**Proceedings Paper:**

Liao, P., Li, Y., Wang, M. orcid.org/0000-0001-9752-270X et al. (2 more authors) (2017) Review of dynamic modelling, system identification and control scheme in solvent-based post-combustion carbon capture process. In: Energy Procedia. The International Conference on Applied Energy, ICAE2017, 21-24 Aug 2017, Cardiff, UK. Elsevier , pp. 3505-3510.

https://doi.org/10.1016/j.egypro.2017.12.237

Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 142 (2017) 3505–3510

Energy Procedia

www.elsevier.com/locate/procedia

the International Conference on Applied Energy, ICAE2017, 21-24 August 2017, Cardiff, UK

# Review of dynamic modelling, system identification and control scheme in solvent-based post-combustion carbon capture process

Peizhi Liao[a], Yiguo Li[a, *], Meihong Wang[b, *], Xiao Wu[a], Jiong Shen[a]

[a]*Key laboratory of Energy Thermal Conversion and Control of MOE , Southeast Univerisity, Nanjing 210096, China*
[b]*Department of Chemical and Biological Engineering, Univerisity of Sheffield, Sheffield S1 3JD, UK*

**Abstract**

Solvent-based post-combustion carbon capture (PCC) process is widely viewed as the most viable option for reducing $CO_2$ emission. This technology has been deployed globally and many researches have been conducted in this area. In this paper, current status of dynamic modelling, system identification and control scheme of solvent-based PCC process is reviewed. Different research directions of these areas are discussed to conclude the existing challenges. Based on this, this paper is also trying to provide potential solutions as possible pathways for flexible and economical operation.


Peer-review under responsibility of the scientific committee of the 9th International Conference on Applied Energy.

*Keywords:* Post-combustion Carbon capture; Chemical Absorption; Dynamic modelling; System identification; Control scheme; Review

## 1. Introduction

Due to the increasing public concern on global warming, extensive efforts have been made to combat this trend. Among all emission reduction technologies, carbon capture and storage (CCS) is proved to be the most appealing and economical alternative. Solvent-based post-combustion carbon capture (PCC) is viewed as the most mature option compared with other CCS techniques [1].

Fig 1 shows the schematic diagram of a typical solvent-based PCC plant, the process includes two major packed columns, namely absorber and stripper. The flue gas from power plant or industrial process contacts with lean MEA solvent counter currently. $CO_2$ is absorbed chemically and the low $CO_2$ concentration gas leaves from the top of

* Corresponding author. Tel.: +86 83795951-804; +44 (0)-114-222-7160.
*E-mail address:* lyg@seu.edu.cn; Meihong Wang@sheffield.ac.uk

1876-6102 
Peer-review under responsibility of the scientific committee of the 9th International Conference on Applied Energy.
10.1016/j.egypro.2017.12.237

absorber. Rich MEA solvent, is pumped from the bottom of absorber into a cross heat exchanger and preheated before entering stripper. The solvent is regenerated in the stripper using low-pressure steam extracted from IP/LP turbine in a typical power plant. The vapor from the top of the stripper is cooled and separated in the condenser. Finally, the hot lean solvent flow from the bottom of stripper is returned to the absorber after being cooled by heat exchanger.

Solvent-based PCC process is effective in carbon capture, but it requires huge capital and operational costs. Research efforts have been devoted to address these two problems. To date, many studies have contributed to understand the dynamic features and evaluate the flexible and also to economical controllability. However, a critical review on dynamic modelling, system identification and control schemes is not available in open literature. This paper aims to provide a critical assessment of current research and try to point out the challenges and potential solutions. This review paper hopes to be a natural extension from other review papers, such as [1, 2].

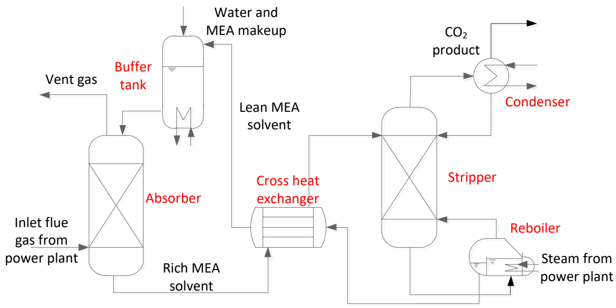


Fig. 1. Schematic diagram of amine-based PCC process [3].

## 2. Literature review of dynamic modelling of solvent-based PCC process

Developing a dynamic model of PCC plant is the first task required to gain enhanced understanding of the process itself. Absorber and stripper, two major components in conventional PCC process are commonly studied. The key point is to develop equations according to physical and chemical principles for mimicking mass transfer and chemical absorption. Two different approaches, equilibrium approach and rate-based approach [1], are employed to describe mass transfer. A comparative evaluation was made in [4] and the results showed that rate-based model yielded a better prediction. Most of the publications used rate-based approach.

### *2.1. Standalone models*

Many studies have been conducted on the development of modelling of standalone absorber (Pintoal and Meisen [5], Lawal et al [4], Kvanstal et al [6], et al) and standalone stripper (Ziaii et al [7], Mores et al [8], et al). The difference is that [5] presented a steady-state model while others are dynamic models. Based on the hypothesis that the reaction with $CO_2$ has quick response, reaction kinetics are ignored in [4,6,7]. However, in [5] and [8], reaction kinetics are taken into consideration and enhancement factors are introduced to estimate actual absorption rates. These models are tested under operational scenarios, namely load-varying and lean loading changing. Simulation shows that mathematical model is able to handle multiple process inputs and disturbances, predicting CO2 absorbing and stripping process in reasonable agreement with experimental data.

### *2.2. Integrated models*

For a further investigation to acquire insights of complete recycling process, dynamic models of integrated process can be seen in open literatures. Lawal et al [9] presented a dynamic model of integrated PCC process. Based on that, a comparative assessment between standalone model and integrated model was carried out, showing that integrated model had a more accurate prediction. Based on this work, Lawal et al [10] scaled up integrated model to an industrial size with consideration of 500MW coal-fired power plant. This study indicated that the capture plant has a larger response time compared with power plant. In Biliyok et al [11], a comprehensive dynamic analysis of solvent-based carbon capture plant pointed out that mass transfer was the dominant factor to affect $CO_2$ absorption. Reaction kinetics are also neglected in these papers, owning to rapid kinetics in chemical absorption between $CO_2$ and MEA. In some other papers, such as [12], the distinguishing feature is that the model uses SAFT-VR equation to predict physical properties. Temperature bulge is analysed critically on the basis of dynamic model.

However, most of the models were validated under steady state conditions only due to lack of experimental data at transient situations. [11] is the only paper addressed an attempt on dynamic model validation. This paper described that moisture content in inlet flue gas had a marginal effect on $CO_2$ removal but significantly affected temperature profile. It is therefore of interest to consider temperature profile for dynamic validation.

### *2.3. Summary*

According to the above discussions, dynamic modelling has been thoroughly discussed, both in model development and sensitivity analysis. Unfortunately, only one paper carried out dynamic validation while others are validated in steady state. However, carrying out dynamic validation is vital to acquire extensive knowledge for flexible operation.

## 3. Literature review of system identification of solvent-based PCC process

Establishment of first principle models is computationally demanding and it also needs an in-depth understanding of the underlying physics of the process involved. Unlike first principle model, system identification only uses input and output data to determine a mathematical model without going into the details. Computational load can be saved. It is therefore of interest to perform a data-driven black-box system identification to serve as an appealing alternative.

### *3.1. Linear models*

Arce et al [13] used Matlab$^{TM}$ identification toolbox (Ljung [14]) to obtain a linear model for solvent regeneration process. This control model was composed of a linear discrete transfer function with a sampling time of 200 ms. For simplicity, the first-order model was obtained and it was critically analyzed to ensure all the poles locate in the unitary circle. However, a first-order model cannot mimic the dynamic characteristics very well compared with a higher order model. Besides, linear models are only suited for specific working conditions.

### *3.2. Nonlinear models*

For better identification results, a multivariable non-linear autoregressive with exogenous input (NLARX) model was acquired in Manaf et al [15]. Models for absorber, rich/lean heat exchanger and stripper were identified respectively and unified as 4-input-3-output PCC model. This is the distinguished novel contribution compared with others. Lean solvent flowrate and reboiler heat duty were regarded as the manipulated variables whiles others are disturbances. The proposed work also considered the identification of the rich/lean heat exchanger, which is a major investment and operating penalty unit [12]. However, this paper did not provide available control structure to operate the heat exchanger.

Neural networks are also able to approximate nonlinear function accurately. It provides a much faster modelling capability compared with that in first principle model [16], which makes it more convenient to implement in computer calculation. Li et al [17] presented a bootstrap aggregated neural approach to build a multiple inputs single output dynamic model. Results showed superiority in predicting capture level compared with other neural networks. One-step-ahead and multi-step-ahead prediction were used as the neural network input. It was found that one-step-ahead prediction is more accurate, because the prediction errors were accumulated every sampling time in a multi-step-head prediction and this would increase the prediction error at the following sampling time.

The statistic model, which embodies the assumptions concerning the sample data, is used to study the nonlinear relationships among key variables influencing $CO_2$ capture rate. Zhou et al [18] modelled the solvent based carbon capture process by adopting a multiple regression technique. The statistical-based model was found to be satisfactory to predict the capture plant within linear region, but it failed to mimic the non-linear relationships among these variables. Input data adopted for analysis was also strongly dependent on the expert's knowledge. In his follow-work, Zhou et al [19] compared three different analysis methods, namely a statistic study, artificial neural network (ANN) modelling combined with sensitivity analysis (SA) and neuro-fuzzy technique. The simulation showed that the neuro-fuzzy modelling technique had the most accurate prediction ability in $CO_2$ removal.

### *3.3. Summary*

Existing publications comprise linear and nonlinear system identification. However, all of the published identification methods have one common drawback, they can only work well in open-loop system. The result of any of the open-loop algorithm will be asymptotically biased when the data is gathered under closed-loop scenario.

## 4. Literature review on Control of solvent-based PCC process

The deficiency of amine-based carbon capture is that it poses an intensive energy penalty in solvent regeneration process, which may result in a huge reduction of power generation thermal efficiency. In this regard, minimizing the total energy consumption is the main task with highest priority in a control structure design. To operate the process flexibly, many researches have been implemented. Overall, the aims included in the published papers can be summarized as: (a) Target tracking and disturbance rejection; (b) Hydraulic stability; (C) Optimization on minimizing the overall cost under varying price scenarios.

### *4.1. Decentralized control*

Proportional-integral controller (PI) is the most widely used decentralized control technique in PCC carbon capture process. It has the advantage of strong robustness and the parameters can be easily tuned. PI control structures are built using RGA analysis or a heuristic-based approach, to determine the optimal manipulated-controlled variables.

Ziaii et al [7] proposed two control loops (keep rich solvent loading constant and keep rich solvent flowrate constant) to run stripper in a flexible manner during peak load. After a continuous step reduction of steam extraction, the results showed that the controller with adjusting rich solvent flowrate resulted in a high $CO_2$ capture level. In Lawal et al [9,10], the importance of maintaining hydraulic stability was pointed and in Lin et al [20], water balance was kept by tracing liquid level in reboiler. The controller is tested in the presence of water make-up disturbance and load changing. In [21], manipulating on lean solvent flow rate and lean loading were evaluated. Simulation shows that variation of lean loading is preferable for the purpose of water inventory balance, while variation of lean MEA flowrate can achieve a faster capture level tracking ability. Therefore, for the overall benefits, we would suggest to use lean-loading controller at off-peak period and switch it to solvent-flowrate controller at peak time.

In the context of plant-wide control, Panahi and Skogested [22,23] provided a self-optimizing control structure to make the process run at optimum track. It gave several different control topologies. However, controllers need to be switched at different scenarios. Similarly, Nittaya et al [3] presented 3 different decentralized control loops. Each controller has its own superiority in some scenarios and may fail in the other cases.

### *4.2. Centralized control*

Parameter-tuned decentralized controller is only effective for several limited operation scenarios and performance may deteriorate when the controller is out of linear region. Besides, it cannot handle constraints. MPC scheme can incorporate constraints and multivariable optimization, which makes it favourable compared with a conventional PI structure.

Bedelbayev et al [24] adopted MPC for standalone absorber and Mehleria et al [25] extended it to the whole capture process. Both of the work were carried out in the presence of set point tracking and step changes in flue gas flowrate. Different from previous two studies， Zhang et al [26] applied a linear MPC controller in a parallel-train absorption capture process. Disturbance model estimator is adopted to compensate model mismatch. To our knowledge, this is the only paper addressed this technique in carbon capture controllability process. MPC allows different trains to realize different capture rate on the basis of absorber efficiency.

To minimise the overall cost, researcher addressed scheduling process in the controller design. Arce et al [13] presented a two-level control structure, whose high-level control regulates the set points of solvent regeneration while low-level control aims to track these set points. However, this paper only concentrates on regeneration process. Sahraei, et al [27] and He et al [28] covered an optimization structure pertaining to environment constraints in the presence of periodical disturbance in flue gas flow rate. The aim is to minimize energy requirements and $CO_2$ emission. The simulation showed that the process can absorb more $CO_2$ by adjusting MPC weights without additional steam extraction. The difference between these two papers is that [28] optimized weight factors in every sampling period, while those in [27] were defined in advance.

### *4.3. Summary*

By comparison, centralized controller, especially MPC, can realize a more favorable control result, which makes it appealing in the future research. However, current work is limited to the steady-state optimization and disturbance rejection technique is rarely seen in the previous studies. Further understanding is needed in this area.

## 5. Conclusion：Challenges ahead and potential solutions

### *5.1. Dynamic modelling*

Currently, almost all the models were validated at steady-state conditions, only [11] addressed dynamic validation. This is owing to the lack of experimental data. Moreover, almost all the paper focused on capture plant. However, the upstream power plant can strongly affect capture plant and the steam feed to reboiler has influence on output electricity. Dynamic modelling and simulation from integrated capture plant and power plant have good potential, since the steam supplied to reboiler can be managed to reduce to make more steam available for electricity generation [9]. Therefore, the insights gained will aid in improving economical controllability. The challenge ahead is how to link the power plant and capture plant. [10] indicated an initial work with integrated power plant and capture plant, and it pointed following 3 links between power plant and capture plant, which may support modelling and simulation work for future research: (a) Flue gas from power plant; (b) Steam draw-off from IP/LP turbine; (c) The condensate from reboiler.

### *5.2. System Identification*

System identification of carbon capture process has not yet been properly studied and only a few papers published in this area. For system identification, excitation signal should be designed critically considering the characteristics of carbon capture process, and model output should contain all the model information. Future efforts should be directed towards designing signal bandwidth and amplitude. For controller design and parameter tuning, nonlinear degree affects control performance. The concern is to analyse process nonlinearity, qualitatively and quantitatively. For application, closed-loop identification is essential if open-loop system is unstable, or the feedback is an inherent feature of the system. It is therefore recommended to adopt closed-loop identification in this area.

### *5.3. Control scheme*

System optimization published in open literatures [13,27,28] is steady-state optimization which only regulates optimal set points. For economical control purpose, dynamic optimization is desired to determine optimal manipulated variables and state variables. Challenges expected involve construction of performance index and the solution of multi-objection optimization. Besides, only linear controllers are studied and disturbance rejection is achieved by controllers' own robustness. Accordingly, future progress in this aspect can be: (a) Dynamic optimization considering environment constraints, electricity prices and emission penalty; (b) Disturbance rejection technique for measurable and unmeasurable disturbances; (c) Nonlinear controllers for flexible controllability at all operating conditions.

More importantly, these techniques can be combined in one control design.

## Acknowledgements

The authors acknowledge the National Natural Science Foundation of China (NSFC) under Grant 51506029, the

Natural Science Foundation of Jiangsu Province, China under Grant BK20150631, China Postdoctoral Science Foundation and EU FP7 International Staff Research Exchange Scheme on power plant and carbon capture (Ref: PIRSES-GA-2013-612230) for funding this work.

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