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Flexible operation of post-combustion solvent-based carbon capture for coal-fired power plants using multi-model predictive control: a simulation study

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Abstract— Solvent-based post-combustion CO₂ capture plant has to be operated in a flexible manner because of its high energy consumption and the frequent load variation of upstream power plants. Such a flexible operation brings out two objectives for the control system: i) the system should be able to change the CO₂ capture rate quickly and smoothly in a wide operating range; ii) the system should effectively remove the disturbances from power plant flue gas. To achieve these goals, this paper proposed a multi-model predictive control (MMPC) strategy for solvent-based post-combustion CO₂ capture plant. Firstly, local models of the CO₂ capture plant at different operating points are identified through subspace identification method. Nonlinearity analysis of the plant is then performed and according to the results, suitable local models are selected, on which the multi-model predictive controller is designed. To enhance the flue gas disturbance rejection property of the CO₂ capture plant and attain a better adaption to the power plant load variation, the flue gas flow rate is considered in the local model identification as an additional measured disturbance, thus the predictive controller can calculate the optimal control input even in the case of flue gas flow rate variation. Simulation results on an MEA-based CO₂ capture plant developed on gCCS show the effectiveness and advantages of the proposed MMPC controller over wide range capture rate variation and power plant flue gas variation.

Keywords: Post combustion CO₂ capture; Power Plant; Flexible Operation; Multi-model predictive control; Nonlinearity analysis; System Identification

I. INTRODUCTION

1.1 Background

With the increasing concern on global warming and its potential effect on climate, ecology and environment, CO₂ emission

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32 reduction has been regarded as a key step in the international community to alleviate these issues[1]. As the main power
33 generation devices, coal-fired power plants (CFPPs) are the largest stationary emission source of CO₂ worldwide [2]. For this
34 reason, while extensively promoting the renewable energy and making effort to improve the efficiency of conventional CFPPs,
35 CO₂ capture from CFPPs has been recognized as the most effective and direct way to achieve a large-scale CO₂ emission
36 reduction in the future 30 years [3].

37 Among various CO₂ capture technologies, solvent-based post-combustion CO₂ capture (PCC) using MEA solvent proves to
38 be the most promising technology for CO₂ capture in power plants. Because it is well suited for treating flue gas at low CO₂
39 partial pressure of power plants, and can be easily installed for existing power plants retrofitting. In recent years, many PCC
40 pilot plants have been developed and put into use [4] – [5].

41 The biggest issue for the operation of solvent-based PCC plant is the high heat consumption used for solvent regeneration.
42 Such heat is generally provided by the steam extracted from the intermediate/low pressure turbine of the power plant, thus
43 results in a significant power reduction of the CFPPs. To this end, many steady-state optimization studies such as equipment and
44 solvent selection [6]-[9], system configuration[10]-[12], parameter settings [8] - [9] have been carried out, trying to improve the
45 efficiency of the capture system. However, in the face of high energy consumption, more and more researchers realize that
46 implementing flexible dynamic operation for CO₂ capture is of great importance to make the technology be widely used in
47 power engineering practice [4], [5], [13]-[20]. During the electricity peak load, the capture system should be able to reduce its
48 capture rate rapidly to avoid the high cost of energy. On the other hand, when there is tight restriction on CO₂ emissions or the
49 carbon price is higher, the capture system could increase its capture rate quickly [21].

50 Another big issue, which has critical impact on the operation of the PCC system is from the integrated CFPPs. In the context
51 of growing electric power demand, the magnitude of the cyclic variation of the grid load is increased, and the extensive use of
52 renewable sources such as solar, wind and hydro power are severely influenced by the season and the weather condition, thus,
53 CFPPs have to participate in the grid power regulation frequently and quickly in a wide range nowadays [22]. As a result, the
54 flue gas flow rate of CFPPs will follow the load variation and change rapidly, which brings in strong disturbances to the capture
55 plant [5]. Therefore, to achieve a wide range application, the PCC plants are forced to have a flexible adaption to the flue gas
56 flow rate variation of upstream CFPPs.

57 1.2 Motivation

58 To overcome the aforementioned issues and to attain a flexible operation of PCC system, a well-designed control system is
59 required to ensure the correct operation of the entire process, i.e. to follow the capture rate demand rapidly and smoothly in a
60 wide range and to alleviate the influences of flue gas variation effectively.

61 Currently, most of the control studies of the PCC system are still stayed in the conventional PI/PID control stage [4], [5], [15],

62 [16], [23]-[26] . Such a design has been proved for its value for regulation and disturbance rejection during normal operation
63 around a given capture rate, however, it may not meet the design specifications for a high level flexible operation of PCC
64 process, the reasons are: i) The CO₂ capture system is a multi-input multi-output (MIMO) system, while the PI/PID control
65 systems are designed based on separate single-input, single-output (SISO) loops, thus the interactions among different variables
66 and properties cannot be taken into account; ii) Due to the slow dynamics of chemical reaction and heat transfer, the PCC
67 system has a typical large inertial behavior [5], while the control action of PI/PID controllers can only be made in the presence
68 of deviation. This control manner may not meet the quick regulation need of the PCC system; iii) in general, the parameters of
69 the PI/PID controllers are set at a given load condition. Therefore, when the flue gas flow rate of the upstream CFPP varies or
70 the capture system changes its capture rate in a wide range, the operation performance of the PCC system is degraded because
71 the dynamics at other operating points may become different.

72 Recently, model predictive control (MPC) [27], which uses a process model to predict the future response of the plant and
73 calculate the optimal future control sequence has been employed in the PCC system control [13], [14], [17], [18], [28]-[34].
74 Since MPC is naturally suited for multi-variable and large inertial system control, better performance has been shown compared
75 with the conventional PI/PID controls. For most of the MPC designs in the CO₂ capture system, a linear model developed
76 around a given operating point is used for the prediction [13], [17], [18], [29], [30], [33], [34], such a design may not be suited
77 for a wide range capture rate variation because it is impossible for the linear model to approximate the global nonlinear
78 dynamics. The resulting model mismatch will cause a severe control performance degradation or even unstable of the closed-
79 loop system. To this end, a few scholars proposed to use nonlinear model predictive control (NMPC) [14], [28], [31], [32].
80 However, it is hard to develop a satisfactory nonlinear model with high accuracy and good structure easy for advanced control
81 design. Moreover the nonlinear optimization during the implementation of the NMPC is weak in robustness and time consuming.

82 On the other hand, the validations of the control systems in the case of upstream flue gas flow rate variation have been made
83 in some studies. To our best knowledge, it still has not been studied regarding how to actively deal with its impact in the control
84 design stage. Therefore, in spite of the effectiveness of MPCs in tracking the desired capture rate, it cannot remove or alleviate
85 the flue gas disturbances rapidly.

86 **These shortcomings motivate us to investigate the nonlinearity distribution of the solvent-based PCC system and to design a**
87 **multi-model predictive control (MMPC) system using the combination of several local linear models and predictive controllers.**
88 **The flue gas flow rate is considered as a measured disturbance in the developed model, so that correct model prediction can be**
89 **made even in the presence of flue gas flow rate variation. The resulting MMPC system is expected to have a satisfactory capture**
90 **rate tracking performance and flue gas disturbances rejection performance, and to provide a powerful method towards the**
91 **flexible operation of the PCC system.**

92 1.3 Literature Review

93 The earliest studies of solvent-based PCC process were focused on the steady state optimization. A steady state plant model
94 was first developed and simulated under various conditions such as different solvent concentrations, operating parameters and
95 configurations, better choices which can provide a lower cost for the capture system can then be found through comparisons [6]-
96 [12].

97 The steady state model is impossible to represent the dynamics of this process, thus cannot provide enough information for
98 control design. For this reason, much attention has been paid to the dynamic modelling of the solvent-based PCC system . In the
99 first stage, models for standalone absorber and stripper were developed, the behavior of these columns was then tested through
100 dynamic simulations. For example, Lawal and et al [35] built a dynamic absorber model using both the equilibrium and rate-
101 based approach, and the dynamic simulation showed that the ratio between lean solvent flow rate and flue gas flow rate is
102 critical to maintain the performance of absorber. Ziaii and et al [36] developed a model for the amine regenerative system,
103 dynamic simulation found that lean solvent loading has key influence on the reboiler temperature. Nevertheless, analysis of the
104 stand-alone columns is insufficient to thoroughly understand the dynamics of the integrated PCC process since there exists a
105 strong coupling between two linked columns. To this end, many efforts have been made to develop detailed first principle
106 models for the PCC system using various simulation software such as gPROMS [4], [5], Aspen Dynamics [15], [16], Modelica
107 [37], Matlab [38] and gCCS [39], [40]. Numerous simulations are then performed and the transient influences of flue gas flow
108 rate/composition, rich/lean solvent flow rate and reboiler heat duty on CO₂ capture rate and thermal energy consumption are
109 fully investigated. These studies clearly showed that the influence of lean solvent flow rate and reboiler heat duty on the capture
110 rate has big time constant, while the variation of flue gas flow rate will change the capture rate very quickly, moreover, there are
111 strong couplings among key loops of the capture system. In many of these studies, it was also pointed out that the capture
112 system is highly nonlinear [41], [42]. These investigations provided good guidance for the controller design. As an alternative
113 method to the first-principle modeling, data-driven identification of PCC system has also been studied. In [43], the technique of
114 bootstrap aggregated neural network is used to develop an 8×2 first order model for the PCC system. In [44], NARX models are
115 identified for the absorber, heat exchanger and stripper respectively, these models are then combined according to the physical
116 process to form the integral PCC process model. Although the data-driven model may not be as accurate as the first principle
117 model, it can be easily developed without much knowledge of the process and design specifications. Moreover, the explicit
118 model structure is more convenient and direct for the control design purpose.

119 Based on the dynamic modelling and process analysis, many studies have been done in the control system development of
120 PCC process. Most of these studies focused on the PI/PID based control loop design. Lawal et al. [4], [5], Lin et al. [15] both
121 proposed a PI based control structure, which used the lean solvent flow rate to control the capture rate and the extracted steam

122 flow rate to control the reboiler temperature. Such a design can attain a quick control of the capture rate even in the presence of
123 flue gas flow rate and CO₂ concentration change. To maintain the hydraulic stability in the absorber and stripper, Lin et al. [16]
124 proposed another structure, which kept the lean solvent flow rate constant and used the lean solvent loading to regulate the CO₂
125 capture rate. Nittaya et al. [23] investigated the interactions among multi-variables within the PCC system through Relative Gain
126 Array (RGA) analysis. The input-output variables which have the strongest relationship were paired in one control loop. A 6-
127 input 6-output PI control system was then developed centering on manipulating extracted steam flow rate to control the CO₂
128 capture rate. In [24]-[26], variables which have the closest relationships with the performance of PCC system were selected as
129 controlled variables according to the steady state optimization results, SISO PI control loops were then designed for these
130 variables.

131 To overcome the SISO PID control's drawbacks in dealing with strong coupling multi-variable system and large inertial
132 behavior, MPCs have been applied in the PCC process to achieve a better flexible control performance. The first attempt was
133 made by Bedelbayev et al [28], who directly used an first principle model based predictive controller for the standalone absorber
134 column. Simulation studies showed that the proposed MPC has a satisfactory performance in case of capture rate tracking and
135 flue gas flow rate variation. In [13], a linear MPC was devised in a double-layer optimal solvent regeneration control system to
136 achieve a fast track of the optimal set-points. In [17], [29]-[32], multivariable MPCs were developed to control the key variables
137 of the integrated PCC process. Owing to the outstanding advantages of MPC in handling strong coupling, large inertial and
138 constraint issues, their results all showed that superior performance can be attained by the MPC compared with the PI/PID based
139 control configurations. In [18] and [33], energy consumptions and CO₂ emissions were considered in the MPC's objective
140 function, and an optimal scheduling sequence of the PCC plant was calculated.

141 Model is the fundamental and most important element in the MPC design, its accuracy and expression determine the
142 controllers' performance and complexity to a large extent. In most of the mentioned MPC works, a linear model of the PCC
143 system is utilized [13], [17], [18], [29], [30], [33], [34]. However, because the linear model is impossible to approximate the
144 behavior of nonlinear plant, the designed MPC is only suited for a small operating range change. In [14], [28], [31], [32]
145 nonlinear identified or analytical models were directly used for MPC design, however, the nonlinear optimization solving large
146 number of differentia equations lacks of robustness and is time consuming.

147 *1.4 Novel Contributions*

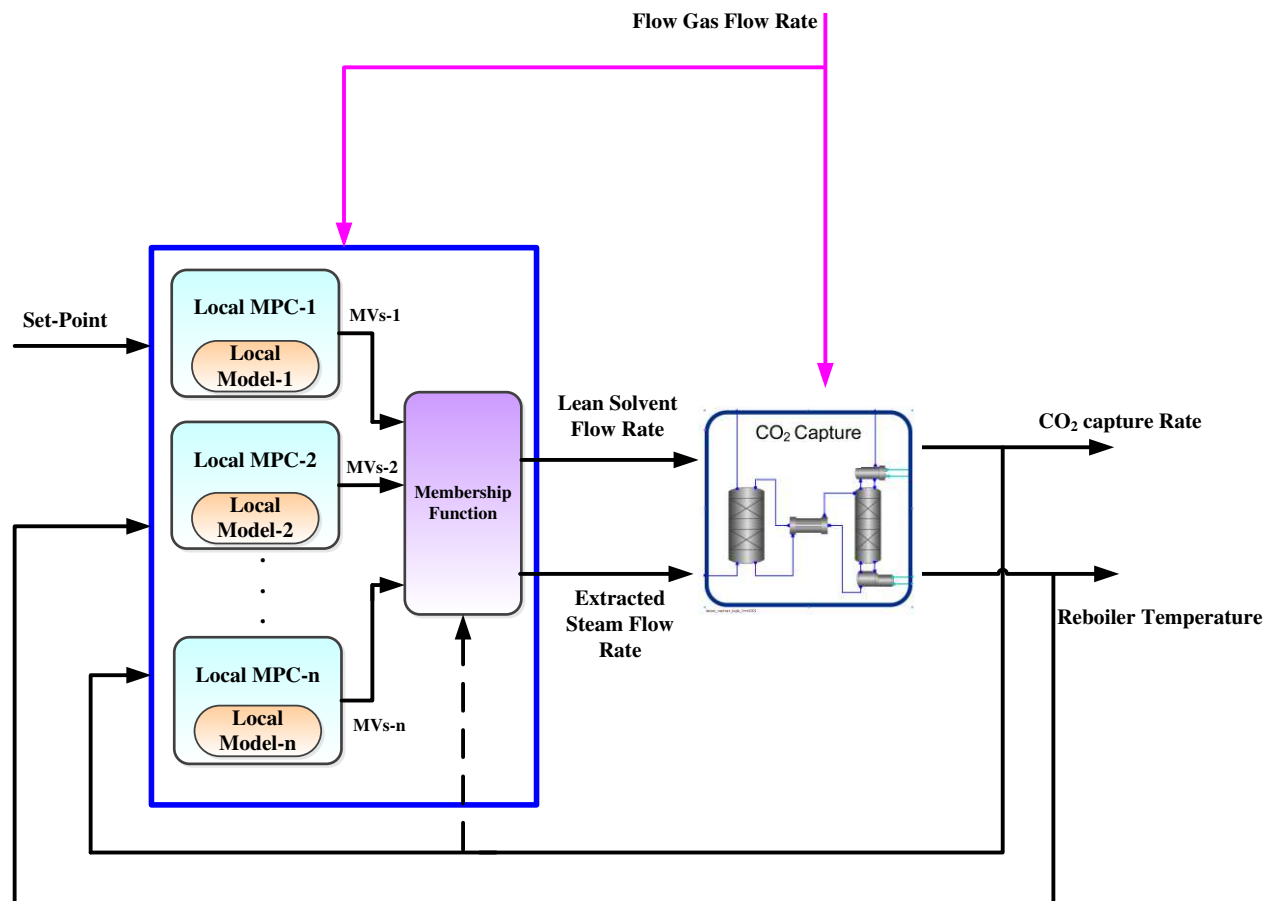
148 To overcome the aforementioned issues, this paper proposes an MMPC for flexible operation of the solvent-based PCC
149 process, the main contributions and novelties of the paper are given as follows:

- 150 1) a nonlinearity investigation is made for the solvent-based PCC process using the method of gap-metric;
- 151 2) according to the nonlinearity investigation results, an MMPC is designed for a wide range capture rate change of the CO₂

152 capture plant;

153 3) the flue gas flow rate is taken into account as a measured disturbance in the MPC design, so that correct model prediction
 154 can be made even in the presence of flue gas flow rate variation, and a satisfactory flue gas flow rate disturbance rejection
 155 performance can be attained by the proposed MMPC.

156 The schematic diagram of the proposed MMPC is shown in Fig. 1. Set-point (for carbon capture rate) can be given by the
 157 user. Flue gas flowrate changes according to power plants operating load, the signal is utilized in the MMPC design framework
 158 to achieve an effective flue gas flowrate disturbance rejection. According to the current CO₂ capture rate, at each sampling time,
 159 the local predictive controllers are combined together through the membership function and the calculated global control action
 160 is implemented on the capture plant. In essence, this research proposes to use the combination of multiple MPCs designed at
 161 different operating points to replace one NMPC for the whole operating range.



162 Fig.1 Schematic diagram of the proposed MMPC for the solvent-based post combustion CO₂ capture process
 163

164

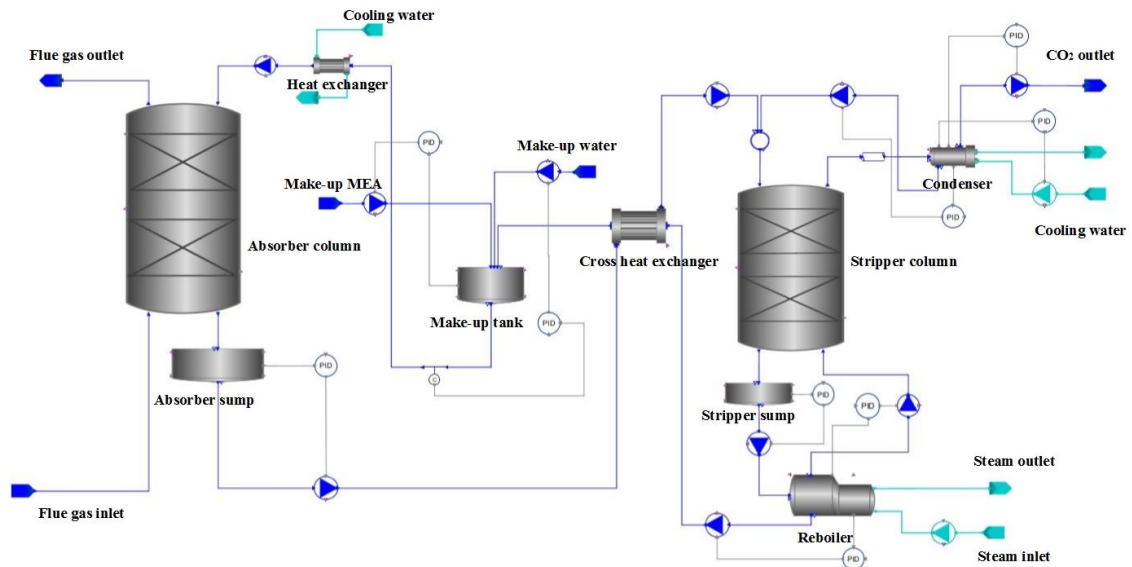
165 1.5 Outline of the paper

166 Section I gives the background, motivation and novel contribution of this paper. Section II briefly describes the developed
 167 simplified dynamic model for solvent-based carbon capture based on the gCCS (gCCS was developed in gPROMS for power

168 plants, carbon capture, transport and storage by PSE Ltd based in London and is commercially available). The nonlinearity
 169 investigation and the MMPC system design is presented in Section III and the validation of the controllers is described in
 170 Section IV. Finally, conclusions are drawn in Section V.

171 II. SYSTEM DESCRIPTION

172 A dynamic model of the solvent-based carbon capture plant is developed and used as a simulation platform for control design
 173 and validation. The PCC plant under consideration is matched with an 1 MWe coal-fired power plant, which can produce 0.13
 174 kg/s flue gas (CO₂ concentration: 25.2 wt%) at full load condition. 30wt% MEA solvent is used as the sorbent and the
 175 specifications of the equipment such as absorber, stripper, reboiler, condenser and cross heat exchanger are selected according to
 176 the model developed in [5], which has been validated through operating data of pilot capture plant. To provide a high-fidelity
 177 description of the PCC process, the model for these unit operations were developed from the first-principles and then connected
 178 based on the working process of CO₂ capture using the gCCS toolkit [39], [40]. The process topology of the PCC model
 179 developed in gCCS is presented in Fig. 2.



180

181 Fig. 2 Schematic diagram of the PCC process as presented in gCCS

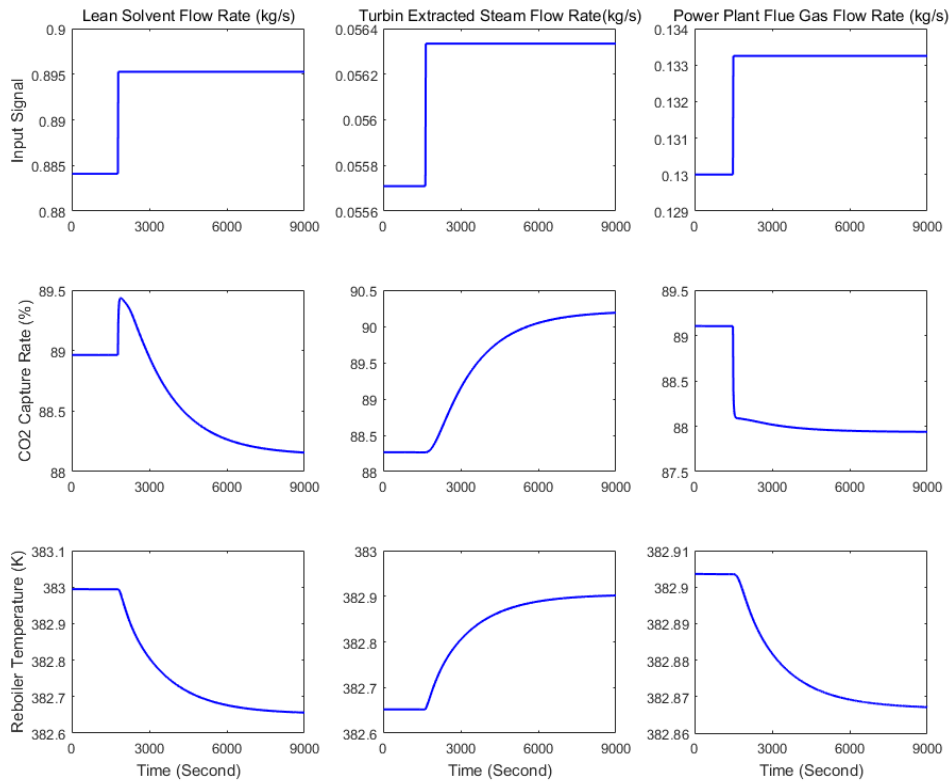
182 For the control system of the PCC process, many variables need to be strictly controlled to guarantee a safe and efficient
 183 operation of the plant. Among them, the CO₂ capture rate y_1 ,

184

$$185 \quad y_1 = \frac{CO_2 \text{ in the flue gas} - CO_2 \text{ in the clean gas}}{CO_2 \text{ in the flue gas}} \quad (1),$$

186 and the reboiler temperature y_2 are two of the most critical variables [4], [5], [15]. The capture rate indicates whether the capture

187 system can fulfill the carbon capture task according to the environmental protection requirements. Reboiler temperature is
 188 closely related to the lean solvent loading, which determines the CO₂ absorption ability of the solvent, and an excessively high
 189 temperature will cause solvent degradation. For this reason, this paper is focused on controlling these two key variables, the lean
 190 solvent flow rate u_1 and turbine extracted steam flow rate u_2 are selected as manipulated variables because they have big
 191 influences on the capture rate and reboiler temperature[4], [5], [15]. For other variables such as sump tank level,
 192 reboiler/condenser pressure and so on, conventional PI controllers are designed to regulate them within a given operating range.



193 Fig. 3. Responses to three individual step tests for the PCC model developed on gCCS (Left column: step response of lean solvent flow rate u_1 ;
 194 Middle column: step response of turbine extracted steam flow rate u_2 ; Right column: step response of power plant flue gas flow rate d).

196 Fig. 3 shows the step response test results around 90% capture rate operating point for the considered variables, which can
 197 guide us in the controller design:

198 1) As indicated in the left column of Fig. 3, an increase of lean solvent flow rate can quickly increase the CO₂ capture rate.
 199 However, since the steam supplied to the reboiler does not change, the reboiler temperature will drop and less CO₂ will be
 200 stripped off the solvent and the loading of the solvent to the absorber will rise. Therefore, the capture level will drop after a
 201 while;

202 2) As indicated in the middle column of Fig. 3, turbine extracted steam flow rate can change the CO₂ capture rate ultimately.
 203 However, its influences on the capture rate and reboiler temperature have large time constants;

204 3) As indicated in the right column of Fig. 3, the flue gas flow rate will change the CO₂ capture rate immediately because

205 "the capture rate is defined as $(\text{CO}_2 \text{ in the flue gas} - \text{CO}_2 \text{ in the clean gas}) / \text{CO}_2 \text{ in the flue gas}$ ", it will influence the reboiler
206 temperature slowly and then further change the CO_2 capture rate.

207 These step response tests showed that the key variables within the PCC process are strongly coupled and has a large inertial
208 behavior, the external flue gas flow rate has a significant impact on the system. Moreover, the wide range flexible operation of
209 the capture process brings severe nonlinearity to the system and higher requirements for the control. Therefore, we propose an
210 MMPC system for the solvent-based PCC process to overcome the weaknesses of the conventional controllers.

211 III. NONLINEARITY ANALYSIS AND MULTIMODEL PREDICTIVE CONTROL DESIGN

212 3.1 Nonlinearity Analysis of CO_2 capture system

213 Under the ordinary MPC design framework, modeling is the first and foremost important step because both the control
214 performance and computational complexity heavily depend on the model's accuracy and structure. For the multi-model control
215 system development, it is important to know the level and distribution of the nonlinearity along the whole operation range so
216 that a minimum number of local linear models can be selected and combined to approximate the nonlinear behavior of the plant.
217 To this end, the nonlinearity of the PCC process along the considered operating range is analyzed first using the approach of
218 gap-metric, which is a measure of the distance between linear models around adjacent operating points [45] - [46].

219 Because flexible operation of the PCC process requires the control system to be able to change the capture rate quickly in a
220 wide range and meanwhile have a good adaptation to the power plant flue gas flow rate variation, the nonlinearity level along
221 the capture rate side and flue gas side both need to be analyzed.

222 To investigate the nonlinearity level along the capture rate side, we keep the flue gas flow rate fixed at 0.13kg/s to avoid its
223 influences. The method of subspace identification is then used to identify the local state space linear models around 50%, 60%,
224 70%, 80%, 90% and 95% capture rate points (the reboiler temperature is kept around 383K during the identification
225 experiment). The gap metric values between the adjacent linear models are calculated and shown in Fig. 4. The gap value is
226 bounded between 0 and 1, and a large value represents a large difference between the two linear models, thus reflects a strong
227 nonlinearity along this range[45] - [46].

228 For the flue gas side investigation, we keep the CO_2 capture rate within 70%-80% operating range, and identify the local state
229 space linear model at 0.07kg/s, 0.10kg/s, 0.13kg/s and 0.15kg/s operating points (the reboiler temperature is kept around 383K
230 during the identification experiment). The gap metric value are calculated as shown in Fig. 5.

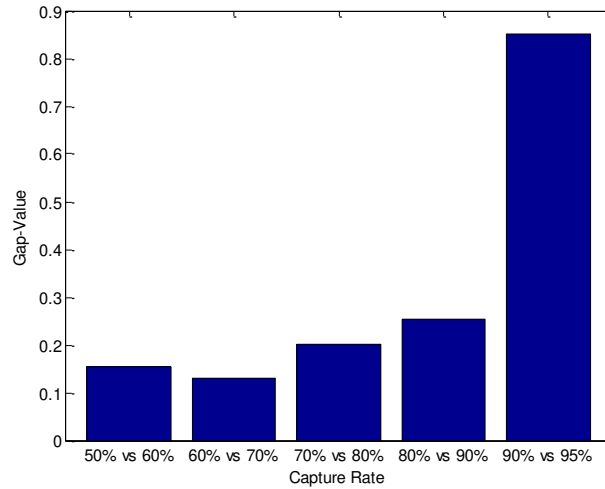


Fig. 4 Gap metric values between adjacent linear models along the CO₂ capture rate side

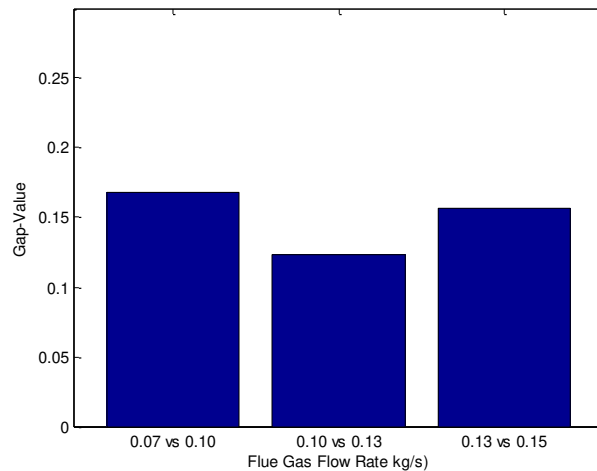


Fig. 5 Gap metric values between adjacent linear models along the flue gas side

Figs. 4 and 5 show that along the CO₂ capture rate side, the level of nonlinearity increases as the capture rate increases, it is weak between 50%-90% operating range, but strong around 95% operating point. On the other hand, along the flue gas side, the level of the nonlinearity is not strong within the range of 0.07-0.15kg/s. Although increasing the number of local model/controllers will enhance the performance of the multi-model control system, it will also increase the complexity of the system structure and the computational effort. Therefore, according to the nonlinearity analysis results, we develop three local models and predictive controllers around 50%, 80% and 95% CO₂ capture rate points to compose the integrated multi-model system, the flue gas flow rate is taken into account in the local model/controller development as an measured disturbance.

3.2 MMPC of PCC process

3.2.1 Local Disturbance Model with Flue Gas Flow Rate Disturbance

Because the flue gas flow rate d can be considered as a measured disturbance, the following state space disturbance model can be used as a local prediction model:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + Ed_k \\ y_k = Cx_k + Du_k + Fd_k \end{cases} \quad (2)$$

where $u_k = [u_{1k} \quad u_{2k}]^T$ is the input vector composed by the lean solvent flow rate u_1 and turbine extracted steam flow rate u_2 ,

$y_k = [y_{1k} \quad y_{2k}]^T$ is the output vector composed by the CO₂ capture rate and reboiler temperature, d_k is the flue gas flow rate, x_k

is the state vector; A, B, C, D, E, F are the local model matrices.

Equation (2) can be rewritten into an augmented form (3),

$$\begin{cases} x_{k+1} = Ax_k + \tilde{B}\tilde{u}_k \\ y_k = Cx_k + \tilde{D}\tilde{u}_k \end{cases} \quad (3)$$

where $\tilde{u}_k = [u_k^T \quad d_k^T]^T$ is the augmented input, and $\tilde{B} = [B \quad E]$, $\tilde{D} = [D \quad F]$ are the augmented system matrices. Since equation

(3) is a typical state space type model, with the input, output and disturbance data being collected, conventional subspace

identification approach can be directly used to identify the local system matrices.

To ensure that the generated data are suited for the local model identification, we keep all the control loops within the gCCS model closed except the CO₂ capture rate and reboiler temperature loops. The excitation signals for flue gas flow rate, lean solvent flow rate and turbine extracted steam flow rate are then designed and implemented on the gCCS model to achieve a persistent excitation of the system around the given CO₂ capture rate and reboiler temperature set-points. The corresponding data are then generated and collected for system identification.

The method of subspace identification is selected for the local model identification due to its following advantages:

a) it can identify the state-space model, which is suitable for advanced multi-variable control design directly from the input-output data;

b) the subspace identification is based on the computational tools such as orthogonal triangular decomposition and singular value decomposition (SVD), thus is computational efficient, and can avoid the problem of local minimum and convergence;

c) the system order can be easily selected during the identification procedure.

The detailed algorithm can be found in [47] and is not repeated here.

Remark 3.1 Different from the conventional MPC, the flue gas flow rate is considered in the prediction model (2) in the proposed method. Therefore, a more accurate prediction in the presence of flue gas flow rate variation can be made, and a quick rejection of this disturbance may be achieved by the developed MPC.

Remark 3.2 CO₂ concentration in the flue gas can be another factor which have significant impact on the PCC process.

However, during the load change of coal-fired power plants, CO₂ concentration in flue gas only varies within a very small range

(According to the design specification of a 1000MWe supercritical coal-fired power plant, CO₂ concentration in flue gas varies

from 21.62wt% to 22.86wt% corresponding to power plant load changes from 50% to 100%, the variation is typically less than

274 1.5%). The reason is that the flue-gas oxygen content is strictly controlled by the power plant combustion system during the
 275 operation and meanwhile a suitable ratio between the amount of fuel and supplied air is always maintained to guarantee the
 276 efficiency of the combustion [48]. For this reason, CO₂ concentration variation is not considered in this study.

277 3.2.2 Local Predictive Control Design

278 Since the identification method is used for the local state-space model development, the derived state variables do not have
 279 physical meanings and thus cannot be measured. For this reason, build the following observer (4) to estimate the state x is
 280 necessary for the model prediction:

$$281 \begin{aligned} \hat{x}_{k+1} &= A\hat{x}_k + B\tilde{u}_k + K[\hat{y}(k) - y(k)] \\ \hat{y}(k) &= C\hat{x}_k + D\tilde{u}_k \end{aligned} \quad (4)$$

282 in which the symbol “ $\hat{}$ ” indicates the estimate. Following the method in Feng [49], the observer gain K can be calculated if
 283 there exist matrices H and G , and a symmetric positive definite matrix X , such that the following LMI problem is feasible:

$$284 \begin{bmatrix} H^T + H - X & (HA + GC)^T \\ HA + GC & X \end{bmatrix} > 0 \quad (5)$$

285 and the observer gain $K = H^{-1}G$.

286 Then considering the following dynamic control objective function:

$$287 J = (\hat{y}_f - r_f)^T Q_f (\hat{y}_f - r_f) + \Delta u_f^T R_f \Delta u_f \quad (6)$$

288 where $\hat{y}_f = [\hat{y}_{k+1}^T \quad \hat{y}_{k+2}^T \quad \cdots \quad \hat{y}_{k+N_y}^T]^T$ is the prediction of future output within the predictive horizon N_y , it can be expressed by

289 the future augmented input sequence $\tilde{u}_f = [\tilde{u}_{k+1}^T \quad \tilde{u}_{k+2}^T \quad \cdots \quad \tilde{u}_{k+N_u}^T]^T$ for a control horizon N_u , by stacking up the predictive

290 model (3) according to the current augmented input \tilde{u}_k , output y_k and estimated state \hat{x}_k :

$$291 \hat{y}_f = \psi_x \hat{x}_k + \psi_u \begin{pmatrix} \tilde{u}_k \\ \tilde{u}_f \end{pmatrix} + \psi_y y_k \quad (7)$$

292 in which,

$$293 \begin{aligned} \psi_x &= \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{N_y-1} \end{bmatrix} (A + KC), \quad \psi_y = - \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{N_y-1} \end{bmatrix} K, \\ \psi_u &= \begin{bmatrix} C(B + KD) & D & 0 & \cdots & 0 \\ CA(B + KD) & CB & D & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{N_u-1}(B + KD) & CA^{N_u-2}B & \cdots & CB & D \\ CA^{N_u}(B + KD) & CA^{N_u-1}B & \cdots & CAB & CB + D \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ CA^{N_y-1}(B + KD) & CA^{N_y-2}B & \cdots & CA^{N_y-N_u}B & \sum_{j=0}^{N_y-N_u-1} CA^j B + D \end{bmatrix}; \end{aligned}$$

294 $r_f = [r_{k+1}^T \quad r_{k+2}^T \quad \cdots \quad r_{k+N_f}^T]^T$ is the desired output set-points; Δu_f is the increment of future control input sequence

295 $u_f = [u_{k+1}^T \quad u_{k+2}^T \quad \cdots \quad u_{k+N_u}^T]^T$, which can be expressed by:

296
$$\Delta u_f = \psi \begin{bmatrix} u_k \\ u_f \end{bmatrix} \quad (8)$$

297
$$\psi = \begin{bmatrix} -I_2 & I_2 & 0 & \cdots & 0 \\ \cdots & -I_2 & I_2 & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & \cdots & -I_2 & I_2 \end{bmatrix}$$

298 in which, I_2 stands for a 2×2 identity matrices. $Q_f = I_{N_f} \otimes Q_0$, $R_f = I_{N_u} \otimes R_0$ are the weighting matrices of output and input,
299 respectively.

300 Substitute equations (7) and (8) into the objective function (6), and at each sampling time, the optimal future control sequence
301 u_f can be calculated by minimizing (6) subject to the input magnitude and rate constraints (9) and (10),

302
$$\begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} u_{\min} \leq u_f \leq \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} u_{\max} \quad (9)$$

303
$$\begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{\min} \leq \psi \begin{bmatrix} u_k \\ u_f \end{bmatrix} \leq \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{\max} \quad (10)$$

304 and the first element in u_f , u_{k+1} can be obtained as the optimal local control action.

305 *Remark 3.3* Note that only the current flue gas flow rate value d_k can be measured at time instant k , and its future values d_{k+1} ,
306 $d_{k+2}, \dots, d_{k+N_u}$ are unknown to the system. Therefore, we assumed that the future values of flue gas flow rate are fixed as d_k over
307 the control horizon N_u in this work, which brings the optimal control sequence into a suboptimal one. If future flue gas flow rate
308 can be estimated correctly by the power plant, the information can be used to further improve the control performance.

309 3.2.3 Integral Action for Offset Free Tracking

310 In spite of the effectiveness of advanced identification methods, the model mismatch is unavoidable, therefore it is necessary
311 to include the integral action into the predictive controller so that an offset-free tracking of the desired set-points can be attained.

312 To add the integral action, an incremental form of augmented model (3) is used for model prediction [46]. Following the
313 same procedure, the future output can be predicted by:

314
$$\hat{y}_f = \mathbf{y}_k + \zeta \Delta \hat{y}_f \quad (11)$$

315 where $\mathbf{y}_k = [y_k^T \quad y_k^T \quad \dots \quad y_k^T]^T$, $\zeta = \begin{bmatrix} I_2 & 0 & \dots & 0 \\ I_2 & I_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I_2 & I_2 & \dots & I_2 \end{bmatrix}$, and $\Delta \hat{y}_f = \psi_x \Delta \hat{x}_k + \psi_u \begin{pmatrix} \Delta \tilde{u}_k \\ \Delta \tilde{u}_f \end{pmatrix} + \psi_y \Delta y_k$.

316 The input magnitude and rate constraints are changed to

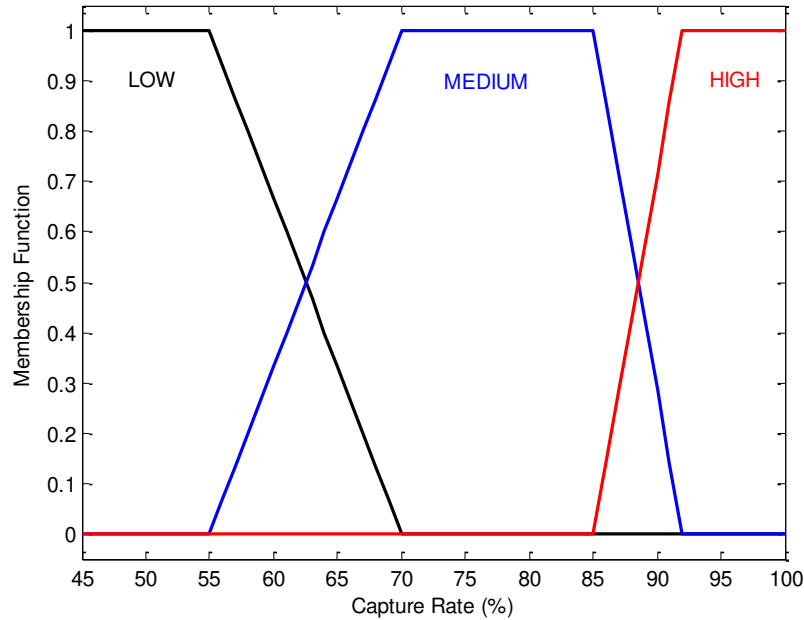
$$317 \quad \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} (u_{\min} - u_k) \leq \zeta \Delta u_f \leq \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} (u_{\max} - u_k) \quad (12)$$

$$318 \quad \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{\min} \leq \Delta u_f \leq \begin{bmatrix} I_2 \\ I_2 \\ \vdots \\ I_2 \end{bmatrix} \Delta u_{\max} \quad (13)$$

319 At each sampling time, substitute equation (11) into the objective function (6), the optimal future incremental control
 320 sequence Δu_f can be calculated by minimizing (6) subject to the input magnitude and rate constraints (12) and (13). The value of
 321 $u_{k+1} = u_k + \Delta u_{k+1}$ can then be obtained as the optimal local control action.

322 3.2.4 Fuzzy Membership function design

323 With the three local predictive controllers being developed, a three rule fuzzy membership function $\omega_i(y_{1k})$ is designed as
 324 shown in Fig. 6 to connect them smoothly together and build the integrated MMPC system for the PCC process.



325

326

Fig. 6 Fuzzy membership functions of the MMPC system

327 CO₂ capture rate is selected as the scheduling variable and according to its current value y_{1k} , the fuzzy membership function
 328 value for the three local predictive controllers $\omega_i(y_{1k})$, $i=1, 2, 3$ can be obtained. The global optimal control action

$$u_{k+1} = \sum_{i=1}^3 \omega_i (y_{1k}) u_{k+1}^i \quad (14)$$

can be calculated at each sampling time and implemented on the PCC system to achieve a wide range flexible control (u_{k+1}^i is the optimal control action calculated by local predictive controller- i).

Remark 3.4 The objective of this paper is to design an MMPC for the PCC process to improve its flexible operation performance. Therefore, the main content of this paper is focused on the control layer (i.e. how to track the CO₂ capture rate set point quickly in a wide range and effectively handle the influences of flue gas flowrate variation), not the scheduling and optimization layer. The set-points are assumed to be given already and dynamic tracking performance (6) is considered as the objective function. How to develop an economic MPC which directly consider the operating cost in the objective function instead of the dynamic control objectives will be our future interest.

IV. SIMULATION RESULTS

This section demonstrates the MMPC controller design for the PCC process. The proposed controller is tested and compared with conventional PI controller and other types of predictive controllers. The sampling time of all the controllers is set as $T_s=30s$ and for the MPCs, we set predictive horizon $N_y=1200s$, control horizon $N_u=150s$; the weighting matrices are set as $Q_0=diag(40, 2)$; $R_0=100 \times diag(1, 0.75)$ for a best CO₂ capture rate tracking control. The following input constraints are considered: $u_{min} = [0 \ 0]^T$, $u_{max} = [1 \ 0.075]^T$; $\Delta u_{min} = [-0.007 \ -0.001]^T$, $\Delta u_{max} = [0.007 \ 0.001]^T$ due to the physical limitations of the valves and pumps. In all the simulations, the controllers are implemented in MATLAB environment, it is communicated with the gCCS model through gOMATLAB interface at each sampling time.

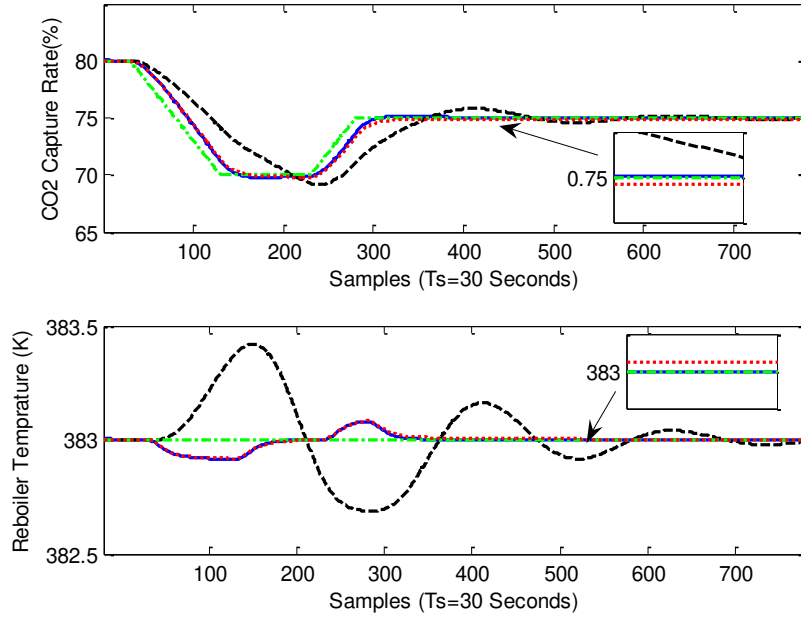
The first case is designed to show the performance of predictive controllers over the PI controller. A small CO₂ capture rate change is considered: at $t = 900$ s the set-points of CO₂ capture rate changes from 80% to 70% at the ramping rate of 0.1%/30s and changes to 75% at $t = 6900$ s at the same ramping rate. The reboiler temperature set point is fixed at 383K.

Three controllers are used for comparison:

- (1) MMPC using the integral action (MMPC_I);
- (2) MMPC without using the integral action (MMPC);
- (3) PI controllers (the parameters are tuned using the MATLAB PID Tuner toolbox at 80% capture rate operating point).

The simulation results in Figs. 7 and 8 show that the predictive controllers have the best performance, which can track the desired CO₂ capture rate quickly and closely during the simulation while maintaining the reboiler temperature well around 383K. The MPCs advantages in multi-variable, large inertial and constrained system control are clearly shown through this simulation. For the PI controller, although its parameters are already well tuned, due to its error based regulating mechanism and SISO loop

357 design approach, the tracking speed is much slower compared with the MPCs, which cannot attain a satisfactory control
 358 performance for the complex PCC process. We can also find from Fig. 7 that, without using the integral action, there exists
 359 small control offset for the MMPC because the modeling mismatches are unavoidable.

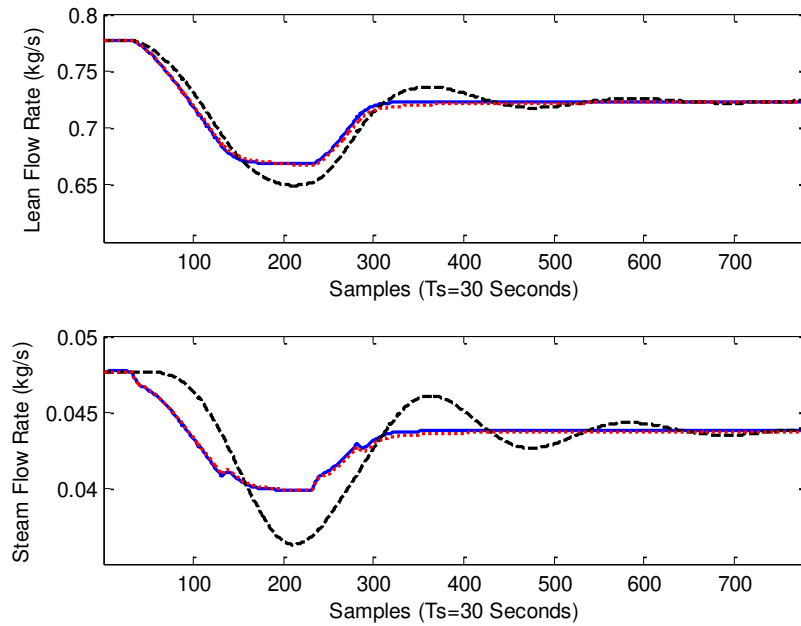


360

361 Fig. 7 Performance of the PCC system for a 80%-70%-75% CO2 capture rate change: output variables (solid in blue: MMPC_I;

362

dotted in red: MMPC; dashed in black: PI; dot-dashed in green: reference)



363

364 Fig. 8 Performance of the PCC system for a 80%-70%-75% CO2 capture rate change: manipulated variables (solid in blue:

365

MMPC_I; dotted in red: MMPC; dashed in black: PI)

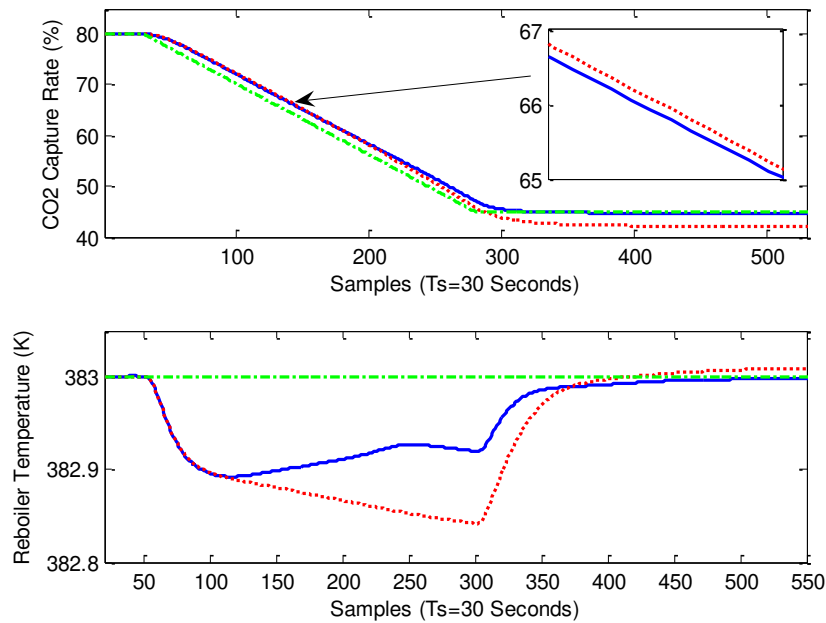
366

367 Then we designed the second and third cases to test the effectiveness for the multi-model predictive controllers for wide
 368 range operating point change. In Case 2, we suppose that at $t=900s$, the set-point of CO_2 capture rate decreases from 80% to
 369 45% at the ramping rate of 0.14%/30s and the reboiler temperature set point is fixed at 383K. Two predictive controllers without
 370 using the integral action are used for comparison:

371 (1) Multi-model predictive controller without using the integral action (MMPC);

372 (2) Linear model predictive controller without using the integral action (linear-MPC), (predictive model is identified around
 373 80% capture rate operating point).

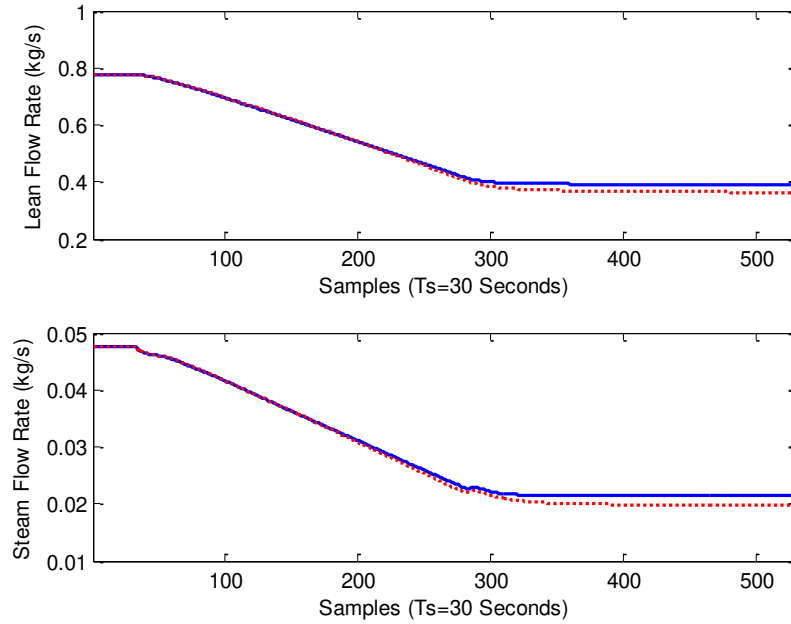
374 The simulation results are shown in Figs. 9 and 10.



375

376 Fig. 9 Performance of the PCC system for a 80%-45% wide range CO_2 capture rate change: output variables (solid in blue:

377 MMPC; dotted in red: linear-MPC; dot-dashed in green: reference)



378

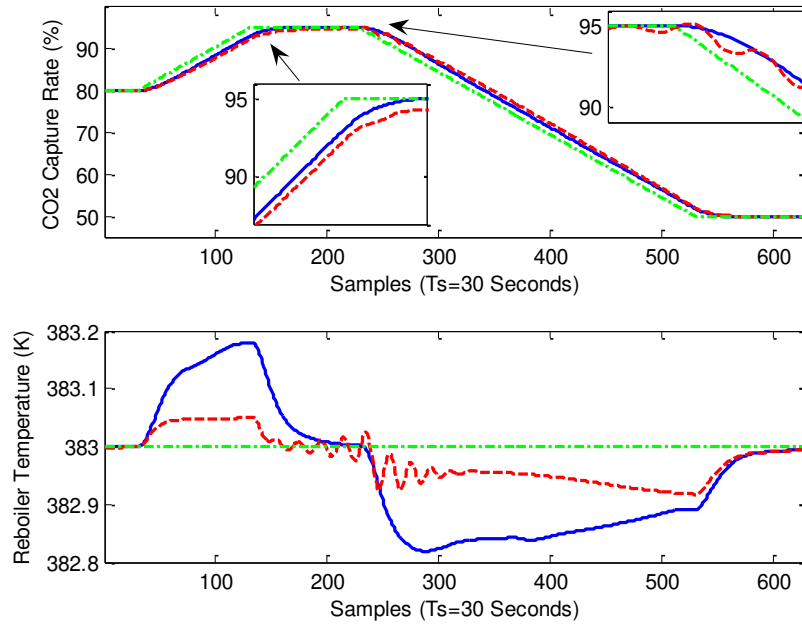
379 Fig. 10 Performance of the PCC system for a 80%-45% wide range CO₂ capture rate change: manipulated variables (solid in
380 blue: MMPC; dotted in red: linear-MPC)

381 The results show that, around 80% capture rate operating point where the linear MPC is developed, both MPCs have almost
382 the same performance, which can control the PCC system satisfactory. However, as the operating point deviates away from 80%
383 point, the modeling mismatch of linear-MPC becomes bigger and thus the control performance is degraded. At 45% operating
384 point, significant control offset can be viewed from Fig. 9 for the linear-MPC. On the other hand for the MMPC, because a
385 combination of several linear MPCs is used, better model prediction can be made during the whole operating range change,
386 therefore faster CO₂ capture rate tracking and better reboiler temperature regulating can be achieved by the MMPC, the control
387 offset at 45% operating point is also much smaller compared with the linear-MPC.

388 Then another wide range operating point variation is considered in Case 3. We suppose that at $t=900s$ the set-point of capture
389 rate changes from 80% to 95% at the ramping rate of 0.15%/30s and changes to 50% at $t=6900s$ at the same ramping rate. The
390 reboiler temperature set point is fixed at 383K. Two predictive controllers using the integral action are used for comparison:

- 391 (1) Multi-model predictive controller using the integral action (MMPC_I);
392 (2) Linear model predictive controller using the integral action (linear-MPC_I), (predictive model is identified around 70%
393 capture rate operating point).

394 The simulation results are shown in Figs. 11 and 12.



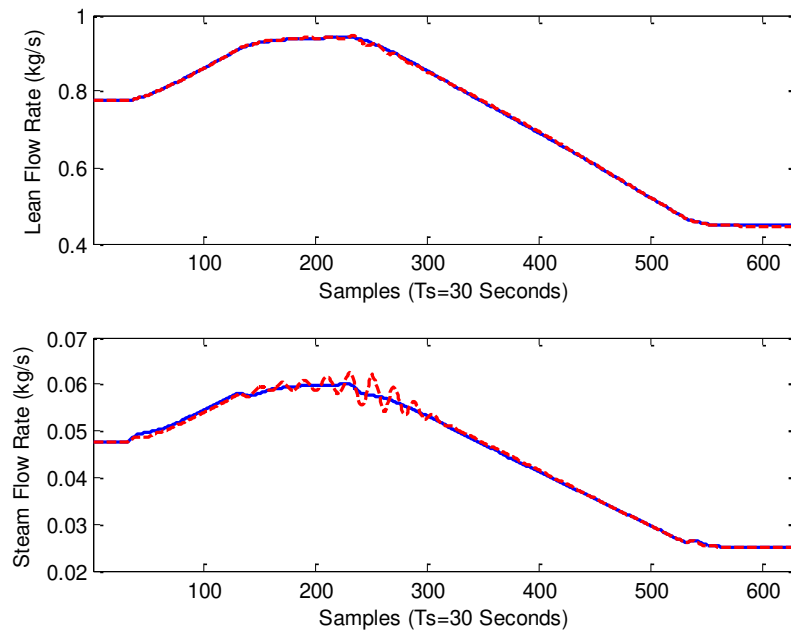
395

396 Fig. 11 Performance of the PCC system for a 80%-95%-50% wide range CO₂ capture rate change: output variables (solid in

397

blue: MMPC_I; dotted in red: linear-MPC_I; dot-dashed in green: reference)

398



399

400 Fig. 12 Performance of the PCC system for a 80%-95%-50% wide range CO₂ capture rate change: manipulated variables

401

(solid in blue: MMPC_I; dotted in red: linear-MPC_I)

402 The results show that, in order to better respond to the wide range CO₂ capture rate change, when the capture rate rise/ drop

403 demand is given, the MMPC_I quickly increases/ decreases the extracted flow rate. Although a bigger reboiler temperature

404 rise/drop can be viewed in Fig. 11, this action can change the CO₂ loading in lean flow more effectively and is helpful for
405 achieving a rapid capture rate control performance, which is the primary objective of the control system. The results also show
406 that a severe performance degradation and system unstable is occurred for the linear-MPC_I around the 95% capture rate
407 operating point. The reason is that, the nonlinearity of the system is extremely strong around 95% operating point, the resulting
408 significant modeling mismatch exceeds the preconfigured robustness bound of the linear-MPC_I.

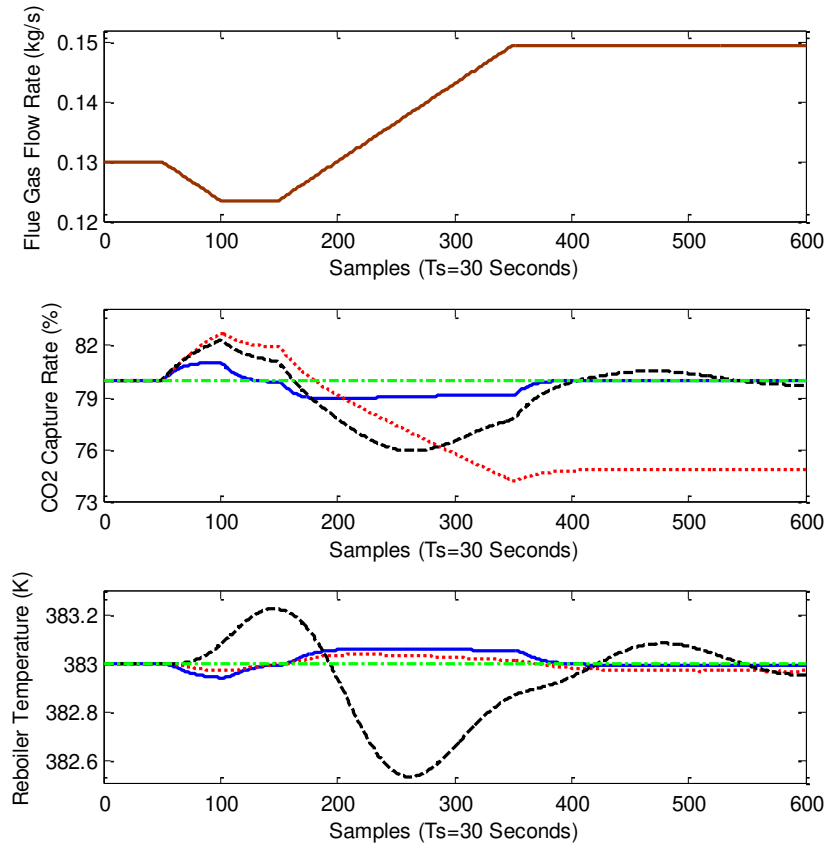
409 Cases 2 and 3 clearly demonstrate the proposed MMPC strategy in the condition of wide range CO₂ capture rate change.
410 Then we devise the last simulation to show the effectiveness of the proposed controller in the presence of power plant flue gas
411 flow rate change. We suppose that, the system is operating at 80% capture rate point, and at $t=1500s$ and $t=4500s$, the power
412 plant changes its loading condition, resulting in a flue gas flow rate change from 0.13kg/s to 0.1235kg/s and to 0.15kg/s as
413 shown in the upper figure of Fig. 13. Three controllers are used for comparison:

414 (1) Multi-model predictive controller without using the integral action (MMPC);

415 (2) Multi-model predictive controller without using the integral action and without using the flue gas disturbance model
416 (MMPC_2);

417 (3) PI controllers (the parameters are tuned using the MATLAB PID Tuner toolbox at 80% capture rate operating point).

418 The simulation results are shown in Figs. 13 and 14.



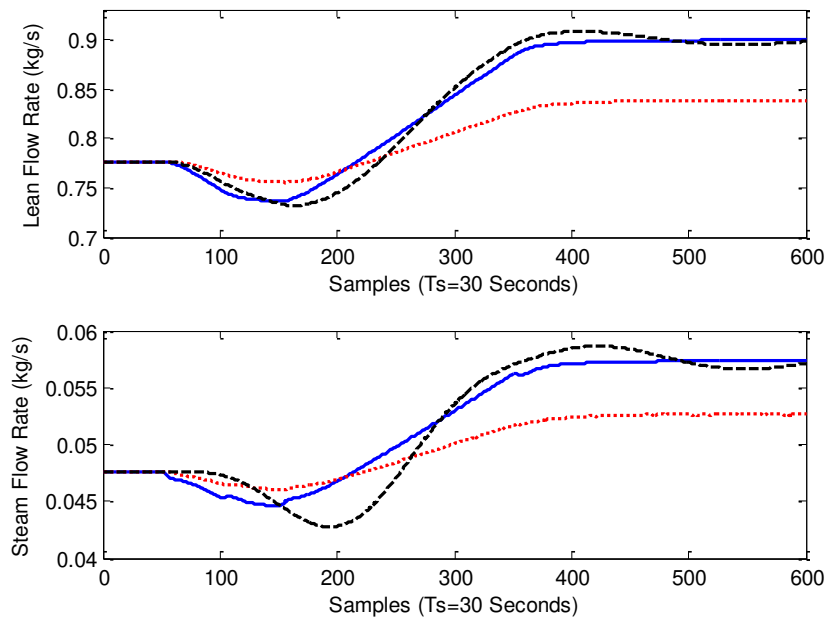
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Fig. 13 Performance of the PCC system in the presence of power plant flue gas variation: output variables (solid in blue: MMPC;

421

dotted in red: MMPC_2; dashed in black: PI; dot-dashed in green: reference)



422

423

Fig. 14 Performance of the PCC system in the presence of power plant flue gas variation: manipulated variables (solid in blue:

MMPC; dotted in red: MMPC_2; dashed in black: PI)

The results show that the proposed MMPC can effectively handle the flue gas variation and keeps the PCC plant operating in an expected condition. On the other hand, without using the flue gas disturbance model, a big prediction error is produced by the MMPC_2 in the case of flue gas variation, therefore, its control performance is degraded severely and a huge control offset is occurred. The dynamic performance of PI controller is also worse than the proposed MMPC, which needs a much longer regulation time to bring the far deviated capture rate and reboiler temperature back to their set points. However, by using the integral action, an offset-free control can be attained by the PI finally.

It should be emphasized that, the use of multiple models instead of one can be viewed as an approach to reduce the modeling mismatches of the single linear model in the case of wide range CO₂ capture rate change. Besides this, two other techniques are used in the proposed MMPC design to further alleviate the impact of uncertainty:

1) For measured uncertainty: the flue gas flow rate is considered in the MMPC design stage, so that the model mismatches or uncertainties caused by flue gas flow rate variation can be effectively dealt with; 2) For unmeasured uncertainty: integral action is taken into account in the MMPC design to guarantee an offset-free control performance.

Nevertheless, if the plant variations or other disturbances are too strong and exceed the pre-configured robustness bound of the MMPC, severe degradation of control performance will still be encountered. In that case, online update of the model may be necessary for the MMPC system.

V. CONCLUSION

To achieve a wide range flexible operation of the post combustion CO₂ capture process, a novel multi-model predictive control system is developed in this paper using the combination of several local linear predictive controllers. Nonlinearity of the solvent-based capture system along the operating range is firstly investigated to provide a guidance for the local model/controller selection and connection. Subspace identification method is then used to build the state space local models around the selected operating point, and predictive controllers are designed based on these models. To improve the adaption ability of the capture system to the power plant load variation, the flue gas flow rate of power plant is considered as an additional measured disturbance in the local model identification, so that an accurate prediction can be made by the developed model in the presence of flue gas flow rate variation. Combined together by a fuzzy membership function, the resulting multi-model predictive control system can attain a rapid change of the CO₂ capture rate in a wide range and reject the power plant flue gas disturbance effectively. The advantages of the proposed multi-model predictive controller design are demonstrated through the simulations on an MEA-based CO₂ capture process developed on gCCS platform.

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