Computers and Chemical Engineering 71 (2014) 220–234

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Plant-wide control system design: Primary controlled variable selection

Dustin Jones[a], Debangsu Bhattacharyya[a,*], Richard Turton[a], Stephen E. Zitney[b]

[a] *Department of Chemical Engineering, West Virginia University, Morgantown, WV 26506, USA*
[b] *National Energy Technology Laboratory, U.S. Department of Energy, Morgantown, WV 26507, USA*

ARTICLE INFO

Article history:
Received 2 May 2014
Received in revised form 2 August 2014
Accepted 5 August 2014
Available online 19 August 2014

Keywords:
Primary controlled variable
Self-optimizing
Parallelized branch and bound
AGR
IGCC

ABSTRACT

This work is focused on the development of a rigorous, model-based approach for the selection of primary controlled variables as part of a plant-wide control system design methodology. Controlled variables should be selected for their self-optimizing control performance and controllability while ensuring satisfactory performance in terms of dead-time and closed loop interactions. This work has considered both self-optimizing and control performance as well as has addressed issues related to loop-interactions and superstructure constraints. The new three-stage approach developed in this work results in a large-scale, constrained, mixed-integer multi-objective optimization problem. For solving this problem, a parallelized, bi-directional branch and bound algorithm with dynamic search strategies has been developed to solve the problem on large computer clusters. The proposed approach is then applied to an acid gas removal unit as part of an integrated gasification combined cycle power plant with CO_2 capture.

1. Introduction

Most of the works in the existing literature in the area of plant-wide control system design have focused on controller design. Traditionally, control structures are designed based upon heuristic methods (Luyben et al., 1998; Murthy Konda et al., 2005) that do not use the process knowledge in a systematic manner. Recently, a systematic, model-based approach for control structure design has been proposed (Skogestad, 2004). The proposed approach is a two-stage method starting with a top-down analysis and ending with a bottom-up design. In the first stage, a top-down approach is taken to generate a list of manipulated, control, and disturbance variables considering a scalar operation objective and other process constraints. In the second stage, a bottom-up approach is used for designing the control system taking into account the results from the previous stage. Use of this approach has been reported in a number of papers (Araujo et al., 2007; Jones et al., 2013; Panahi and Skogestad, 2011, 2012; Larsson et al., 2003). Readers interested in a more detailed discussion of this method are directed to those works.

One important step in the systematic design of a control system is the selection of the primary controlled variables. It has been suggested that the primary controlled variables should be selected based on their economic performance (Skogestad, 2004). The suggested approach is to perform optimization studies where the objective is to minimize a scalar cost function subject to operational constraints (Skogestad, 2004). The active constraints found by the optimization studies are selected as the primary controlled variables. Generally, the number of manipulated variables available within a process will be greater than the number of active constraints; therefore, it is required to select additional primary controlled variables so that they are self-optimizing. The self-optimizing controlled variables are those that when held constant result in an acceptable economic loss in the face of disturbances (Morari et al., 1980).

However, primary controlled variables should have all the following properties (Skogestad and Postlethwaite, 2005):

1. Optimal value insensitive to disturbances (self-optimizing).
2. Easy to measure and control.
3. Sensitive to changes in the manipulated variable.
4. Independent of one another.

Our previous work in the area of primary controlled variables selection has been concerned largely with the selection of self-optimizing controlled variables as the additional primary controlled variables (Jones et al., 2013). However, during this work it has been found that considering only the economic performance

---

* Corresponding author. Tel.: +1 3042939335; fax: +1 3042934139.
E-mail address: Debangsu.Bhattacharyya@mail.wvu.edu (D. Bhattacharyya).

http://dx.doi.org/10.1016/j.compchemeng.2014.08.004
0098-1354/

Nomenclature

A	Pareto solution sets values of first objective function
B	Pareto solution sets values of second objective function
C_n	candidate set of the n^{th} node
F_n	fixed set of the n^{th} node
G	process gain matrix without active constraint controls
G_{AC}	process gain matrix with active constraint controls
J	objective function used for steady-state economics optimization
M_r	vector of the lower bound of the values of the r^{th} objective function for a single controlled variable
n_{cv}	number of candidate controlled variables
n_d	number of disturbance variables
n_u	number of input variables
P_n	union of the sets F_n and C_n
Q	set of K logical vectors that define a subset
α_i	lower bound on the i^{th} RGA pairing
β_i	upper bound on the i^{th} RGA pairing
χ_k	maximum number of controlled variables from a subset of the candidate controlled variable set defined by Q

of the primary controlled variables will yield uncontrollable and/or infeasible controlled variables. This can be due to the lack of manipulated variables with the necessary gain to control the primary controlled variables and/or a high degree of interaction between the primary controlled variables. In addition, one or more controlled variable(s) can have large dead-time due to the available set of manipulated variables resulting in poor control performance. Furthermore, the algorithm for primary controlled variable selection should be capable of screening trillions of candidate sets, as would be expected for a large scale plant, within reasonable amount of time. The method for primary controlled variables selection proposed in this paper addresses these issues. Our proposed method involves a three-stage procedure: a priori analysis, controlled variable selection, and a posteriori analysis. The controlled variable selection stage includes measures for control performance in addition to the economic performance proposed by Skogestad (2004). These stages are summarized below.

- A priori analysis
  - Prescreening criteria have been added to the control structure design procedure to help eliminate infeasible controlled variable sets from further consideration and to reduce the size of the large scale combinatorial optimization problem. The prescreening criteria identify controlled variables that would show either poor servo or regulatory control performance and eliminates them.
- Controlled variable selection
  - A controllability measure has been added within the framework of the primary controlled variable selection problem that has been proposed by Skogestad (2004).
  - Loop interactions are included within the framework as a controlled variable set may show good economic and control performance, but fail to attain satisfactory control performance due to strong loop interactions.
  - A constraint is added to the selection methodology to address the issue of poor control performance for time-delay systems. The constraint is formulated by considering the dead-time of the paired manipulated variable with the controlled variable.
  - A parallelized, bi-directional, multi-objective branch and bound (BB) algorithm has been developed for solving the resulting large scale optimization problem. This BB algorithm is capable of running on large computer clusters to efficiently solve the mixed integer optimization problem where the number of inputs and outputs are fairly large resulting in a very large-scale combinatorial problem. This algorithm has been developed by modifying the BB algorithm proposed by Kariwala and Cao (2010a,b) so that the problem can be solved on a computer cluster using the MATLAB® Distributed Computing Server™. The modified algorithm has been developed by incorporating dynamic search strategies to further increase the efficiency of the algorithm.
- A posteriori analysis
  - In addition to the evaluation of the economic performance of the selected controlled variables by using the nonlinear model, control performance is also evaluated by using the nonlinear model. Examination is undertaken at off-design operations considering the presence of a real-time optimizer (RTO) (process is at the optimal operational point) and the absence of an RTO (primary controlled variables are left constant at their nominal values).

Finally, the proposed methodology for the primary controlled variable selection is applied to an acid gas removal (AGR) unit that is part of an integrated gasification combined cycle (IGCC) power plant with CO_2 capture. The AGR unit considered here is based upon the work of Bhattacharyya et al. (2011). The AGR unit consists of 16 manipulated variables, 5 recycle loops and over 20 unit operations. This is a highly nonlinear process that allows for testing the robustness of the proposed primary controlled variable selection procedure. Additionally, designing an optimal control system for an IGCC plant with CO_2 capture addresses the challenge of efficiently operating and controlling coal-fed IGCC plants with the desired extent of CO_2 capture in the face of disturbances without violating operational and environmental constraints. The design of such a control system makes the plant suitable to play an active role in the smart grid era.

2. Primary controlled variable selection

The proposed methodology is a three-stage process: a priori analysis, selection of Pareto-optimal controlled variable sets, and a posteriori analysis.

2.1. A priori analysis

The a priori analysis begins by defining an operational objective that is to be optimized. Operational and other constraints are then identified along with likely disturbances to which the process may be subjected. The process is then optimized with respect to this operational objective at the nominal operating point as well as under the identified disturbances. From these optimization studies, active constraints are identified (Skogestad, 2004). Further analysis is required however to determine appropriate pairings of manipulated variables to active constraints as well as identification of a candidate set of controlled variables for controlled variables analysis.

2.1.1. Optimization

The process of selecting primary controlled variables begins with the definition of an operational objective that is to be optimized. This is followed by a degree of freedom analysis to identify the manipulated variables available for the control of the system. This is preceded by the identification of process constraints which can be operational or environmental constraints. Finally, the disturbances likely to affect the process must be determined. At this point, the process is optimized in relation to the operational objective using the identified degrees of freedom and subject to the identified constraints. This optimization study is completed at the