30], [35]. However, most of these models have only been validated through steady state pilot plant data, which cannot be used to assess the transient performance of the model. Dynamic validation is thus important to further improve the models' accuracy and reliability, so that better guidance can be provided for the flexible operation and control design of the PCC process. In addition to [37] and [74], the following studies also tested the dynamic performance of the models through comparisons against pilot-plant experimental data.

Kvamsdal et al. [80] presented a rate-based dynamic model for the CO_2 absorption process using Matlab®. Two groups of dynamic experimental data collected at VOCC (Validation Of Carbon Capture) rig in Norway was used to validate the model: 1) liquid and gas flow rates change; 2) CO_2 content in flue gas change. The model outputs of CO_2 removal rate and rich solvent loading were compared with the experimental data; and the results showed that the developed model can reflect the main dynamics of the absorber satisfactorily although there is a certain degree of steady state deviation. In addition, the performance of models using different reaction rate coefficients was evaluated and compared. The study revealed that model fitted for one specific pilot plant may not be valid for other plants of different sizes under other operational conditions.

A rate-based dynamic model of the complete PCC process was developed by Åkesson et al. [61] using Modelica® and validated against dynamic experimental data collected from Esbjerg pilot plant in Denmark. The validation experiment was conducted in an open loop condition that all input variables were kept constant except for the flue gas flow rate, which was reduced by 30% stepwisely. The dynamic responses of the model, including CO_2 removal rate, re-boiler temperature and stripper top temperature were compared to those of the pilot plant. The CO_2 removal rate was shown to increase rapidly in response to the flue gas flow rate decrease while more than 1 hour is required for the stripper top temperature to rise to a new steady- state. The flue gas flow has little effect on re-boiler temperature. The comparison results illustrated that the developed model was in close agreement with the experimental data.

To better understand the transient changes of the absorber temperature profile, Posch and Haider [71] developed a dynamic rate-based model for the absorber within the Aspen Custom Modeler® modelling/simulation environment. Dynamic simulation was carried out in closed-loop condition, the flue gas temperature and lean solvent temperature were increased linearly from 30°C to 50°C respectively. Experimental data from the CO_2SEPPL test rig located at the Dürnrohr power station in Lower Austria are used for validation purpose. Comparisons of the transient temperature changes at different heights of the absorber indicate that the presented absorber model predicted the situation in the absorber in a sufficient way.

Enaasen et al. [67] presented various transient test results collected from Brindisi pilot plant in Italy. Step-wise changes in steam flow rate to re-boiler, lean solvent flow rate and flue gas flow rate were performed while the responses of key operational parameters of the capture plant were monitored and analyzed. The decrease of steam flow rate to re-boiler was found in the experiment to have little impact on the rich solvent loading but could slowly increase the lean solvent loading. As a result, the produced CO_2 flow rate at the top of the stripper and the CO_2 capture level of the plant would be reduced. The decrease of lean solvent flow rate would quickly decrease the capture level in several minutes, however, since less solvent was flowed into the stripper and re-boiler while the re-boiler heat duty remained the same, the lean solvent loading was decreased. Consequently, the capture level would slowly rise back close to the initial level. It was also observed that the flue gas flow rate had little impact on the rich/lean solvent loading but had a rapid and strong effect on the CO_2 capture level. A rate-based dynamic model representing the Brindisi pilot plant was then implemented in K-Spice general simulation tool and compared to the dynamic pilot plant data [67]. It showed that the model and experimental results had good agreement in the transient performance. In some cases, there are some steady state deviations between the model prediction and the experimental test data. This was mostly caused by the fact that the pilot plant was not at steady state at initial time.

A rate based dynamic model for the complete CO_2 capture process of Gløhaugen (NTNU/SINTEF) pilot plant was developed by Flø et al. [68] in MATLAB®. Eight groups of steady state pilot plant data were used to modify certain correlation parameters in the model, so that the developed model could match the pilot plant better. Dynamic experiments in cases of 17% re-boiler duty step increase and 21.8% solvent circulation rate step increase were carried out respectively (the CO_2 concentration in the flue gas varied during the two experiments) and the experimental data sets were used to validate the model. The comparison results showed adequate agreement between the model and pilot plant that only 0.3%

and -2.8% deviations could be observed in the absorbed CO_2. The dynamic responses of the PCC plant also indicated that, changes in solvent flow rate or essentially the L/G ratio, caused stronger process disturbances compared to the changes of re-boiler heat duty.

Gáspár et al. [69] compared the transient performance of a dCAPCO2 in-house model [72] against the dynamic experimental data collected from a 1t/h CO_2 capacity pilot plant using 30wt% MEA in cases of flue gas flow rate step changes. The responses of key operating parameters such as: vent gas CO_2 concentration, CO_2 product flow leaving stripper and liquid temperature at the top/middle/bottom of absorber/stripper demonstrated the accuracy of the model. In most of the simulations, the model and pilot plant responses almost overlapped. However, under low CO_2 concentration condition, around 0.5 mol % steady state deviation in vent gas CO_2 concentration could be observed between the model prediction and the experimental data. This was likely due to the greater measurement errors or higher uncertainty of the physical and thermodynamic model at low CO_2 concentrations. Since the sump of the absorber was not included in the PCC model, the model predictions were easier to fluctuate compared with the pilot plant. Authors then scaled up the model to a 200t/h CO_2 capture capacity and investigated the dynamic performance of the PCC process using two different solvents (MEA and PZ) at two different concentrations (30 and 40 wt%). It could be seen that the decrease of flue gas flow rate resulted in a significant increase of the CO_2 removal rate and vice versa. For increased flue gas flow, MEA system reached a new steady state faster than PZ for both concentrations. Nevertheless, for flue gas ramp down, PZ system reached steady state conditions before MEA. This behavior might be related to the stronger influence of the flue gas flow on the temperature for the PZ system compared to MEA. Another simulation was then conducted to analyze the load following behavior of PCC system under different solvent circulation rates. The results showed that, desired CO_2 removal rate could not be maintained if the solvent flow rate was limited. It was thus important to regulate the solvent flow rate to maintain the capture rate in case of flue gas flow rate change, and avoid sudden change of the re-boiler duty.

Haar et al. [43] presented an equilibrium based PCC plant model developed through the open source ThermalSeparation Modelica library. Model coefficients regarding the mass/heat transfer and chemical reaction were tuned using the steady state experimental data to make the model better fit the pilot plant at nominal operating condition. Flue gas flow rate step tests were carried out to produce dynamic experimental data for model validation. Comparison results in the responses of capture level, absorber temperature and rich solvent loading demonstrate that the equilibrium based model could represent the transient behavior of the PCC process satisfactory, however, large steady state deviations were discovered, especially in the absorber temperature profile. This finding was consistent with the observations in [75]. In addition, authors of [43] proposed to change the steam flow rate to re-boiler to improve the load following performance of power plant; and conducted simulations on the model to analyze the dynamic behavior of PCC system in response to the re-boiler steam flow rate change.

Although different modelling approaches are used in these studies to develop models for various PCC system configurations, their test results all reported that the model predictions are in good agreement with the pilot plant dynamic experimental data, especially for the changing trend and response time. The main model mismatch is only reflected in the steady state responses. According to these conclusions, it is now safe to say that the first principle modelling theory of PCC system has been studied sufficiently and become mature. Nevertheless, more dynamic experiments for different variable changes under wide operating conditions are still required in the future to fully validate the model.

The studies on dynamic validation of PCC first principle models are summarized in Table 1.

Table 1. Summary of studies on dynamic validation of PCC first principle models

Year	Research Institute	Model Category and Simulation Platform	Validation Cases	Validation Data Source	Reference
2011	SINTEF Materials and Chemistry (Norway) and Department of Chemical	Model 4 for absorber using MATLAB®	1) Liquid and gas flow rates change; 2) CO_2 content in flue gas change.	Dynamic experimental data collected at VOCC (Validation Of Carbon	[80]

	Engineering, Norwegian University of Science and Technology (Norway)			Capture) rig in Norway	
2012	School of Engineering, Cranfield University (UK), Process Systems Enterprise Ltd (UK), University of Texas at Austin (USA)	Model 3 for integrated PCC process with intercooled absorber using gPROMS®	1) Changes in lean solvent flow rate, inlet flue gas temperature and CO_2 concentration fluctuation; 2) Changes in flue gas flowrate, intercooler solvent return temperature and inlet flue gas CO_2 concentration; 3) Changes in intercooler solvent return temperature, inlet flue gas CO_2 concentration, lean solvent temperature and inlet flue gas temperature	Experimental data collected from the SRP pilot plant in the University of Texas at Austin, USA	[37]
2012	Modelon AB (Sweden), Department of Chemical Engineering, Texas A&M University (USA), Department of Automatic Control, Lund University （Sweden） and I'Eau et I'Environment (France)	Model 4 for integrated PCC process using Modelica®	Decrease in flue gas flow rate	Dynamic experimental data collected from Esbjerg pilot plant in Denmark	[61]
2013	Institute for Energy Systems and Thermodynamics, Vienna University of Technology (Austria)	Model 5 for absorber using Aspen Custom Modeler®	1) Change in lean solvent temperature; 2) change in flue gas flow rate	Dynamic experimental data from the CO2SEPPL test rig located at the Dürnrohr power station in Lower Austria	[71]
2014	Department of Chemical Engineering, Norwegian University of Science and Technology (Norway), ENEL Engineering and Research Division (Italy) and Department of CO_2 Capture Process Technology, SINTEF Materials and Chemistry (Norway)	Model 4 for integrated PCC process using K-Spice general simulation tool®	1) Step changes in steam flow rate to re-boiler; 2) Step changes in solvent flow rate; 3) Step changes in flue gas flow rate	Dynamic experimental data collected from Brindisi pilot plant in Italy	[67]
2015	Department of Chemical	Model 4 for	1) Step change in re-boiler	Dynamic experimental	[68]

	Engineering, Norwegian University of Science and Technology (Norway) and Department of CO_2 Capture Process Technology, SINTEF Materials and Chemistry (Norway)	integrated PCC process using MATLAB®	duty; 2) Step change in solvent flow rate	data collected from Gløhaugen (NTNU/SINTEF) pilot plant	
2016	Department of Chemical Engineering, The University of Texas at Austin (USA)	Model 5 for integrated PCC process with intercooled absorber and flash stripper using MATLAB® (PZ solvent)	Stepwise increase of stripper pressure control valve	Dynamic experimental data collected from the SRP pilot plant in UT Austin	[74]
2016	Department of Chemical and Biochemical Engineering/Department of Applied Mathematics and Computer Science, Technical University of Denmark (Denmark)	Model 4 for integrated PCC process using dCAPCO2 in-house model®	Flue gas flow rate changes	Dynamic experimental data collected from a 1t/h CO_2 capacity pilot plant using 30wt% MEA	[69]
2017	Propulsion & Power, Delft University of Technology (The Netherlands), Institute of Thermo-Fluid Dynamics, Hamburg University of Technology (Germany) and TNO (The Netherlands)	Model 1 for integrated PCC process using ThermalSeparation Modelica library®	Step changes in flue gas flow rate	Pilot plant operated at the Maasvlakte power station in the Netherlands	[43]

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2.5. Advantages, limitations and future directions for the first-principle dynamic modelling of PCC process

The advantages of first principle modelling are that:1) both the model structure and parameters have very clear physical meanings, thus are easily tuned; 2) as the model is based on first principle analysis, it can reflect the internal status of the PCC system and is allowed for in-depth understanding of the PCC process; and 3) can better portray the dynamics of the PCC process.

However, developing an accurate first principle model is difficult without the knowledge of chemical reactions, thermal dynamics and design specifications of the PCC system. During the model development, reasonable assumptions are also required to simplify the complexity of the model while ensuring the accuracy. In addition to this, composed by a series of partial differential equations, the computational expense of first principle dynamic models may become demanding for large scale simulations, thus limiting the use for the purpose of dynamic process control or even real-time process prediction. For this reason, an alternative approach, the data driven identification has been used in the PCC modelling.

3. Data driven system identification of solvent-based PCC

The motivation of the data-driven approach rises from the explosive growth of process data. Owing to the rapid development of computer and network technologies, convenient data access through the distributed control systems (DCS) is now the normal practice rather than the exception in most of the industrial process [81]. No matter experimentally designed or even routinely operated, the input-output data contain tremendous intricate information of the process and are good manifestation of the process characteristics. If suitable data can be selected and properly archived, desired models can be extracted from them to be used in process simulation, prediction, optimization and control design.

3.1. Steady state identification of the solvent-based PCC

The data-driven modelling of the solvent based PCC process started from the steady state system identification. Zhou et al. [82, 83] developed four statistical regression models for the re-boiler heat duty, absorption efficiency, CO_2 lean loading and CO_2 production rate of the PCC process. The input variables of these models are selected first by prior expertise of the PCC process and further filtered through the method of partial correlation analysis. Routinely operated data collected at International Test Center for CO_2 capture (ITC) located at University of Regina, Saskatchewan, Canada were used in the identification. Only the stable data within a given operating range were selected to ensure the accuracy of the steady state models. The reliability of the models was tested and shown to be satisfactory. The resulting models explicitly unraveled the relations among the critical variables within the PCC process and could provide guidance for the operation and performance prediction of the plant.

These studies were then extended by Wu et al. [84] through developing single-hidden layer feed-forward back-propagation neural networks (NN) to capture the steady state relationships among these variables. Sensitive analysis and prior expertise were then utilized to eliminate the insignificant input variables and simplify the NN model. It was discovered that the NN model predicts the performance of the PCC process more accurate than the statistical regression approach. The authors further improved the identification using adaptive network based fuzzy inference system (ANFIS) approach [85, 86]. Human knowledge in the form of fuzzy if-then rules was used to reflect the complex relations between the inputs and outputs of the PCC process. The learning ability of NN was used to adjust the rules and their combination modes in the fuzzy inference system through the data. Simulation results showed that the ANFIS could attain even higher prediction accuracy for the PCC process compared with the NN.

Sipocz et al [87] also developed a single-hidden feed-forward back-propagation NN model for the steady state PCC process. The captured CO_2 mass flow rate, rich solvent loading and re-boiler heat duty were considered as the model outputs; and the temperature, flow rate, CO_2 concentration of inlet flue gas, lean solvent loading, solvent circulation rate and CO_2 removal efficiency were considered as the model inputs. The training and validation data are obtained from a rigorous process simulator CO2SIM over a wide operating range. The Levenberg-Marquardt (LM) algorithm was used to train the ANN and can attain better accuracy compared with the NN trained with scaled conjugate gradient (SCG) algorithm. Sensitivity analysis was used to find the minimum number of inputs. The validation results showed that the NN model has very high congruence with the rigorous simulator but is 1000 times faster.

In Li et al. [31], a steady state NN model of the PCC absorber was also developed to predict the CO_2 production rate and capture level. The input variables taken into account include: flow rate, pressure, CO_2 concentration, temperature of the flue gas and flow rate, MEA concentration and temperature of the lean solvent. The training data were generated from a first principle PCC model built in gPROMS® [36] and were bootstrap re-sampling replicated to train multiple single-hidden layer feedforward NNs. The identified NNs could have different number of hidden layer neurons and were combined together to improve model accuracy and robustness.

3.2. Dynamic identification of the solvent based PCC

The static PCC model can only reflect the relationship between inputs and outputs under steady state conditions. However, the flexible operation requires the PCC system to continually adjust its working conditions and adapt to the impact of various disturbances. A dynamic PCC model is thus necessary to understand the transient relationship between inputs and outputs.

Li et al [31] extended the steady state model of the absorber to a dynamic model based on the same bootstrap aggregated NN modelling approach. The input and output data at the previous sampling instant were used as the inputs of the NN (first order model) to capture the dynamic characteristics of the absorber which is related to the change in time. One-step and multi-step prediction results illustrated that the developed bootstrap aggregated-neural network (BA-NN) have satisfactory accuracy and reliability.

In [88], the BA-NN model was further modified to a bootstrap aggregated extreme learning machine (BA-ELM) model. The proposed ELM model had the same structure as the single-hidden layer feedforward NN. The difference lies in that the weights between hidden and output layers were determined by the principal component regression method to overcome the multicollinearity problems. The comparison with the BA-NN showed that the BA-ELM model has better generalization performance and faster training speed.

The aforementioned steady state or dynamic NNs only have one hidden layer, thus may have limitations in approximating the complex process dynamics. However, the use of multiple hidden layer NN was difficult since the gradient-based training of the weights from random initialization is easily stuck in local optima. The bottleneck was broken with the development of deep learning technique [89], in which a deep belief network is pre-trained to obtain the initial weights and supervised back-propagation is then used to fine tune the weights. Li et al [90] established a deep belief network (DBN) to capture the dynamic behavior of PCC absorber based on the same data used in [31]. The proposed DBN was composed by two hidden layers which were pre-trained by Gaussian Restricted Boltzmann Machine (RBM) and binary RBM to drive the initial weights to optimum solution. The advantages and properties of DBN are analyzed in details and the validation results showed that the accuracy of the DBN was 10 times higher than the conventional single hidden layer NN. However, the dynamic validation of these three models did not consider the disturbances of different variables in a wide operating range.

Due to the complexity of the system, it is challenging to directly identify a satisfactory dynamic model for the entire PCC unit. Instead, a “divide and conquer” approach was proposed by Manaf et al. [32]. Three key components within the PCC process, the absorber, rich/lean solvent heat exchanger and the desorber were identified individually through the dynamic operating data of a pilot plant. The resulting multivariable nonlinear autoregressive with exogenous input (NLARX) models were tested and found can match the experimental data very well. Therefore, the three models were linked together to form a 4-input, 3-output PCC process model, in which the flue gas flow rate, CO_2 concentration, lean solvent flow rate and re-boiler heat duty were considered as the input variables; and the CO_2 concentration of absorber off gas, CO_2 concentration at the top of the desorber and the flow rate at the top of the desorber were selected as the output variables. Step tests were then carried out on the integrated PCC model and the results indicated that the power plant flue gas had a quick impact on the PCC process while the re-boiler heat duty’s influence was slow. Sensitivity analysis was also performed to identify the relative importance of model inputs on the model outputs. It was discovered that, the CO_2 concentration of absorber off gas was mainly influenced by the flue gas flow rate, while re-boiler heat duty was the most influential parameter to the flow rate and CO_2 concentration at the top of the desorber. The model investigation offers a good understanding for the dynamic behavior of the PCC process and was useful in control design.

Most recently, Akinola et al. [91] also developed an NLARX model for the PCC process using the dynamic operating data obtained from a gPROMS® PCC model [47]. The CO_2 concentration at absorber outlet gas and lean solvent CO_2 loading are selected as the model outputs; and the flue gas flow rate, lean solvent flow rate and the re-boiler temperature were used as the model inputs. The work was featured that the forward regression with orthogonal least squares (FROLS) algorithm was applied to select the most significant terms in the model. The validation results demonstrated that the identified model well represented the underlying dynamics of PCC process and could further be used in control design.

Liao et al. [92] analyzed the input-output dynamics for main control loops of PCC, including the lean solvent flow-CO_2 capture level, steam flow rate- reboiler temperature, condenser cooling water flow rate- condenser temperature and lean solvent cooling water flow rate- lean solvent temperature loops respectively. Local single-input single-output (SISO) transfer function models were identified under different CO_2 capture levels using the data generated from gCCS simulator. The differences among these local models were measured through step tests and gap-metric calculations. Suitable local models were then selected and connected with each other by a fuzzy membership function to approximate the nonlinear behavior of the PCC system. The piecewise linear model obtained has good approximation accuracy for the nonlinear PCC system and has simple linear expression.

The fuzzy modelling technique was also used in Liang et al [93], where local state-space models were identified from data and then linked together according to the CO_2 capture level. The developed fuzzy model was used to capture the dynamics among CO_2 capture level, re-boiler temperature, lean solvent and re-boiler steam flow rates. The test results showed that the fuzzy model had better performance than the linear model. Moreover, the linear state-space formation of the model made it very suitable for advanced controller design.

3.3. Advantages, limitations and future directions for the system identification of PCC process

The data-driven identification modelling approach has several distinct advantages:

1) The modelling is based on data, thus it does not require an in-depth understanding of the PCC process and the internal working principles;

2) Due to the data-driven nature, the modelling is easily adapted and extended to other PCC process;

3) The model is simple in structure and efficient in calculation. Although the accuracy is slightly lower than the first principle model, the computational effort is greatly reduced. The model is suitable for real time control of PCC system.

In most of model-based PCC control design studies, for example, the model predictive control (MPC), the data-driven model has been well developed and used to approximate the dynamics of PCC process. Reviews for these studies will be given in details in Section 4.

The identification modelling also has some evident shortcomings:

1) It cannot reflect the physical process and working principle of the PCC system. The model parameters do not have physical meanings and the model is weak in explaining the input-output relationship and modelling mismatches. Therefore, the accuracy of the identification model is generally lower than the first-principle model.

In [43] and [68], the accuracy of first principle model was improved by correcting the model parameters using the pilot-plant experimental data. Such a hybrid modelling method, which uses the fundamental knowledge to develop the basic physical model of PCC and then uses the modern data-driven approach to fine tune the model parameters. This may enable more accurate and efficient predictions of PCC performance, reliability and flexibility.

2) Before the identification, the selection of input variables and their corresponding model order also have strong impact on the modelling results. The model accuracy can be insufficient if key influenced variables are not taken into account; while the complexity of the model can be excessively high if less-relevant variables are considered. Therefore, the identification also needs some fundamental expertise of the PCC process. Combining the prior knowledge of the PCC process with advanced data analytical approach to determine the proper model inputs is an important future direction.

3) The identification approach is highly dependent upon data from the PCC processes. Although massive data can be provided, high-quality data are often limited for the following reasons: i) Many variables such as flow rate, solvent loading, concentration are difficult to be accurately measured in real time; ii) The data sets obtained are often mixed with measurement noise and contain many outliers; and iii) a successful identification require data that can reflect critical information of the PCC process. However, designing open-loop experiments to fully excite the PCC system and obtain useful information under various conditions is difficult to carry out owing to the safety reasons. Direct use of the closed-loop operating data for identification is an alternative method, nevertheless, since the input output data are highly correlated in the closed-loop condition, the difficulty of the identification has been increased.

For these reasons, only a few data-driven PCC models were identified from pilot plant operating data, while other models were all developed based on the data obtained from simulators. Applications are sought which utilize modern measurement, data processing, and identification technologies for the PCC process. Additionally, the characteristics of PCC systems easily change due to solvent degradation and corrosion of equipment. The application of adaptive data-driven approaches on the PCC is also of interest.

The studies on data-driven identification of solvent-based PCC are summarized in Table 2.

Table 2. Summary of studies on data-driven identification of solvent-based PCC

Year	Research Institute	Model category	Modelling approach	Model outputs and inputs	Data source	Reference
2008/ 2009	Energy Informatics Laboratory, Faculty of Engineering/ Process Systems Engineering Laboratory and International Test Centre for CO_2 Capture, University of Regina (Canada)	Steady state data-driven model	Multiple-regression technique using the software of SPSS	Four regression models for the re-boiler heat duty, absorption efficiency, CO_2 lean loading and CO_2 production rate were identified. The input variables of these models are selected by prior knowledge of the PCC process and further filtered through the method of partial correlation analysis.	Routinely operated data collected at International Test Center for CO_2 capture (ITC) located at University of Regina, Saskatchewan, Canada	[82], [83]
2010	Energy Informatics Laboratory, Faculty of Engineering, University of Regina (Canada)	Steady state data-driven model	Single-hidden layer feed-forward back-propagation neural networks	Four NN models for the re-boiler heat duty, absorption efficiency, CO_2 lean loading and CO_2 production rate were identified. Solvent circulation rate, steam flow rate, steam pressure, flue gas CO_2 concentration, absorber inlet gas actual flow factored for concentration and off gas flow rate are selected as inputs for all the four models. Insignificant inputs are then eliminated through sensitive analysis and expertise.	Routinely operated data collected at International Test Center for CO2 capture (ITC) located at University of Regina, Saskatchewan, Canada	[84]
2010/ 2011	Faculty of Engineering and Applied Science, University of Regina (Canada)	Steady state data-driven model	Adaptive network based fuzzy inference system	Four ANFIS models for the re-boiler heat duty, absorption efficiency, CO_2 lean loading and CO_2 production rate were identified. The inputs of the model are selected the same as the NN model	Routinely operated data collected at International Test Center for CO_2 capture (ITC) located at	[85], [86]

				(after eliminating the insignificant inputs through sensitive analysis and expertise)	University of Regina, Saskatchewan, Canada	
2011	Department of Mechanical & Structural Engineering & Material Science, University of Stavanger (Norway) and SINTEF Materials and Chemistry, Department of Process Technology (Norway)	Steady state data-driven model	Single-hidden layer feed-forward back-propagation neural networks	Three NN models for the captured CO_2 mass flow rate, rich solvent loading and re-boiler heat duty. The inlet flue gas temperature, flow rate, CO_2 concentration, lean solvent loading, solvent circulation rate and CO_2 removal efficiency are selected as inputs for all the four models. Insignificant inputs are then eliminated through sensitive analysis.	CO2SIM simulator from SINTEF, Norway	[87]
2015	School of Chemical Engineering and Advanced Materials, Newcastle University (UK) and School of Engineering, University of Hull (UK)	Steady state data-driven model/ Dynamic data-driven model	Bootstrap aggregated neural network (Composed by several single-hidden layer feed-forward networks)	PCC absorber model to predict the CO_2 capture rate and capture level. using flue gas flow rate, pressure, CO_2 concentration, temperature, lean solvent flow rate, MEA concentration and temperature	Rate-based first principle PCC model developed in gPROMS® [47]	[31]
2016	School of Chemical Engineering and Advanced Materials, Newcastle University (UK) and School of Engineering, University of Hull (UK)	Dynamic data-driven model	Bootstrap aggregated extreme learning machine	PCC absorber model to predict the CO_2 capture rate and capture level. using flue gas flow rate, pressure, CO_2 concentration, temperature, lean solvent flow rate, temperature, loading and re-boiler temperature	Rate-based first principle PCC model developed in gPROMS® [47]	[88]
2016	School of Chemical and Biomolecular Engineering, The University of Sydney (Australia) and CSIRO Energy (Australia)	Dynamic data-driven model	Multivariable nonlinear autoregressive with exogenous input (NLARX) model (Three NLARX models were developed for the absorber, heat	Flue gas flow rate, CO_2 concentration, lean solvent flow rate and re-boiler heat duty were considered as the input variables; and the CO_2 concentration of absorber off gas, CO2 concentration at top desorber and the flow rate	Tarong CO_2 capture pilot plant located at Tarong power station, Nanango, Queensland, Australia	[32]

			exchanger and desorber respectively. There were combined together to form an integrated PCC process model.)	at top desorber were selected as the output variables.		
2018	School of Chemical Engineering and Advanced Materials, Newcastle University (UK), Department of Automation, Tsinghua University (China) and Department of Chemical and Biological Engineering, University of Sheffield (UK)	Dynamic data-driven model	Deep belief network	PCC absorber model to predict the CO_2 capture rate and capture level. using flue gas flow rate, pressure, CO_2 concentration, temperature, lean solvent flow rate, MEA concentration and temperature	Rate-based first principle PCC model developed in gPROMS [47]	[90]
2018	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China), Department of Chemical and Biological Engineering, University of Sheffield (UK) and Process Systems Enterprise Ltd (UK)	Dynamic data-driven model	Piecewise linear transfer function model (local models identified through System Identification Toolbox in MATLAB)	Models for four main control loops of PCC, including the lean solvent flow- CO_2 capture level loop, steam- re-boiler temperature loop, condenser cooling water- condenser temperature loop and lean cooling water- lean temperature loop	Rate-based first principle PCC model developed in gCCS®	[92]
2018	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China) and Department of Electrical and	Dynamic data-driven model	Fuzzy state-space model (local model identified through Subspace Identification)	CO_2 capture level, re-boiler temperature are selected as the model outputs; lean solvent and re-boiler steam flow rates are selected as the model inputs	Rate-based first principle PCC model developed in gCCS®	[93]

	Computer Engineering, Baylor University (USA)					
2019	Department of Chemical and Biological Engineering/ Department of Automatic Control and Systems Engineering, University of Sheffield (UK)	Dynamic data-driven model	multivariable nonlinear autoregressive with exogenous input (NLARX) model	CO_2 concentration at absorber outlet gas and lean solvent CO_2 loading are selected as the model output; and the flue gas flow rate, lean solvent flow rate and the re-boiler temperature were used as the model input	Rate-based first principle PCC model developed in gPROMS [47]	[91]

4. Control of solvent-based PCC

4.1. Control objectives and challenges for the PCC process

As the electricity selling price and electricity demand vary for the CFPP, the flue gas flow rate and re-boiler steam drawn-off from the turbine will change frequently in a wide range. As a result, optimal operation of the PCC at given operating condition can no longer meet the operation requirement. In this context, an increasing attention has been drawn on the flexible operation of PCC process [23], [24], which expects the PCC system can change the CO_2 capture level rapidly and smoothly; and also adapt to the disturbances caused by the upstream CFPP in a timely manner.

The key issue towards the flexible operation of PCC is to design a proper control system. Some basic requirements for the flexible control of PCC system are listed as follows [25], [29], [30], [33], [39], [47], [51]:

1) Be able to track the desired CO_2 capture level set-points and to maintain the process operating at a given capture level in the presence of various disturbances;

2) Be able to minimize the variation of condenser pressure and temperature to guarantee the quality of CO_2 product;

3) Be able to maintain the liquid levels of inventories to achieve a water balance of the system;

4) Be able to minimize energy consumption during the operating condition change; and

5) Avoid an excessively high re-boiler temperature, which may cause solvent degradation.

However, the following dynamic characteristics of the PCC process make the control design challenging:

1)The overall dynamics of PCC system is very slow since a series of mass transfer, heat transfer and chemical reactions between gas and liquid phases are involved in the process. In addition, the absorber, desorber sumps and the lean MEA tanks provide buffer to the solvent flow rate and further slow down the response of the PCC system. Lawal et al [47] showed that for a reduction in re-boiler heat duty, the PCC system takes more than two hours to enter new steady state, which is much slower than the upstream CFPP;

2) Composed by the reversible processes of absorption and desorption, there are significant couplings among multivariable within the PCC system. This feature is particularly evident among the key variables of CO_2 capture level, re-boiler temperature (lean solvent loading), lean solvent flow rate and re-boiler heat duty [94];

3)The frequent change of flow rate and composition in flue gas will have strong impact on the PCC operation. Meanwhile, there may be many unknown disturbances in the system, such as failure of the pumps, stiction of valves, corrosion of the equipment and solvent degradation;

4) The nonlinearity of the PCC process is strong, the dynamics of the system will change when the operating conditions change [95];

5) There are strict constraints for the controlled variables (MV) and manipulated variables (CV) within the system considering the safety issues and physical limitations of the actuators.

Therefore, many efforts have been made in control design to overcome these issues and achieve a flexible and efficient operation of PCC.

4.2. Decentralized feedback control design for PCC

As the most conventional and reliable control approach, the proportional integral derivative (PID)-based decentralized feedback controllers have been extensively applied in the solvent-based PCC process to ensure a correct operation of the entire process. Because the decentralized control system is developed based on the SISO loops, how to pair the CVs and MVs is key to control design.

4.2.1 Control design based on heuristics of the PCC

Based on the insights gained from the PCC process dynamics (i.e. heuristics), a general control structure was applied in [25], [29], [30], [33], [39], [47], [51], [96-100], as illustrated in Fig. 3. The sump levels are controlled by the downstream liquid valves; the pressures are controlled by the vapor outlet valves; the re-boiler, condenser, lean solvent temperatures are controlled by the flowrates of steam/ cooling water supplied. The water balance of the system is maintained by manipulating the makeup water flow to control the level of the buffer tank, while an additional makeup MEA flow rate is used to control the lean solvent concentration; and the CO_2 capture level, which is defined as:

$$\text{CO}_2 \text{ Capture Level} = \frac{\text{CO}_2 \text{ in flue gas} - \text{CO}_2 \text{ in vented flue gas}}{\text{CO}_2 \text{ in flue gas}} \quad (1)$$

is controlled by the lean solvent flow rate.

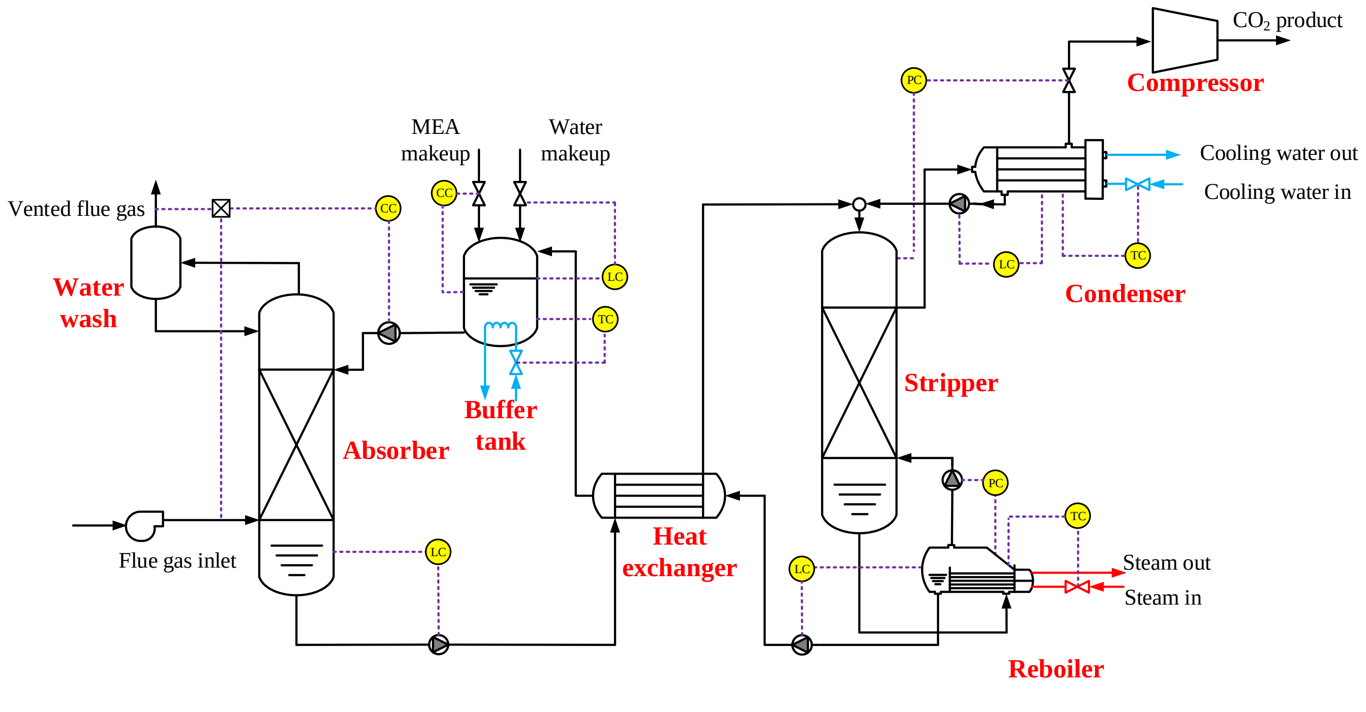

Fig. 3 Conventional control structure of the solvent-based PCC process

Based on this control configuration, Lawal et al [47] designed a series of PI controllers for the integrated PCC process. The dynamic impact of water makeup stop, re-boiler heat duty reduction and flue gas flow rate increase were investigated in closed-loop condition. The control performance of the PCC was tested in case of flue gas CO_2 concentration increase and showed that the given CO_2 capture level can be well maintained. Under the same control structure, Lawal et al [51] conducted dynamic simulations of the integrated CFPP and PCC for reduction of target power output and increase of target CO_2 capture rate. Different responses of the two plants were clearly shown. Since the interactions between them were not taken into consideration, strong oscillations and overshoots in capture level, re-boiler steam and solvent flow rates were observed.

Lin et al. [25] designed the PI controllers under the similar configuration. Since the buffer tank was not used in their studies, the water makeup was manipulated to control the re-boiler sump level. The control performance was evaluated in the presence of flue gas flow rate/composition step changes and showed that the desired capture level and re-boiler temperature can be successfully maintained. The importance of water makeup control and the optimal re-boiler temperature under different operating conditions were also discussed in their work.

Mechleri et al. [96] simulated a PCC plant for a 200MWe nature gas combined cycle (NGCC) plant in ASPEN HYSYS Dynamics® and designed the PI control system according to the conventional configuration. Control performance evaluation was carried out in cases of ±10% flue gas flow rate change. It was discovered that effective disturbance rejection for the capture level and re-boiler temperature can be achieved by the controller. However, it took a very long time for the PCC system to finish the transition process.

Rodriguez et al. [29] tested the performance of the conventional PCC PI control system under the actual load varying operation of the connected CFPP. The upstream CFPP was supposed to change its load from 100% to 75% and then returned back to 100% at the ramping speed of 5% /min. Such a rapid change of load will cause a rapid change of flue gas flow rate and bring in significant disturbances to the PCC system. The simulation results showed that 0.5 hour was needed for the CO_2 capture level to return to steady state and apparent oscillations occurred during the transition. For the re-boiler steam and CO_2 product, almost 1 hour is required to attain new steady state values. The simulation manifested the slow dynamics of the PCC process and indicated that the PI control of PCC may not meet the operating expectations.

Gaspar et al. [97] implemented the conventional decentralized control structure to a PCC process and evaluated its performance in cases of start-up and power plant load changes. Normally distributed pseudo-random noise was added to the flue gas flow rate and CO_2 content to mimic the operation condition of real power plant. Rich and lean solvent storages were considered in the process to better decouple the operation of absorber and stripper, and to improve the flexibility of the process. The results reveal that the conventional PI controllers were able to keep the PCC process operating at the desired point with small deviations during the transition.

Sharifzadeh and Shah [98] selected the same control structure for the PCC process and assessed the controllability and flexibility of the system under a wide range of disturbances such as capture level set-point change and power plant load change. The dynamic impact of re-boiler temperature, MEA concentration, load ramping speed and capture level set-point change speed on the PCC operation was also tested. The flow rate and composition of the flue gas during load change was calculated by steady state CFPP and NGCC power plant models; and a high degree of flexibility was observed for both the coal and gas fired scenarios, demonstrating the effectiveness of the control framework. The PCC for CFPP was found more challenging to control since larger amount of CO_2 has to be removed.

Among multiple variables within the PCC, CO_2 capture level and re-boiler temperature are two most important CVs. The capture level reflects the degree of CO_2 removal from the flue gas. The re-boiler temperature is an indicator of the lean solvent CO_2 loading, which determines its CO_2 absorption ability. Moreover, solvent degradation will occur under an excessively high re-boiler temperature. Many studies of the PCC control focused on how to select MVs to control these two variables [30], [33], [99]. According to the dynamics of PCC, the lean solvent flow rate and the re-boiler steam flow rate are good candidates. Increasing the lean solvent flow rate will increase the amount of solvent directly contacted with the flue gas and rapidly increase the CO_2 capture level. However, as more solvent will flow into the re-boiler, the re-boiler temperature will drop, leading to a rise in lean solvent loading. Therefore, the capture level will gradually return to the previous level [33]. On the other hand, the increase of re-boiler steam flow rate will increase the re-boiler temperature, release more CO_2 from the solvent and reduce the lean solvent loading. The CO_2 absorption capability of the solvent will thus be enhanced and the CO_2 capture level will be increased.

Lin et al. [99] proposed two PI control modes for the integrated PCC system: (Mode-1) the conventional one, which used the lean solvent flow rate to control the capture level and used the steam flow rate to control the re-boiler temperature; (Mode-2) keeping the lean solvent flow rate constant and controlled the capture level through the steam flow rate. Simulations were conducted in case of 1%/min capture level set-point ramping change and Mode-2 was observed to have more stable hydraulic condition. However, it should be noted that, the optimal re-boiler temperature cannot be maintained under control Mode-2, thus the energy performance may be worse. Mechleri et al. [30] further tested the operational flexibility and economic performance of the two PCC control strategies in case of wide range CFPP and NGCC power load change. The performance of another operating scheme which used a dynamical switch between the aforementioned two strategies according to the power plant loading was also assessed. The evaluation results showed that using appropriate control strategy, satisfactory performance can be achieved by the PCC, avoiding the additional need for expensive solvent storage tanks. Among the three control strategies, the conventional control structure provided the best operating flexibility and was most efficient. This advantage was especially evident for CFPP case. Nevertheless, the authors pointed out the other two strategies may still be useful during system start-up and shut-down when there are stringent constraints on the steam supply.

Nittaya et al. [33] compared the conventional decentralized control structures of PCC with another one, which paired the capture level with re-boiler steam flow rate and re-boiler temperature with the rich solvent flow rate. The performance of the control schemes was evaluated under different scenarios such as flue gas flow rate change, capture level set-point change and lean solvent flow valve stiction. Although temporary, the quick impact of lean solvent flow rate on the CO_2 capture level was proven to be very helpful for improving the flexibility of the PCC. The conventional control scheme was shown to have faster responses in flue gas disturbance rejection and capture level tracking. However, the performance of this control scheme may be greatly degraded in case of constraint of re-boiler steam flow rate or the stiction of the lean solvent flow valve.

Garðarsdóttir et al [100] used the conventional control strategy for the PCC in case of CFPP part load operation, where the flue gas flow rate frequently changed along with the power plant load. In CFPP peak load operation, where the steam to re-boiler is decreased for more electricity production, they suggested to use the lean solvent flow rate to maintain the lean solvent loading at a given optimal value. They concluded that, manipulating the solvent flow rate can improve the response time for both the capture level and solvent loading of the PCC.

4.2.2 Control design using RGA analysis

To identify the pairing of CVs and MVs with minimal interactions among multiple control loops, relative gain array (RGA) analysis [101] was used in PCC control designs [23], [33], [102-105]. Nittaya et al. [33] performed RGA analysis for their PCC model and the results suggested that the liquid levels of absorber and re-boiler should be controlled by their downstream solvent flow rate, the temperature of condenser and the lean solvent should be controlled by the cooling water flowrates, which were the same as the conventional control structure. The difference is, the capture level was suggested to be controlled by manipulating the re-boiler steam flow rate and the re-boiler temperature controlled by the lean solvent flow rate entering the absorber. The parameters of the PI controllers were set using internal model control approach initially and then fine-tuned during the simulation. However, the performance of this control structure was found worse than the conventional one in terms of flue gas disturbance rejection and capture level tracking. The reason may be that the RGA analysis only considered the steady state correlation between CVs and MVs and ignored the dynamic effect between them. For the PCC process, the RGA analysis cannot completely reflect the impact of lean solvent flow rate on capture level since only the steady state relationships can be revealed. Considering this limitations, in their following study for an industrial scale PCC control design [102], the authors manually paired the capture level with lean solvent flow rate and re-boiler temperature with steam flow rate. RGA analysis was only used for remaining control loops pairing. The resulting control structure becomes the same as the conventional one and was shown to have smooth transitions in the presence of disturbances or operating condition changes.

Gaspar [103] applied the RGA analysis to design controllers for both the PZ and MEA based PCC plant. The results indicated that, for the PZ plant, the capture level was better to be controlled by the re-boiler duty, whereas the lean solvent loading is controlled by the lean solvent flow rate. The pairing for the MEA plant was found to be consistent with the RGA analysis results given in [104]. They then carried out various dynamic simulations to compare the performance of the two plants. The PZ plant was shown to have slower response, thus required larger gains and small time integrals. The performance of two plants in the presences of solvent flow valve stiction and steam supply shortage was also tested and the performance of PZ plant was more easily degraded. However, since the control structure and parameters settings of the two plants were different, it remained unsure whether the controller or the solvent itself caused this outcome.

In Luu et al [23] and Manaf et al. [32], [105], CO_2 capture level and energy performance (energy consumption per unit CO_2 captured) were defined as two CVs of the PCC system to improve the energy efficiency of the process. Considering that the behavior of PCC is variable, RGA analysis was performed under different operating conditions [105]. The results suggested to pair the capture level and energy performance with lean solvent flow and re-boiler heat duty respectively. Effectiveness of the controller was demonstrated through simulations of capture level/ energy performance set-points changes and flue gas flow rate random changes. However, since the re-boiler temperature was not taken into account, it could not be maintained within the proper range during the transition. To deal with this issue, the authors modified the conventional re-boiler heat duty-energy performance controller to a cascade PID controller [23]. The master controller received energy performance set-point and calculated the re-boiler temperature set-point for the slave controller, from which the appropriate re-boiler heat duty was computed.

4.2.3 Control design through optimization

One key problem with the operation of solvent based PCC is the high energy requirement for solvent regeneration. To reduce the energy consumption a self-optimization control approach [106] was applied to the PCC to find the best CVs in such a way that the process can be kept close to its optimum if the CVs are maintained at their given optimal set-points, even in the presence of disturbances.

Panahi et al. [79] comprehensively analyzed the available MVs, the requirements and constraints for the PCC operation, through which the degree of freedom (DOF) of the optimization was determined. Power and heat consumptions were considered in the objective function to calculate the optimal steady state value of candidate CVs under major disturbances and operating condition changes. Temperature on tray no. 4 of the stripper was found to have minimal sensitivity to the disturbances, thus was selected as CV of the PCC instead of the conventional re-boiler temperature. Heuristics of the process was then used to pair the CVs and MVs; the presented control structure was similar to the conventional one. Simulations in case of flue gas flow rate/ composition change and stripper pressure change illustrated that the proposed control structure has better economic performance. However, since no direct control was imposed on the re-boiler temperature which was the highest within the process, there might be potential problems during PCC operation. In case of strong disturbances or equipment failure, the re-boiler temperature was easily become too high, which could cause solvent degradation.

In Panahi and Skogestad [107, 108], a tax on the CO_2 released to the air was taken into account in the objective function, in addition to the power and heat consumptions. Operating range of the PCC was divided into three regions according to the flue gas flow rate: 1) nominal flue gas flow rate; 2) larger flue gas flow rate that the re-boiler heat duty was saturated; and 3) even larger flue gas flow rate that the process reached minimum allowable CO_2 recovery. Different constraints were considered in the three cases, resulting in different optimization DOF and different CV selections. Various decentralized control configurations were developed using RGA analysis and heuristics. The control structure which used the steam flow rate, rich solvent flow rate and lean solvent flow rate to control the capture level, temperature of tray no. 16 of stripper and absorber sump level was found to have satisfactory performance in all the operating regions.

Schach et al. [109] applied the self-optimization approach in control structure development of two different PCC processes, one with intercooling absorber and the other with two strippers. Ten best CV candidates were found for each process and the coupling of different control structures were analyzed through RGA. The CO_2 separation performance and energy cost of the candidate control structures were evaluated in steady state under 40%, 60% 80% power plant loads. However, the dynamic performance of the proposed control structures was not tested.

Although the self-optimization approach can improve the operation performance of PCC under the simple decentralized control configuration, its advantages are mainly reflected in steady state condition. Thus may have the following limitations for the flexible operation of the PCC:

1) In case of wide range operating condition changes or strong disturbances, the optimal set-points of CVs may change; thus the self-optimization approach can only make the system close to the optimum, but not attain the optimum; and

2) The self-optimization approach is developed based on steady state optimization, thus cannot guarantee a dynamic optimum during the transient changes.

Sahraei and Ricardez-Sandoval [110] proposed a novel process design approach, which simultaneously determine the equipment specifications and controller parameters of the absorber through optimization. The control structure of the absorber was pre- determined, the lean and rich solvent flow rates were selected to control the capture level and absorber sump tank level respectively. Optimization indexes such as capital cost, operating cost and carbon tax were considered in an integrated objective function, which was then minimized under minimal CO_2 capture level requirement and sinusoidal type flue gas flow rate disturbance. Since the dynamic operation performance was pre-considered in the equipment design stage, much lower costs can be achieved by the proposed approach.

4.2.4 Considering ratio control in the decentralized feedback control structure

The most commonly used ratio control in the PCC system is to keep the ratio between lean solvent flow rate and flue gas flow rate (L/G ratio) constant. Lawal et al [36] and Posch and Haider [71] developed absorber models of the PCC and found that the operation of absorber was more sensitive to the L/G ratio. Manipulating the lean solvent flow rate to keep a given constant L/G ratio could improve the performance of absorber and make the absorber quicker respond to the flue gas flow rate change. It was also discovered that, keeping a constant L/G ratio can maintain the CO_2 capture level close to the given value even though the capture level is not closed-loop controlled.

The effectiveness of the L/G ratio control should be tested through the integrated PCC process simulation since the performance greatly depends on how well lean solvent loading is maintained. Based on the conventional PCC decentralized control structure, Lawal et al. [47] put the lean solvent flow control in an open loop condition and make it change synchronously and proportionally according to the variation of flue gas flow rate. A simulation of 10% flue gas flow rate increase showed that, as the lean solvent loading can be roughly maintained due to the constant re-boiler temperature control, the CO_2 capture level could be maintained at almost the same level before the disturbance.

Gaspar et al. [97] compared the performance of constant L/G ratio control with the conventional PI control during the start-up of the PCC plant. In their simulation, the given L/G ratio was not attained until the flue gas flow rate was in steady state. Due to this reason, slow and less accurate CO_2 capture level tracking performance was discovered in the simulations. In Garðarsdóttir et al. [100], the two control schemes were again compared in case of flue gas flow rate change, their results indicated that maintaining a constant L/G ratio in the absorber was slightly better than feedback control of the CO_2 capture level.

Waters et al. [111] developed control structure for a PZ based PCC plant with intercooled absorber and advanced flash stripper. The lean solvent flow rate was used to control the L/G ratio for absorber performance. In the real process, continuous and accurate online measurement of flue gas flow rate is challenging to achieve, which may limit the application of the L/G ratio control. To this regards, waters et al. [73] tested the temperature profiles of absorber and found that the solvent temperature at a certain level of absorber can be a good indicator of the L/G ratio. However, the temperature set-point may need to be modified in the presence of flue gas composition change, lean solvent temperature change etc., so that the desired L/G ratio can be maintained.

Actually, to a large extent, implementing the ratio control can compensate the shortcoming of feedback control in slow response. As we know, the adjustment of the conventional PI/PID based feedback controller is based on the deviations of the CVs from their set-points. For the slow PCC process, it takes quite a long time from the occurrence of the disturbances to the process entering new steady state. Therefore, using the feedback control can easily lead to slow responses or frequent oscillations of the PCC system. By appropriate use of the ratio control, some MVs can change synchronously with the disturbances, which can effectively suppress the further increase of control deviations and accelerate the response of the PCC system.

Besides the constant L/G ratio control, Ziaii et al. [48] proposed to adjust the rich solvent flow rate proportionally to the change of re-boiler steam rate. Their simulation showed that by implementing such a ratio control for the stripper, the lean solvent loading and re-boiler temperature could be maintained almost constant, meanwhile the response time of the system was greatly reduced. To improve the response time of the integrated PCC system, Ceccarelli et al. [112] proposed to manipulate both the solvent flow rate and re-boiler steam flow rate proportionally to the flue gas flow rate. Schach et al. [109] used self-optimization method in their control design studies and suggested to keep the L/G ratio constant for the economic operation of the PCC with intercooled absorber; whereas for the PCC equipped with two strippers, the best control scheme was to regulate the lean solvent flow rate, steam flow rate and split ratio all proportionally to the flue gas flow rate.

Flue gas flow rate is the main disturbance to the PCC process. Similar as feedforward control, directly adjusting the MVs according to the changes of flue gas flow rate can speed up the response of the PCC system. However, the use of the ratio control in open loop condition may easily lead to large control offset since the MVs are regulated completely according to the variation of flue gas flow rate. It is impossible for the ratio control to accurately control the CVs such as capture level. Moreover, in the occurrences of unknown disturbances, the optimal ratio may change and the effect of ratio control may be degraded.

4.2.5 Limitations and future directions of decentralized PCC feedback control

The conventional PI/PID based decentralized control has been successfully used in industrial processes for its simple structure, convenient tuning, higher robustness and satisfactory performance in disturbance rejection during the operation maintained around a base load. However, as the PCC is required to be operated in a flexible manner, the conventional PI/PID control schemes may no longer meet the operating specifications, owing to the complex behaviour of PCC such as severe nonlinearity over wide operating range, strong couplings among multi-variables, slow responses and disturbances. The main limitations of the decentralized feedback control using PID are concluded as follows:

1) The control mechanism of the feedback control is based on the deviations of CVs from their references, therefore, its control action is not in time and cannot speed up the slow response of the PCC in the best way;

2) In general, the parameters of the feedback controller are tuned under the designed operating conditions and then fixed. During the flexible operation, severe performance degradation may occur when operating condition changes;

3) There are strict limitations for the CVs and MVs on the PCC operation, however, the decentralized feedback control is not capable to consider these constraints in the design stage. When the constraints are involved during the regulation, the performance is still decreased even the controllers are well designed and tuned. Moreover, under long-term of this state, integral windup may occur for the controller, which will further degrade the control performance; and

4) The decentralized feedback control is developed based on the SISO loop, which cannot consider the interactions among multiple loops and implement a comprehensive control for the integrated system.

Therefore, 1) combining feedforward and feedback control to accelerate the response of PCC while guaranteeing the robustness and accuracy of the control; 2) developing gain-scheduling or auto-tuning PI controller to improve the control performance of wide range load change; 3) considering active disturbance estimation and compensation in the control structure to handle the unknown disturbances and plant behaviour variations; and 4) design more advanced de-coupling control scheme to alleviate the interactions among multi-variable, are potential directions for decentralized control studies of the PCC.

The progression in decentralized control of solvent-based PCC is summarized in Table 3.

Table 3. Summary of studies on decentralized control of solvent-based PCC

Year	Research Institute	Process model	Control structure/ design strategy	Simulation cases for control test	Reference/ Section Discussed
2009	Department of Chemical Engineering, The University of Texas at Austin (USA)	PCC stripper model in Aspen Custom Modeler®	Adjusting the rich solvent flow rate proportionally to the change of re-boiler steam rate	10% step reduction of re-boiler heat duty	[48]/ Section 4.2.4

2010	School of Engineering, Cranfield University (UK), RWE npower (UK) and Process Systems Enterprise Ltd (UK)	PCC model in gPROMS®	1) Conventional control structure; 2) Constant L/G ratio, re-boiler temperature controlled by re-boiler steam flow rate	i) switching off water balance control; ii) Increasing flue gas flow rate iii) reducing re-boiler heat duty iv) Increasing CO_2 concentration of flue gas	[47] / Section 4.2.1& 4.2.4
2010	Department of Chemical Engineering, Norwegian University of Science and Technology (Norway)	PCC model in UniSim®	Self-optimizing control design	Power plant load changes and stripper pressure changes	[79]/ Section 4.2.3
2011	Department of Chemical Engineering, National Tsing-Hua University, (Taiwan, China) and School of Electrical and Information Engineering, Jiangsu University (China)	PCC model in Aspen Dynamics®	Conventional control structure (re-boiler sump level controlled by water makeup)	i) change of water makeup ii) disturbances in flue gas flow rate and composition	[25] / Section 4.2.1
2011/ 2012	Department of Chemical Engineering, Norwegian University of Science and Technology (Norway)	PCC model in UniSim®	Self-optimizing control design for different operating conditions+ RGA analysis/ heuristics	Flue gas flow rate change	[107], [108] / Section 4.2.3
2012	National Tsing-Hua University, (Taiwan, China) and China Steel Corporation (Taiwan, China)	PCC model in Aspen Plus®	1) Conventional control structure; 2) Constant solvent flow rate, capture level controlled by re-boiler steam flow rate	CO_2 capture level set-point ramping change	[99] / Section 4.2.1
2012	School of Engineering, Cranfield University (UK) and RWE npower (UK)	Integrated CFPP-PCC model in gPROMS®	Conventional control structure	i) reducing target power output ii) increasing CO_2 capture level set point	[51] / Section 4.2.1
2013	Institute of Thermal, Environmental and Natural Products Process Engineering, TU Bergakademie Freiberg (Germany) and Siemens AG Energy Sector, Fossil Power Generation	Two PCC models ,one with intercooled absorber and one with two strippers	Self-optimizing control design + RGA analysis	CO_2 removal and energy Performance analyzed in given steady state conditions	[109] / Section 4.2.3

	(Germany)				
2014	Department of Chemical Engineering, Imperial College London (UK) and School of Engineering, Cranfield University (UK)	PCC model in Aspen HYSYS Dynamics®	Conventional control structure	10% step increase/ decrease of flue gas flowrate	[96] / Section 4.2.1
2014	Process Systems Enterprise Ltd (UK)	PCC model in gCCS®	Conventional control structure	Power plant load change	[29] / Section 4.2.1
2014	Department of Chemical Engineering, University of Waterloo (Canada)	PCC model in gPROMS®	1) Conventional control structure; 2) capture level controlled by re-boiler heat duty rate-; re-boiler temperature controlled by lean solvent flow rate 3) RGA analysis	i) flue gas flow rate change ii) flue gas composition change iii) change of capture level set-point iv) change of CO2 purity in product's stream v) lean solvent valve stiction vi) constant water and MEA makeup during flue gas flow rate change vii) limited re-boiler heat duty during flue gas flow rate change viii) Step-wise increments in the flue gas flow rate	[33] / Section 4.2.1 & 4.2.2
2014	Department of Chemical Engineering, University of Waterloo (Canada)	PCC model in gPROMS® (with three absorbers and two strippers)	CO_2 capture level controlled by lean solvent flow rate, re-boiler temperature controlled by steam flow rate, remaining CVs and MVs are paired with RGA analysis	i) ramp change in flue gas flow rate ii) CO_2 capture level set-point change iii) flue gas composition change; iv) sinusoidal change in the flue gas flow rate+ scheduled changes in CO_2 capture level set-point	[102] / Section 4.2.2
2014	School of Chemical and Biomolecular Engineering, The University of Sydney (Australia) and Division of Energy Technology, CSIRO (Australia)	multivariable non-linear autoregressive with exogenous input (NLARX) PCC model developed data	RGA analysis: CO_2 capture level controlled by lean solvent flow rate, energy performance controlled by re-boiler heat duty;	i) capture level and energy performance set-points change ii) Flue gas flow rate and composition change	[105] / Section 4.2.2

		identification			
2014	Department of Chemical Engineering, University of Waterloo (Canada)	PCC absorber model in Aspen HYSYS Dynamics®	Fixed absorber control structure, simultaneously determine the equipment specifications and controller parameters through optimization	Sinusoidal flue gas flow rate change	[110] / Section 4.2.3
2014	Shell Global Solutions (The Netherlands) and Process Systems Enterprise Ltd (UK)	PCC model in gPROMS® (with two absorbers)	Manipulating both the solvent flow rate and re-boiler steam flow rate proportionally to the flue gas flow rate	Upstream CCGT load change	[112] / Section 4.2.4
2014	Department of Chemical Engineering, University of Waterloo (Canada)	PCC model in Aspen HYSYS Dynamics®	RGA analysis (results in conventional controls structure)	i) flue gas flow rate increase ii) capture level set-point tracking iii) limited re-boiler heat duty during flue gas flow rate change	[104] / Section 4.2.2
2015	Department of Energy and Environment, Chalmers University of Technology (Sweden) and Modelon AB (Sweden)	PCC model in Modelica®	part load operation: 1) Conventional control structure 2) Constant solvent flow rate, lean solvent loading controlled by re-boiler steam flow rate 3) Constant L/G ratio, lean solvent loading controlled by re-boiler steam flow rate peak load operation: lean solvent loading controlled by lean solvent flow rate	i) pat load: flue gas flow rate change ii) peak load: re-boiler steam flow rate reduce	[100] / Section 4.2.1 & 4.2.4
2015	School of Chemical and Biomolecular Engineering, The University of Sydney (Australia)	First order plus dead time transfer function developed	Two decentralized control structure designed through RGA analysis: 1) CO_2 capture level	Flue gas flow rate and composition change	[23] / Section 4.2.2

		through linearization of PCC model developed in gPROMS®	controlled by lean solve flow rate, energy performance controlled by re-boiler heat duty; 2) CO_2 capture level controlled by lean solve flow rate, cascade PID control for the energy performance		
2015	Department of Chemical and Biochemical Engineering/ Department of Applied Mathematics and Computer Science, Technical University of Denmark (Denmark)	PCC model	1) Conventional control structure; 2) Constant L/G ratio, re-boiler temperature controlled by re-boiler steam flow rate	i) start-up operation of PCC ii) load changes of power plant in the presence of noises in flue gas	[97] / Section 4.2.1 & 4.2.4
2016	Department of Chemical Engineering, The University of Texas at Austin (USA)	PCC model with intercooled absorber, advanced flash stripper based on PZ solvent developed in MATLAB/ SIMULINK®	Conventional plant-wide control structure with constant L/G ratio	i) CO_2 delivery set-point change ii) steam flow rate change iii) CO_2 capture level set-point change iv) striper condition change	[111] / Section 4.2.4
2016	Department of Chemical Engineering, The University of Texas at Austin (USA)	Intercooled PCC absorber model in gPROMS®	Temperature at a certain level of absorber (it was found to be a good indicator of the L/G ratio) controlled by solvent flow rate solvent + set-point modification according to the disturbances	i) Flue gas flow rate change ii) disturbance in intercooling water temperature	[73] / Section 4.2.4
2016	Department of Chemical Engineering/ Department of Applied Mathematics and Computer Science, Technical University of Denmark (Denmark) and	PCC model in dCAPCO2® (based on PZ and MEA)	RGA analysis	i) flue gas ramp change ii) flue gas ramp change with lean solvent flow valve stiction iii) Steam supply shortage under constant	[103] / Section 4.2.2

	Department of Chemical Engineering, University of Waterloo (Canada)			flue gas flowrate	
2016	School of Chemical and Biomolecular Engineering, The University of Sydney (Australia) and CSIRO Energy (Australia)	multivariable non-linear autoregressive with exogenous input (NLARX) PCC model developed data identification	RGA analysis: CO_2 capture level controlled by lean solvent flow rate, energy performance controlled by re-boiler heat duty;	capture level and energy performance set-points change	[32] / Section 4.2.2
2017	Centre for Process Systems Engineering/ Centre for Environmental Policy, Imperial College London (UK), Process Systems Enterprise Ltd (UK) and IEAGHG R&D Programme (UK)	PCC model in gCCS®	1) Conventional control structure; 2) Constant solvent flow rate, CO_2 capture level controlled by re-boiler steam flow rate 3) switch between the aforementioned two scheme according to the power load	Variation in flue gas flow rate	[30] / Section 4.2.1
2019	Department of Electronic and Electrical Engineering, University College London (UK) and Centre for Process Systems Engineering, Imperial College London (UK),	PCC model in gCCS®	Conventional control structure	Capture level set point and NGCC/ CFPP load change under different operating conditions	[98] / Section 4.2.1

4.3 Model predictive control design of PCC

The increasing demand for flexible PCC operations has attracted more and more scholars to pay attention to the use of advanced controllers. Model predictive control (MPC) is one of the best controllers owing to its outstanding ability in handling PCC control issues.

MPC refers to a class of control approaches which utilize an explicit process model to predict the future response of the plant under different input sequences. The best input sequence is then calculated through the optimization of a dynamic objective function [113]. The fundamental idea of the MPC is illustrated in Fig. 4 and its design framework can be briefly concluded in four steps:

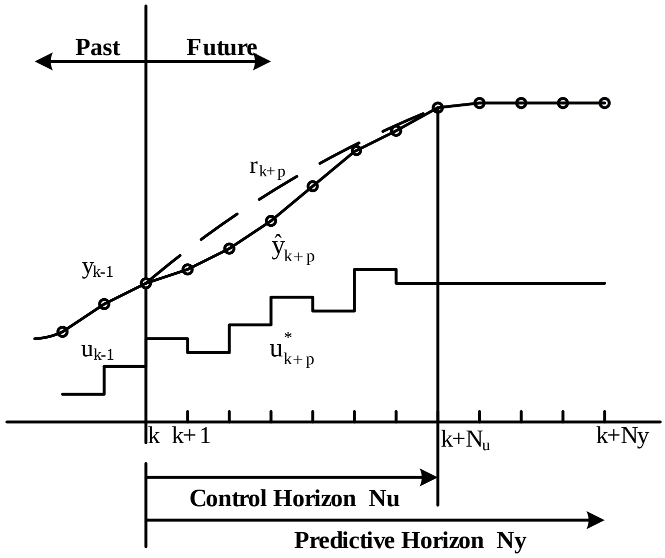

Fig. 4. Basic idea of the MPC.

Step 1. (off-line preparation) Establish a dynamic model of the process to associate MVs with the CVs and other concerned variables;

Step 2 (online implementation) At current sampling instant k, estimate the future response of the process $\{\hat{y}_{k+1}, \hat{y}_{k+2}, \cdots, \hat{y}_{k+N_y}\}$ through the prediction of dynamic model and express it as a function of future input sequence $\{u_{k+1}, u_{k+2}, \cdots, u_{k+N_u}\}$ and available or estimated current state;

Step 3 (online implementation) Calculate the optimal future input sequence $\{u^*_{k+1}, u^*_{k+2}, \cdots, u^*_{k+N_u}\}$ through minimization of a dynamic objective function subject to given input and output constraints. Depending on the operating target, control performance or economic performance of the process can both be considered in the objective function;

Step 4 (online implementation) Apply the first element in the optimal input sequence u^*_{k+1} on the process, and return to Step 2 at next sampling time to implement a receding horizon optimization.

MPC has some distinguished advantages, which make it very suitable for PCC control:

1) The model prediction based working principle makes the MPC possible to speed up the slow response of PCC;

2) MPC is naturally a multi-variable controller which can effectively handle the couplings among multi-variables within the PCC;

3) The operational constraints of the process can be taken into account at the controller design stage, which can increase the flexibility for operation; and

4) Both the control tracking performance and the energy performance can be considered in the objective function of MPC, which can be directly used to improve the dynamic performance of PCC in flexible and economic operation.

Under conventional design framework, modelling is the prerequisite and foremost important step for MPC development. The accuracy of the model determines the performance of the controller, whereas the expression formation of the model determines the computational complexity and robustness. From the perspective of model utilized, the use of MPC in PCC can be divided into two categories: linear MPC and nonlinear MPC. From the perspective of objective function, dynamic control such as set-point tracking is mostly concerned in the objective function, only a few studies consider the economic optimization in the MPC design of PCC.

4.3.1 Linear MPC design for solvent based PCC

The first MPC study on the PCC process was proposed by Bedelbayev et al. [114], for the control of an individual absorber. The complex first principle model was linearized at a given operating point, and used as the predictive model of the MPC. The CO_2 concentration in the vented flue gas was considered as the CV and the lean solvent velocity was selected as the MV. In addition, the inlet gas velocity, temperature and CO_2 content were taken into account in the model to improve the performance of MPC in disturbance attenuation. Simulations in cases of step changes of set-point and inlet flue gas disturbances were conducted. Sufficient good performance was observed from the results.

Similarly, in Cormos et al. [115], MPC was designed to regulate the CO_2 concentration in vented flue gas using the solvent flow rate. Typical disturbance of flue gas flow rate increase was introduced in the simulation and an upper limit of CO_2 concentration was imposed for the PCC operation. The MPC demonstrated to have valuable potential to perform efficient control while complying with the constraints.

To minimize the operation cost of solvent regeneration, Arce et al. [116] proposed a two-level hierarchical control structure for the PCC stripper. The high level control determined the economic CO_2 capture flow set-point through solving a steady state optimization problem on an hourly basis considering the CO_2 price and energy price. Two generalized predictive controllers (GPC) were developed in the lower layer to track the optimal set-points. The first GPC controlled the re-boiler pressure by manipulating the vapor molar flow, while the constraints of re-boiler temperature were included in the formulation. The other GPC controlled the CO_2 capture flow and re-boiler level by manipulating the solvent inlet flow and heat supply, whereas the solvent outlet flow was considered as a measured disturbance. First order transfer function models were identified through the System Identification Toolbox of MATLAB® and used as the predictive models. Simulation results illustrated the advantages of the proposed hierarchy in operating cost saving and showed that GPC could respond faster than the conventional PID control and better eliminate the effects of disturbances.

Sahraei and Ricardez-Sandoval [104] presented an MPC for the flexible operation of the integrated PCC process. Input output data collected from open-loop simulations of the ASPEN HYSYS® process model were used to identify the linear first order models, which were then transformed into the state space model and used as the predictive model. The MPC was designed for the dynamic control purpose that considered the conventional set-point tracking and actuator moving performance in the objective function. Simulation was carried out in cases of flue gas flow rate change, capture level set-point change and limited re-boiler heat duty. A decentralized feedback control under the conventional structure was used for comparison. Simulations discovered that superior response speed, dynamic error and compliance of the constraints could be achieved by the MPC. Based on the MPC, a simultaneous scheduling and control scheme was then proposed by the authors to determine the optimal operating strategy under environmental and operational constraints. The energy consumption and CO_2 emission of the plant were considered when formulating the objective function of the optimization, in which their weights were set according to the current operating scenario. A sinusoids flue gas flow rate was introduced to the PCC plant in the simulation and showed that the proposed scheduling strategies was more feasible and efficient for the PCC operation compared to the normal steady state optimization results. He et al. [117] extended this work by dynamically adjusting the weights of the MPC in the scheduling optimization. The increase of the freedom made the integrated scheduling and control structure very close to an economic MPC, which directly calculate the optimal control sequence by dynamically minimizing an economic objective performance. Better scheduling and control performance has been achieved for the PCC according to their results.

Mehleri et al. [118] evaluated the controllability of the solvent-based PCC process under the implementation of MPC. An MIMO state-space model obtained through transformation of several identified linear transfer function models was used as the predictive model. Their simulation results have again shown that, the implementation of MPC provided a good option for the PCC operation in terms of flue gas flow rate disturbance rejection and capture level set-point tracking.

Luu et al [23] designed a linear MPC to control the CO_2 capture level and energy performance of the PCC plant. The lean solvent flow rate and re-boiler heat duty were selected as the MVs, whereas the flue gas flow rate and CO_2 concentration were regarded as the measured disturbances. The re-boiler temperature was not strictly controlled in their design, but was required to be maintained within a given range for the safe operation of PCC. First order plus dead time transfer functions among these variables were identified and used as the predictive model. A case study with step wise flue gas flow rate/ CO_2 concentration variations and set-point changes was presented and the MPC was compared with two other decentralized PID controllers. The comparisons highlighted the distinguished advantages of MPC in handling the operational constraints, which could provide the most satisfactory control performance while guaranteeing the input-output variables within the specified operating range. The MPC was further used in [119], [120] as a lower layer controller to track the ideal CO_2 capture level set-point, which was optimized at the upper layer for maximizing the operating revenue of the integrated CFPP-PCC plant under the changing electricity price. According to their results, the MPC exhibited good performance by minimizing the controller error to an average of 4% [119] and the proposed flexible operating mode can increase the net revenue by approximate 6% against the fixed operating mode [120].

Directly developing an MPC involving too many variables will lead to too high prediction dimensions, thus degrade the efficiency and robustness of calculation. In fact, there is no need to design MPCs for all the variables within the PCC. Some variables, for example, the sump and tank levels, which are weakly coupled with other variables, simple in characteristics and low requirements in control. It is sufficient to use conventional feedback control to achieve a satisfactory performance. For these reasons, some MPC studies [34, 94, 95] only considered the adjustment of CO_2 capture level and re-boiler temperature by manipulating the lean solvent flow rate and re-boiler steam flow rate, because they are most important variables within the PCC process and can reflect the main couplings between the absorber and stripper.

Zhang et al. [34] developed such a linear MPC controller for the integrated PCC process via MATLAB® MPC Toolbox. The flue gas flow rate, CO_2 concentration and rich solvent flow rate were considered in the predictive model identification as measured disturbances. For simulated power plant load and target capture level changes, the control performance of MPC in capture level control was much better than the PID controller. However, regarding the re-boiler temperature, the performance of MPC becomes similar to that of PID, mainly due to the modelling mismatches. Effective control strategies to avoid flooding in absorber were also discussed in their study.

Wu et al. [94] analyzed the dynamic behavior variation and nonlinearity of the PCC at different operating points. They found that if the re-boiler temperature could be maintained closely around the optimal set-point, the nonlinearity was not strong within 50%-90% CO_2 capture level range. Therefore, a linear MPC was developed for the flexible operation of PCC within this range and was shown to have better performance in capture level tracking compared to the conventional PI control structure. In addition, the flue gas flow rate was considered in their predictive model as measured disturbance, so that a quick alleviation for the effect of flue gas variation could be attained.

Although an excellent control performance of MPC has been shown in these studies, its robustness is not as good as the conventional PID, since the performance of MPC greatly depends on the accuracy of the model. During the flexible operation of the PCC, the operating point can deviate far away from the designed condition under which the linear predictive model is developed. Strong modelling mismatches may thus occur which will severely degrade the control performance or even cause the control system unstable. To these regards, a disturbance rejection predictive controller was proposed in [95] for the operation control of PCC in the presences of model mismatches, plant behavior changes and unknown disturbances. A disturbance observer was designed in the MPC structure to estimate the values of disturbances, through which the predictive control signal can be compensated for quick disturbance rejection control.

In recent studies presented by Wu et al. [121], [122], MPCs were designed for the integrated operation of CFPP-PCC system based on the understanding of how the two system were dynamically interacted with each other. A centralized MPC controlling the key variables within the entire CFPP-PCC system was developed in [121]; and a coordinated control system composed by two MPCs developed for the CFPP and PCC respectively was presented in [122]. Different operating modes were proposed in these studies to better achieve the functions of the CFPP-PCC system in power generation and CO_2 reduction. By fully estimating and utilizing the interactions between the two system, better control performance could be achieved by the proposed controllers.

4.3.2 Nonlinear MPC design for solvent based PCC

Developed based on a linear model of the process, the linear MPC is mature in technique and has advantages in efficient and robust computation, thus it has been extensively used in PCC control. However, with the increasing demand of flexible operation, the PCC system is required to face the varying flue gas and adjust its CO_2 capture level over a wide range. During the transition, the other variables within the PCC system such as the re-boiler temperature may change significantly. As these key variables deviate from the designed conditions, the dynamics of the plant will change and strong nonlinear behavior will be exhibited. Since the linear model developed around a given operating point may no longer be sufficient to reflect the behavior of PCC in this situation, it is inevitable to use the nonlinear MPC to improve the operating performance of PCC.

Åkesson et al. [59], [61] proposed the first nonlinear MPC for the PCC process. To develop an appropriate model efficient for on-line calculation of MPC, the complex PCC process model was simplified by replacing the chemical reactions in the liquid phase with an interpolated table having equilibrium data. Two nonlinear MPCs were then designed based on the model, which aimed to control the CO_2 capture efficiency of the PCC. One MPC used the re-boiler heat duty as the only MV, while both the re-boiler heat duty and solvent recirculation rate were selected as MVs in the other MPC [61]. The results indicated the feasibility of nonlinear MPC in PCC process and showed that it was essential to control the PCC process by manipulating the solvent circulation rate.

Zhang et al. [123] developed a nonlinear MPC for the PCC process using a nonlinear additive autoregressive model with exogenous inputs (NAARX). The identified NAARX model is superior to the linear model in wide range capture level and re-boiler temperature prediction, resulting in better performance of the nonlinear MPC compared with the linear MPC. However, the improvement was very limited since it was challenging to select suitable cross-terms of NAARX model to further modify the approximation accuracy.

He et al. [124] compared the performance of nonlinear MPC, linear DMC and PID controllers for conventional and lean vapor compression PCC configurations. Maintaining the carbon capture level at 90% under the flue gas flow rate change was the primary goal of the MPC, but the power consumption was also considered in the objective function to improve the economic performance. The MPCs were successfully implemented and were shown to have much superior control performance compared to the PID control. However, since different objective functions were used for the DMC and nonlinear MPC, the comparisons between them were unfair. He and Lima [125] modified the nonlinear MPC by including the penalty of MV actions and lean solvent loading control in the objective function. Simulations on a conventional PCC process under flue gas flow rate change demonstrated the effectiveness of the nonlinear MPC in tracking/ maintaining desired CO_2 capture level. The nonlinear MPC outperformed the linear DMC since the mismatch of linear model increased during the operating condition change.

To overcome the nonlinearity of PCC process, Wu et al. [35] proposed a multi-model predictive control strategy for wide range flexible operation of the PCC. Three local linear MPCs developed at low, medium and high CO_2 capture level regions were combined together and scheduled through a membership function determined by the current capture level. Simulations showed that the multi-model predictive control system controlled the PCC plant better than the linear MPC, which could attain a rapid and smooth change of the CO_2 capture level in wide operating range.

Instead of using MPC to track the desired set-points, Chan and Chen [126], [127] proposed an economic model predictive control (EMPC) strategy for the PCC operation. The economic performance such as the cost of MEA solvent and the energy usage for pumps and re-boilers was directly considered in the objective function. The future solvent flow rate and re-boiler duty sequences which could attain the best economic performance within the predictive horizon were calculated through the dynamic optimization. Compared with the conventional design framework composed by steady state set-point optimization and dynamic set-point tracking control, the EMPC has simple structure and can better handle the disturbances in the optimization. Lower cost of CO_2 capture was found with the implementation of EMPC.

4.3.3 Limitations and future directions for predictive control of PCC

MPC has shown good performance in the flexible operation of the PCC process. However, as a model based controller, how to develop a suitable predictive model is the key obstacle limiting the wide application of MPC in the PCC system.

To date, most of the studies have focused on controlling the PCC through linear MPCs, which can be solved efficiently and reliably in the form of standard quadratic programming problem. However, the linear model is only effective in reflecting the dynamics of linear system and cannot capture the nonlinear dynamics of PCC process in a wide operating range. Therefore, many linear MPC designs for the PCC are limited in a small operating range and may not meet the requirement of wide range flexible operation. Some studies have tried to use nonlinear MPC to overcome this issue. However, it is a great challenge to design a satisfactory nonlinear model to capture the global dynamics of PCC: the simple data driven nonlinear model may still not have the expected accuracy, whereas the rigorous first-principle model is too complex to be calculated efficiently and robustly.

From this point of view, future studies should:

1) Gain in-depth knowledge of the nonlinear distribution of the PCC and partition the whole operating range into some small regions with weak nonlinearity; and decompose the complex nonlinear control issue into several simple linear control issues using the multiple model strategy;

2) Integrate the first-principle modelling approach with the state-of-art data-driven artificial intelligent technique, and develop appropriate predictive models with satisfactory accuracy and simple structure for the predictive control of PCC;

3) Online assess and update the PCC predictive model.

In addition, uncertainty is another issue for the MPC of PCC. On one hand, the modelling mismatches were impossible to be completely avoided considering the complex dynamics of PCC. On the other hand, due to changes in flue gas and solvent compositions, there exists frequent dynamic changes and unknown disturbances for the PCC system. Developing advanced MPC algorithm to improve the robustness and disturbance rejection property of the PCC system has to be studied further in future.

Previous MPC studies on the solvent-based PCC process are summarized in Table 4.

Table 4. Summary of the MPC studies on the solvent-based PCC process

Year	Research Institute	Controlled process	Controller	Predictive model	Simulation Case	Reference
2008	Department of Electrical Engineering, Information Technology, and Cybernetics, Telemark University College (Norway)	Single absorber	Linear MPC CV: CO_2 concentration in the vented flue gas MV: solvent velocity Disturbance: inlet gas velocity, temperature and CO_2 content	Developed through linearizing the first-principle model at given operating point.	i) step changes of CO_2 concentration set-point ii) inlet flue gas disturbances	[114]
2011	Modelon AB (Sweden), Vattenfall Research and Development AB (Germany), Department of Chemical Engineering, Texas A&M University (USA) and Department of Automatic Control, Lund University (Sweden)	Integrated PCC process	Nonlinear MPC CV: CO_2 capture efficiency MV: re-boiler heat duty and solvent recirculation rate	Model developed through simplification of first-principle model	CO_2 capture efficiency set-point change	[59]
2012	Modelon AB	Integrated	Nonlinear MPC	Model developed	CO_2 capture	[61]

	(Sweden), Department of Chemical Engineering, Texas A&M University (USA), Department of Automatic Control，Lund University （Sweden）and I'Eau et I'Environment (France)	PCC process	CV: CO_2 capture efficiency MV: re-boiler heat duty and solvent recirculation rate	through simplification of first-principle model	efficiency set-point change	
2012	Departamento de Ingeniería de Sistemas y Automatica, Universidad de Sevilla (Spain), Centre for Process Systems Engineering, Imperial College London （UK）and MATGAS Research Center (Spain)	Single stripper	Two Linear GPCs in lower layer of a hierarchical control structure GPC 1: CV: re-boiler pressure (constraint for re-boiler temperature) MV: vapor molar flow GPC 2: CV: CO_2 capture flow and re-boiler level MV: solvent inlet flow and heat supply Disturbance: solvent outlet flow	First order transfer function model developed through data-driven system identification	solvent outlet flow and rich solvent loading change	[116]
2014	Department of Chemical Engineering, University of Waterloo, Waterloo (Canada)	Integrated PCC process	Linear MPC CV: CO_2 product flow, capture level; absorber level, re-boiler level, condenser level, re-boiler temperature MV: lean solvent flow rate, condenser duty, re-boiler duty, rich solvent flow rate, re-boiler outlet flow rate, condenser outlet flow rate	Linear first order models (transfer into the state-space model) developed through data-driven system identification	i) flue gas flow rate change ii) capture level set-point change iii) limited re-boiler heat duty	[104]
2015	Faculty of Chemistry and Chemical Engineering, Babes-Bolyai University (Romania)	Single absorber	Linear MPC CV: CO_2 concentration in the vented flue gas MV: solvent flow rate	Not specified.	flue gas flowrate change	[115]
2015	Centre for Environmental Policy/	Integrated PCC process	Linear MPC CV: CO_2 product flow,	Linear first order model (transfer into the	i) flue gas flow rate change	[118]

	Centre for Process System Engineering, Imperial College London (UK)		capture level; absorber level, re-boiler level, condenser level, re-boiler temperature MV: lean solvent flow rate, condenser duty, re-boiler duty, rich solvent flow rate, re-boiler outlet flow rate, condenser outlet flow rate	state-space model) developed through data-driven system identification	ii) capture level set-point change	
2015	School of Chemical and Biomolecular Engineering, The University of Sydney (Australia)	Integrated PCC process	Linear MPC CV: CO_2 capture level and energy performance of the PCC plant MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate and CO_2 concentration	First order plus time delay transfer function model developed through data-driven system identification	flue gas flow rate /CO_2 concentration variations and set-point changes	[23]
2016	Department of Chemical Engineering, West Virginia University (USA)	Integrated PCC process	Linear MPC CV: CO_2 capture level and re-boiler temperature MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate, CO_2 concentration, rich flow solvent flow rate	Linear transfer function model developed through data-driven system identification	i) flue gas flow rate /CO_2 concentration variations ii) capture level set-point changes	[34]
2016	Department of Chemical Engineering, University of Waterloo, Waterloo (Canada)	Integrated PCC process	Linear MPC （online tuning the weights in the scheduling optimization ） CV: CO_2 product flow, capture level; absorber level, re-boiler level, condenser level, re-boiler temperature MV: lean solvent flow rate, condenser duty, re-boiler duty, rich solvent flow rate,	Linear first order model (convert into the state-space model) developed through data-driven system identification	i) flue gas flow rate change ii) capture level set-point change	[117]

			re-boiler outlet flow rate, condenser outlet flow rate			
2016/ 2017	School of Chemical and Biomolecular Engineering, The University of Sydney (Australia)	Integrated PCC process	Linear MPC in lower layer of a hierarchical control structure CV: CO_2 capture level and energy performance of the PCC plant MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate and CO_2 concentration	First order plus time delay transfer function model developed through data-driven system identification	flue gas flow rate /CO_2 concentration variations and set-point changes	[119], [120]
2018	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China), Department of Chemical and Biological Engineering, University of Sheffield (UK) and Process Systems Enterprise Ltd (UK)	Integrated PCC process	Linear MPC CV: CO_2 capture level and re-boiler temperature MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate	State space model developed through data-driven system identification	i) capture level set-point change; ii) flue gas flow rate change;	[94]
2018	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China), Department of Chemical and Biological Engineering, University of Sheffield (UK) and Process Systems Enterprise Ltd (UK)	Integrated PCC process	Multi-model MPC CV: CO_2 capture level and re-boiler temperature MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate	State space model developed through data-driven system identification	i) capture level set-point change; ii) flue gas flow rate change;	[35]
2018	Department of Chemical and	Integrated PCC with	Nonlinear MPC (penalty on MV actions	Autoregressive-moving average model with	Maintain the given capture	[124]

	Biomedical Engineering, West Virginia University (USA)	conventional and lean vapour compression configuration	was not considered in the objective function) CV: CO_2 capture level (main control target), power consumption MV: lean solvent flow rate, re-boiler heat duty Disturbance: flue gas flow rate	exogenous variables developed through data-driven system identification	level in case of flue gas flow rate change	
2018/ 2019	Department of Chemical Engineering, Chung-Yuan Christian University (Taiwan, China)	Integrated PCC process	Economic MPC (Directly considering the economic performance in the objective function; outlet CO_2 concentration was considered as a terminal cost) MV: lean solvent flow rate, re-boiler heat duty	Not specified (should be a nonlinear model since “fmincon” function in MATLAB is used for the optimization)	i) flue gas change ii) utility price change iii) different weight of CO_2 outlet	[126], [127]
2019	Department of Chemical and Biomedical Engineering, West Virginia University (USA)	Integrated PCC process	Nonlinear MPC CV: CO_2 capture level (main control target), power consumption MV: lean solvent flow rate, re-boiler heat duty Disturbance: flue gas flow rate	Autoregressive-moving average model with exogenous variables developed through data-driven system identification	Maintain the given capture level in case of flue gas flow rate change	[125]
2019	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China), Department of Chemical and Biological Engineering, University of Sheffield (UK), Process Systems Enterprise Ltd (UK) and Department of Electrical and Computer Engineering, Baylor	Integrated PCC process	Linear MPC (with disturbance observer) CV: CO_2 capture level and re-boiler temperature MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate	State space model developed through data-driven system identification	i) capture level set-point change; ii) flue gas flow rate change; iii) presence of unknown disturbances	[95]

	University (USA)					
2019	Department of Chemical Engineering, West Virginia University (USA)	Integrated PCC process	Nonlinear MPC CV: CO_2 capture level and re-boiler temperature MV: lean solvent flow rate and re-boiler heat duty Disturbance: flue gas flow rate, CO_2 concentration, rich flow solvent flow rate	Nonlinear additive autoregressive model with exogenous inputs developed through data-driven system identification	i) flue gas flow rate /CO_2 concentration variations ii) capture level set-point changes	[123]
2019	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China), Department of Chemical and Biological Engineering, University of Sheffield (UK), Process Systems Enterprise Ltd (UK) and Department of Electrical and Computer Engineering, Baylor University (USA)	CFPP-PCC process	Linear MPC CV: Power output, throttle pressure, CO_2 capture level and re-boiler temperature MV: coal flow command, turbine governor valve, lean solvent flow rate and re-boiler heat duty	State space model developed through data-driven system identification	i) normal set-point change; ii) rapid power ramping iii) strict carbon capture	[121]
2019	Key laboratory of Energy Thermal Conversion and Control of Ministry of Education, Southeast University (China), Department of Chemical and Biological Engineering, University of Sheffield (UK), Process Systems Enterprise Ltd (UK) and Department of Electrical and Computer	CFPP-PCC process	Two coordinated linear MPC CFPP MPC: CV: Power output, throttle pressure MV: coal flow command, turbine governor valve Disturbance: steam to re-boiler PCC MPC: CV: CO_2 capture level and re-boiler temperature MV: lean solvent flow rate and re-boiler heat	State space model developed through data-driven system identification	i) normal set-point change; ii) rapid power ramping iii) strict carbon capture	[122]

	Engineering, Baylor University (USA)		duty Disturbance: flue gas flow rate			

4.4 Other control design of PCC

Besides the conventional PI/ PID based controllers and the MPCs, there are only two studies found in the literature, which used other control approaches for the PCC operation.

Li et. al [128] developed a model-free adaptive controller (MFAC) for the PCC absorber, which controlled the CO_2 capture level by manipulating the solvent flow rate, while considering the flue gas flow rate and CO_2 concentration variations as disturbances. The design idea of the MFAC was essentially the same with MPC, however, different from the MPC, that relies on an explicit model to bridge the gap between process and control, the input-output data of the plant was directly used to calculate and update the control law. The MFAC was simple in design and could avoid the issue of modelling mismatch compared with the MPC. The simulations showed that the performance of MFAC was superior to the PID control and similar to the MPC, however, the operational constraints could not be handled by the MFAC.

Zhang et al. [123] developed an H_∞ robust control for the PCC process, in which an H_∞ norm of the transfer function was minimized to reduce the influence of perturbation while improving the control performance and stability in closed loop. The comparison with a nonlinear MPC has shown that, although the response speed of the H_∞ controller was slower than the MPC in terms of CO_2 capture level set-point tracking, it could yield a smoother performance in complex situations of plant behavior variation and input/output measurement uncertainties.

5. Achievements, challenges and Future Perspectives

Although the working principle and the factors determining the performance of the solvent-based PCC process are clearly understood, crucial issues still remain on the flexible operation of PCC (especially when integrated with the CFPP and reduction of the high energy penalty). In-depth understanding of the dynamic characteristics of the PCC system under various disturbances and developing satisfactory control scheme to adjust the operating parameters rapidly and smoothly in a wide range of operation are two key points towards the flexible operation of PCC.

In the past decade, significant progress has been made for the solvent-based PCC process in first principle dynamic model development, system identification and control strategies design. The developments of these dynamic studies have greatly extended the steady state system analysis and improved the flexibility of the process, which make us convinced that, a safe, efficient and flexible operation of PCC process is ahead of us (especially for commercial scale plants). However, some problems have also been exposed through the review of previous studies. More efforts should be paid in the future to further improve the modelling and control performance of the PCC process.

5.1. First principle dynamic modelling

Dynamic modelling of the solvent-based PCC process using first-principle approach has become mature through many years of development and improvement. Many models have been well developed to gain in-depth knowledge of the PCC dynamics.

However, there are still two difficulties for the first principle modeling of PCC: i) The available dynamic operating/experimental data is still insufficient to verify PCC models at different sizes, under different operating conditions and disturbances; ii) The first-principle PCC model is time consuming to develop and complex in computation, which limit its use in real time model prediction and process control design.

To these regards, from the validation point of view, more experiments should be carried out in the future at both pilot and commercial scale PCC plants. Meanwhile, advanced measurement technology should be developed to monitor the dynamic operation of PCC plants accurately and in real time, so that sufficient dynamic operating data can be archived to fully verify the dynamic models. From the modelling point of view, it is important in future to pay more attention on the hybrid modelling method, which uses the first-principle approach to develop the basic structure of PCC model and then uses the identification approach to fine tune the model parameters.

5.2. Data-driven system identification

The identification of solvent-based PCC system is still in its initial stage, and the research is still insufficient. However, from steady state identification to dynamic identification, from linear identification around a given operating point to nonlinear identification trying to cover wide operating range, increasing interest has been paid in applying modern data-driven identification approach on PCC modelling and control.

The main challenges for the identification of PCC system are i) The performance of the identification is highly dependent on the data. Although massive data can be provided, high quality data which can meet the identification requirements are often limited; ii) The selection of input variables and their corresponding model orders are difficult, which may easily cause the model to be insufficiently accurate or too complex; iii) The identified model is less explanatory to the working principle of the solvent-based PCC process, thus tends to have larger errors compared with the first principle model.

Therefore, modern measurement, data processing and identification technologies, especially the artificial intelligent approach are expected to be applied to the solvent-based PCC process in the future. As mentioned before, it is important to carry out the system identification based on the in-depth understanding of PCC dynamics, making full use of the priori knowledge and the closed-loop operation data to establish a model with satisfactory accuracy and low complexity for PCC simulation, optimization and control.

5.3. Process control design

There have been many studies on the control design of solvent-based PCC process, mostly focusing on the conventional PI/PID based decentralized control, which have shown satisfactory performance and robustness during the PCC operation maintained around a base load. In addition, active promotion of the advanced control techniques such as MPC have been made recently to achieve better flexible operating performance for the PCC process.

However, the control studies of solvent-based PCC process still have following limitations and challenges:

i) From the process design point of view, many studies have been carried out on new solvents, new process configurations and large scale PCC plants, but most of them focused on the steady state system performance [129-131]. Nevertheless, higher CO_2 absorption rate and lower regenerative energy consumption do not mean that the system has better flexibility and is easily controlled;

ii) From the system point of view, most of the current control studies only focus on the independent PCC system [96, 102], its integration with power plants is not fully taken into account. However, the two systems are strongly coupled due to the effects of flue gas and steam extracted. Therefore, study of the independent PCC process is not possible to comprehensively handle the mutual influence between the two systems and maximize the effectiveness of the power generation- carbon capture plants in terms of power supply, emission reduction, economy and safety;

iii) From the optimal scheduling point of view, many studies have considered the conflict targets of energy saving and emission reduction; and carried out a steady state optimization to provide the best operating point for the control system of PCC plant [116]. Nevertheless, the steady state optimization is unable to consider the system performance during transient process when the desired CO_2 capture level or upstream flue gas changes;

iv) From the control point of view, control of the PCC process is challenging owing to its complex behavior such as nonlinearity, large inertia, strong coupling and the presence of measured or unmeasured disturbances.

To overcome these issues, future perspectives for the PCC control studies may include:

i）Integrated design and control at an early stage: considering the dynamic control performance of the solvent-based PCC in the process design stage, rather than steady state performance only, so that the difficulty in control design can be reduced;

ii) Coordinated control design for the integrated power generation and CO_2 capture plants;

iii) Better integration of the scheduling and dynamic control of the PCC process (for example, using the technique of

EMPC), so that the adverse effects of transient disturbances on the optimization can be eliminated;

iv) Design of advanced and appropriate controllers based on the operating requirement and dynamic characteristics of the solvent-based PCC to further enhance the flexible operating performance.

6. Conclusions

Dynamic flexible operation is imperative for the large scale commercialization of solvent-based PCC technology. The key to the flexible operation of PCC process is to gain in-depth knowledge of the transient performance and design appropriate control strategies for it. A state-of-the-art review of the studies carried out so far in this area are provided including first principle dynamic modelling, system identification and control of the solvent-based PCC process. To authors' best knowledge, this paper gives the first critical review on the data-driven system identification and conventional/ advanced process control design studies of the solvent-based PCC process. The existent studies have been classified with their advantages and limitations been analyzed. Research challenges and future perspectives have also been discussed.

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