Control structure decisions in a dual-mode pilot CFB boiler based on self-optimizing control

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ABSTRACT

This paper considers the problem of selecting controlled variables in a pilot CFB, which can be operated in air and oxy combustion modes. For air combustion, a wealth of control designs and experiences are available. For the novel process of oxy combustion (combustion with a mixture of oxygen and recycled flue gas for facilitated CO_2 capture), input gas compositions can be adjusted separately from the flows, which decouples fluidization and oxygen carrying tasks and introduces new degrees of freedom and alternative choices for control.
The approach of self-optimizing control was formulated by Skogestad and colleagues in a series of papers in the 2000s. It acknowledges that obtaining and maintaining exact plant-wide models for centralized online optimization is not likely in practice. Instead, self-optimizing control searches for a set of controlled variables which when kept at their constant setpoints, result in plant performance with acceptable loss despite disturbances. Steady-state economic loss evaluation is used for screening alternative control structures, studies for dynamics and controllability must follow.
Steady-state approximations of a detailed dynamic model for the pilot CFB were used in analysis. Air firing results were in line with common practice which supported method validity. Oxy firing results serve as a first step towards analysing alternative control options; optimal control solutions for air firing might not be optimal for oxy firing.

1 INTRODUCTION

The purpose of automatic feedback control is to enable operating the whole plant in a manner that maximizes profit, in the presence of uncertainties and disturbances, using the measurements and manipulated variables available /1/. Although there is a vast amount of control methodologies and algorithms available, systematic tools for the first tasks in control structure design - choosing controlled variables (CVs) - are rare.

Self-optimizing control involves a systematic procedure that aims at choosing constant-setpoint CVs which result in close-to-optimal performance across the plant despite disturbances in the processes. Since plant performance is often determined by steady state operation economics, the analysis is conducted in steady state, with a priori set scenarios for disturbances and implementation errors. As such the method provides a screening of a (potentially very large) set of CVs and to validate the choices, further studies taking e.g. system dynamics into account must follow.

The self-optimizing control approach to plant-wide control was proposed by S. Skogestad and colleagues in a series of papers (e.g. /6/, /13-14/) and formulated based on ideas drafted by several authors such as Morari, Arkun and Stephanopoulos /8/, Shinnar /12/, Luyben /7/, and others. The approach is based on the fact that in control, model-based control paradigms (such as MPC) require good dynamic models to be successful in practice. However, good plant-wide models are often unavailable or unaffordable. Instead, control is often based on a set of simple SISO loops, and more complicated or unconventional solutions require a demonstration of significant performance improvement and e.g. guarantees of maintainability in order to be accepted. Therefore, a firm motivation for control structures based on “conventional” controllers exists today as strong as ever.

Plant-wide control approaches have been previously studied in industrial process test cases such as reactor-separator-recycles /2/ and Tennessee-Eastman challenge /6/. Applications in power plant processes are few. In /5/, self-optimizing control was applied to a waste incineration plant steam network. Operation range was divided into regions with different constraints and control strategies (MV-CV pairs). Authors state that this intuitive solution of simple control loops is an attractive alternative to complicated MPC (which could handle the constraints implicitly). In /10/ a self-optimizing control structure was presented for a post-combustion flue gas CO_2 capture unit (MEA absorption). Both papers present simple dynamic simulations to justify the results.

In this paper, the self-optimizing method is applied in a pilot CFB (circulating fluidized bed) boiler. The approach was first applied to conventional air-fired CFB /9/ because the available experience and existing solutions allow comparison between the results and practical knowledge. The approach has then been extended to the more complicated oxy-fired CFB, where fuel is not combusted with air but with a mixture of pure oxygen and recycled flue gas to facilitate CO_2 capture from flue gas. When input gas composition can be adjusted separately from the flow, fluidization and oxygen carrying tasks are practically decoupled, introducing new degrees of freedom and alternative choices for control. Hence the control structure choices for oxy combustion can be made in a different manner than in conventional air firing. For CFB oxy combustion, several control issues and strategies have been discussed by Hultgren et al. /3/. The self-optimizing analysis described in this paper serves as the first step towards analyzing control alternatives.

2 DUAL-MODE CFB PILOT MODEL

The studied process is a 20-50 kW pilot circulating fluidized bed (CFB) boiler (detailed description in /14/) that can be operated in two firing modes; conventional air firing and oxy firing. Combustion takes place in a sand bed fluidized with combustion air. To achieve sufficient fluidization and optimal combustion conditions, air/oxidant feed is staged to primary and secondary feeds. Solid particles are entrained in the upward gas flow, transported to the top of the boiler and returned to the bed through a solids separation system (cyclone) while hot flue gas leaves the boiler and enters the heat recovery section. This part of the process can be referred to as the hotloop. In oxy combustion, fuel is not combusted with air but with oxidant, a mixture of pure oxygen and recycled flue gas (RFG), to produce flue gas with very high CO_2 content for facilitated CO_2 capture. Recycled flue gas acts as a thermal diluent, enabling both firing modes in the same boiler. Compared to traditional air firing, oxy combustion in CFB involves a structurally similar process but with additional alternatives and degrees of freedom for control design (see e.g. /3/).

A dynamic Matlab/Simulink hotloop model for the pilot CFB has been adjusted and validated using real measurement data. Detailed description of the simulation model can be found in /11/. The model comprises a furnace, gas-solid separator and solids return system. Furnace model is based on 20 ideally mixed 1-D elements with mass and energy balance calculations. Matlab/Simulink ODE solver is used to solve the differential equations against time. Semi-empirical correlations are used to solve hydrodynamics, combustion characteristics and heat transfer. Vertical density profile is solved with defined empirical functions.

CFB boilers are remarkably difficult to model due to various interactions in the process and physical phenomena. Validated dynamic models (such as /11/ which this study is based on) are invaluable in control design, but complex fluidization engineering models are obviously too heavy to be used online in real time control, or even in off-line approaches requiring iterative computations. In this study, a neural network steady state approximation (see e.g. /4/) of the detailed dynamic air-CFB hotloop model was used to reduce computation times. A model for air-firing steady state behavior was built based on simulation data. A multiple-input multiple-output sigmoid neural network (SNN) /4/ was trained using a set of data points for each disturbance scenario. Main advantage of SNN is in ability to provide smooth mappings (training by adjusting sigmoid-shaped hyperplanes) which are often desired in process engineering applications. The model consisted of three inputs (fuel feed rate, primary air flow, secondary air flow) and outputs that were required either by CVs or evaluation of the cost function J. Model parameters were obtained using the Levenberg-Marquardt technique, number of nodes in the hidden layer (H=4) was based on trial and error, and linear output nodes were selected. Matlab neural network toolbox was used for training and model simulation.

3 SELF-OPTIMIZING CONTROL

3.1 Self-optimizing control – Skogestad method

The self-optimizing control approach to plant-wide control was proposed by S. Skogestad and colleagues in a series of papers (e.g. /6/, /13-14/). Self-optimizing control is optimal in the sense that the minimization of a cost function is considered. The aim is not to directly minimize a cost function, because such optimization would require a perfect dynamic model, complete set of measurements, identification of all possible disturbances, and means to solve the optimization problem online. Such centralized optimization is not likely to be used in practice /13/ even with decreasing computing price, because obtaining and maintaining such a plant-wide model is usually not economical. Instead, self-optimizing control design uses a closed loop implementation and searches for a set of controlled variables called self-optimizing variables, which can be kept constant at all times, resulting in performance with acceptable loss. In some cases there is no loss /13,10/ if the optimum lies at some constraint(s) and constrained variables are used as CVs. Active constraints may change as the operating point changes, which may make direct SISO implementations impractical (reconfigurable control) and MIMO controller could do better. Criteria for good CVs include easy measurement, accurate control, insensitivity to disturbance, and sensitivity to MVs. In a multivariable case, CVs should not be closely correlated. /13/

Structural decisions are followed with control solution refinement, such as choice of algorithms and control laws, but the approach is insensitive to choice of algorithms as long as setpoints are reached: The analysis is based on steady-state performance, as it often determines the economic performance. Therefore, the method only provides a screening of a large set of CV candidates; dynamic studies must follow to justify the results. For each studied control structure, performance is evaluated for of a set of disturbances and implementation errors (set a priori) and compared to truly optimal performance, and the promising choices can be included in e.g. rigorous dynamic studies.

The underlying optimization problem can be formulated as minimizing a cost function $J_u(\boldsymbol{u}, d)$, subject to constraints $g(\boldsymbol{u}, d) \leq 0$. Manipulated variables (MVs) $\mathbf{u}$ can be affected, disturbances d cannot be affected. If the cost of applying disturbance-optimal $\boldsymbol{u_{opt}}$ is $J_{opt}(d)$, then the loss for applying $\boldsymbol{u}$ instead of the optimal is $L(\boldsymbol{u}, d) = J_u(\boldsymbol{u}, d) - J_{opt}(d)$. The problem to be solved is to find a good set of constant-setpoint controlled variables (CVs) among an infinite set of choices (if e.g. combinations of measurements are included as candidates).

The direct loss evaluation method /13/ can be applied to static nonlinear process models, and is hence very general. It is a systematic procedure for selecting CVs based on loss evaluation for a finite set of disturbances:

1) Analysis of degrees of freedom, selection of base variables u.
2) Definition of the (economic) cost function J and constraints g.
3) Identification of important disturbances d (process disturbance, modelling error etc.)
4) Solving the nominal optimization problem $u_{opt}(d^*)$ (and if not too demanding, solving the optimization problem for each d for an easily interpretable calculation of loss i.e. cost compared to optimal).
5) Identification of CV candidate sets. Active constraint control can be considered for variables at their constraints, CVs for remaining degrees of freedom are then proposed.
6) Evaluation of losses for using each candidate set. For each CV candidate set, loss L(u,d) is evaluated. In case of implementation errors, u is adjusted accordingly.
7) Screening promising solutions and conducting further analysis. Solutions with acceptable loss (steady-state performance) are examined for criteria such as performance in different operating regions and closed-loop dynamics.

3.2 Cost function and constraints

When the economic cost function J is well defined, it characterizes the optimal operation of a plant – operation that fulfils power request, process constraints, low operating costs and acceptable flue gas emissions. In this case, profit equals generated power (to setpoint; surplus power is less profitable and deficiency in power induces high cost). Fuel, air and pure oxygen costs can be estimated based on coal and O_2 price and fan operation costs. Emissions of CO_2 and SO_2 involve emission trading or treatment cost (limestone addition). Deviation from the desired flue gas O_2 (2 %) was penalized with a small cost. For the oxy firing case, other species than CO_2 in flue gas were penalized with small cost (to include impurity removal and drying costs in CO_2 processing unit).

Plant operation is restricted by some hard constraints. In this study, upper and/or lower bounds for bed and flue gas temperatures ($830°C \leq T_{bed} \leq 980°C$, $T_{fg} \leq 980°C$), fluidization velocity ($v_f \geq 2$ m/s) and flue gas O2 ($c_{O2} \geq$ 1%) were implemented.

3.3 Control structure alternatives

Manipulated variables for air included fuel feed rate (u_1), primary air flow (u_2) and secondary air flow (u_3) [kg/s].

For oxy, MVs included fuel feed rate (u_1), primary RFG (u_2), primary oxygen (u_3), secondary RFG (u_4) and secondary oxygen flow (u_5) [kg/s].

Out of 30 structures studied, 8 different control topologies are presented here for air and oxy firing.

AIR	1. power [kW], primary air / fuel ratio [-], flue gas O2 [%] 2. fuel feed [kg/s], primary air / fuel ratio [-], flue gas O2 [%] 3. power [kW], fluidization velocity [m/s], flue gas O2 [%] 4. fuel feed [kg/s], fluidization velocity [m/s], flue gas O2 [%], 5. T bed middle [°C], T flue gas [°C], flue gas O2 [%] 6. T bed middle [°C], fluidization velocity [m/s], flue gas O2 [%] 7. T bed middle [°C], primary air / fuel ratio [-], flue gas O2 [%] 8. T bed middle [°C], sec / prim air ratio [-], flue gas O2 [%]
OXY	1. power [kW], prim gas volume [m3/s], T bed bottom [°C], sec RFG / prim RFG [-], flue gas O2 [%] 2. T bed middle [°C], v_f [m/s], T bed bottom [°C], T bed top [°C], flue gas O2 [%] 3. T bed middle [°C], v_f [m/s], prim gas O2% [%], total secondary flow [kg/s], flue gas O2 [%] 4. power [kW], v_f [m/s], prim gas O2% [%], sec RFG / prim RFG [-], flue gas O2 [%] 5. power [kW], v_f [m/s], prim gas O2% [%], sec RFG / prim total flow [-], flue gas O2 [%] 6. power [kW], prim gas volume [m3/s], prim gas O2% [%], sec RFG / prim RFG [-], flue gas O2 [%] 7. power [kW], bed density bottom [kg/m3], T bed bottom [°C], bed density top [kg/m3], flue gas O2 [%] 8. power [kW], v_f [m/s], prim gas O2% [%], bed density top [kg/m3], flue gas O2 [%]

Setpoints for the CVs were picked from the nominal optimum. To find correct MV values, the control problem was solved by optimizing a MIMO problem under constraints: the sum of squared deviations between CVs and their setpoints was minimized, with constraints overruling minimization. Active constraints were thus not explicitly considered in control. Active constraints typically result in reconfigurable SISO control requirements, e.g. with different load levels. These implementation aspects were not in scope of this study. Optimization was performed with enhanced `fmincon` (Matlab), with a few dozen repetitions from random initial search points.

3.4 Disturbance scenarios

Five process disturbance scenarios were studied: d1) no disturbances, d2) fuel heat value -5%, d3) fuel heat value +5%, d4) fuel moisture -10%, d5) fuel moisture +10%. Several additional cases could be included (e.g. air ingress, pressure deviations, O_2 purity etc.)

4 RESULTS

4.1 Air combustion

	control configuration, *c*							
disturbance	*c=1*	*c=2*	*c=3*	*c=4*	*c=5*	*c=6*	*c=7*	*c=8*
d=1 (nom.)	0	0	0	0	3	0	0	0
d=2	0	79	11	77	13	12	1	1
d=3	3	6	3	6	15	13	10	10
d=4	11	12	10	12	15	13	11	12
d=5	4	4	4	5	1	4	4	4
mean loss	0.06	0.33	0.09	0.33	0.15	0.14	0.08	0.09
rank	1	8	4	7	6	5	2	3

Table 1. Air firing – Ranking of control structures based on average loss for disturbances.

	Optimal CV values					**Optimal MV values**		
disturbance	***flue gas O_2 [%]***	***T bed, middle [°C]***	***power [kW]***	***v_f [m/s]***	***prim air/ fuel [-]***	***fuel feed [kg/s]***	***primary air [kg/s]***	***secondary air [kg/s]***
d=1 (nom.)	1.0	933	44.1	2.4	6.3	0.0025	0.0157	0.005
d=2	1.0	930	44.1	2.6	6.6	0.0026	0.0172	0.005
d=3	1.5	941	44.8	2.0	5.2	0.0023	0.0121	0.009
d=4	1.0	937	44.1	2.5	7.3	0.0020	0.0147	0.000
d=5	1.0	934	44.1	2.6	8.1	0.0022	0.0181	0.000

Table 2. Air firing - Optimal CV and MV values for each disturbance.

The outcomes for air-firing (Table 1) are in line with current control practice, which encourages the use of the method. The results support controlling power, primary air / fuel ratio and flue gas oxygen to their setpoints (c=1) using the three MVs available. This is the common approach, usually implemented with SISO controllers so that power is adjusted by fuel, primary air flow is feedforward from the fuel feed and secondary air is used for O_2 trim (flue gas O_2). Bed temperature can surprisingly well compensate for lacking feedback from power (c=7). Open-loop control solutions such as constant fuel feed (c=2,4) cannot handle disturbances, which can clearly be seen for decreased fuel heat value (d=2).

CV setpoints (optimal CV values) and corresponding MV values are given in Table 2. Because one of the criteria for a good CV is insensitivity to disturbance, good CVs should have similar optimal values for each disturbance. It appears to be optimal to operate at flue gas O_2 constraint (1 %) and required power (44 kW) with bed temperatures around 935 °C. Optimal fluidization velocities range from minimum 2.0 to 2.6 m/s. Optimal primary air / fuel ratio is between 5 and 8. MVs corresponding to these optimal CV values are also given. Secondary air flow ranges between 0 and 0.009 kg/s. It must be noted that this is a pilot-size process, where secondary air feed is small in the first place. Accurate NOx modelling could also affect optimal air feed distribution.

4.2 Oxy combustion

Oxy combustion results were obtained using a linearized model around 85% load (evaporator power 39,9 kW). The outcome differs from air-firing. All good topologies suggest controlling power and flue gas oxygen to their setpoints. Here, bed temperature is obviously not a good CV instead of power, and it appears in all of the worst ranked options. Poorly performing structures also use e.g. constant secondary flow and bed temperatures. The best three topologies (c=5,4,6) are very similar, supporting constant primary oxidant O_2 percentage, fluidization velocity or primary gas volume, and secondary RFG / primary RFG or secondary RFG / total primary flow ratio (best structure uses v_f and sec RFG / total primary flow ratio). Fourth (c=7 with a very small additional cost) is completely different and controls bed densities at top and bottom as well as bed temperature at bottom.

disturbance	**control configuration, *c***							
	c=1	*c=2*	*c=3*	*c=4*	*c=5*	*c=6*	*c=7*	*c=8*
d=1 (nom.)	23	6	2	0	0	1	3	1
d=2	23	23	167	5	5	7	10	12
d=3	22	65	6	4	4	4	0	8
d=4	30	1	0	0	0	0	0	0
d=5	22	17	13	4	3	4	3	4
mean loss	0.155	0.145	0.244	0.018	0.016	0.021	0.021	0.032
rank	7	6	8	2	1	3	4	5

Table 3. Oxy firing - Ranking of control structures based on average loss for disturbances.

	Optimal CV values								
	power [kW]	***T bed, bottom [°C]***	***T bed, middle [°C]***	***flue gas O_2 [%]***	***v_f [m/s]***	***bed density, bottom [kg/m³]***	***bed density, top [kg/m³]***	***prim gas vol [m³/s]***	***prim gas O_2 [%]***
d=1 (nom.)	39.9	870	909	2.00	2.0	181.1	3.6	0.011	29.2
d=2	39.9	875	912	2.00	2.0	181.1	3.6	0.011	30.8
d=3	39.9	866	905	2.00	2.0	181.1	3.6	0.011	27.7
d=4	39.9	868	907	2.00	2.0	181.0	3.6	0.011	29.1
d=5	39.9	871	910	1.99	2.0	181.1	3.6	0.011	29.3

Table 4. Oxy firing - Optimal CV values for each disturbance.

	Optimal MV values				
	fuel feed [kg/s]	***primary RFG [kg/s]***	***primary O_2 feed [kg/s]***	***secondary RFG [kg/s]***	***secondary O_2 feed [kg/s]***
d=1 (nom.)	0.0024	0.0118	0.0049	0.0000	0.0000
d=2	0.0025	0.0114	0.0052	0.0000	0.0000
d=3	0.0023	0.0122	0.0046	0.0000	0.0000
d=4	0.0024	0.0119	0.0049	0.0000	0.0000
d=5	0.0024	0.0117	0.0049	0.0000	0.0000

Table 5. Oxy firing - Optimal MV values for each disturbance.

In Table 4, CV setpoints (optimal CV values) indicate that operating at the exact required power (39.9 kW) with flue gas O_2 at its setpoint (2 %) and fluidization velocity at its minimum (2 m/s) is optimal. Optimal primary gas O_2 percentage (27.7-30.8 %) varies, but the optimal primary gas volume is constant (0.011 m^3/s). Disturbance-optimal MV values (Table 5) indicate that in this pilot CFB, secondary flows are optimally minimized.

5 CONCLUSIONS

For air firing, the analysis supported the common industrial approach that can be implemented with SISO control; power is adjusted with fuel feed, primary air flow is feedforward from fuel feed, and secondary air flows are used for flue gas O_2 trim. Controlling bed fluidization with fluidization velocity v_f would require solution such as a soft sensor, but it is not clear if it would be worth the effort. Similarly, bed temperature could compensate lack of power feedback surprisingly well, but since power is the typical and easily measurable quality parameter for a power plant, it would not make sense to exclude it from control. Results for air firing in /9/ show that measurement uncertainty should definitely be included in study.

For oxy firing, the best-ranked structures include power and flue gas oxygen control as well as primary gas O_2 % control, fluidization control by v_f or constant primary gas volume (also easier to achieve than constant mass flow), and feedforward from primary RFG or total primary gas flow to secondary RFG. Secondary gas flows are optimally minimized in the pilot (which probably cannot be generalized to industrial-size CFBs).

The self-optimizing control analysis is a straight-forward method, yet surprisingly tedious to complete - the need for good tools became evident especially during optimization. Analysis results are sensitive to small changes in costs and constraints, which highlights the importance and difficulty of translating economic operation objectives into control. An extensive set of disturbances should be used for ranking is based on average losses. Final decisions for the control structure should naturally not be made based on direct loss evaluation in steady-state operation. Issues of controllability and dynamic behaviour as well as process instrumentation cost should be considered. The self-optimizing approach is useful in screening CV candidates for further studies.

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