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Plant-wide control system design: Secondary controlled variable selection

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ABSTRACT

This work is focused on the development of a rigorous, model-based approach for the selection of secondary controlled variables as part of a plant-wide control system design methodology. Secondary controlled variables should be easy to measure, easy to control, fast to respond to changes in the input variables, and lead to automatic, indirect control of the primary controlled variables. While much of the work on this subject has been based upon ad hoc approaches, here a systematic three-stage approach is proposed that addresses issues of controllability and economic performance of the control system. The first stage involves the generation of an initial set of candidate secondary controlled variables and the generation of selection constraints that are used to determine if manipulated variables can be used for control of candidate controlled variables. During the second stage, secondary controlled variables are selected to minimize integral absolute errors (IAEs) of the primary controlled variables subject to minimal loop interactions as determined by a relative gain array analysis. Finally, during the third stage, control performance of the secondary controlled variables is evaluated at off-design operations using a nonlinear process model. The proposed approach is then applied, as ongoing work in the application of plant-wide control, to an acid gas removal unit as part of an integrated gasification combined cycle power plant with CO_2 capture.

1. Introduction

In a plant-wide control system design procedure, the selection of controlled variables for the regulatory control layer is an important consideration. As discussed by Skogestad (2004), the control layers are generally divided into the upper supervisory controls and the lower regulatory control layers. Supervisory controls are used for the control of the primary controlled variables, associated with the economics of the process, and the regulatory controls are required to stabilize the plant by controlling the secondary controlled variables. Selection of a secondary controlled variable is driven primarily by how well it indirectly controls performance of the primary controlled variables, thereby enabling it to be used as a degree of freedom by the upper layers. Additional important considerations for secondary controlled variable selection are ease of measurement, sensitivity to the input variables, and minimal loop interactions.

As the secondary controlled variables are controlled on a faster time scale, the regulatory control layer should be as simple as possible (i.e. consisting mainly of PID controllers). Traditionally the determination of the indirect control performance of the controlled variable set is determined by a partially controlled plant analysis (Shinnar, 1981; Kothare et al., 2000; Luyben et al., 1998; Konda et al., 2005). A block flow diagram of a partially controlled plant analysis is shown in Fig. 1. Here, y_1 and y_2 are the primary and secondary controlled variables, respectively. From this block flow diagram, it can be shown that, when K_2 approaches infinity, the primary controlled variables are given, as reported by Skogestad and Postlethwaite (2005), as $y_1 = (G_{11} - G_{12}G_{22}^{-1}G_{21})u_1 + (G_{d_1} - G_{12}G_{22}^{-1}G_{d_2})d + G_{12}G_{22}^{-1}((y_2)_{ref} - n_2)$. Here, G_{uy} is the process gain matrix from input u to output y and G_{d1} and G_{d2} are the disturbance gain matrices for the primary and secondary controlled variables, respectively. From this expression it is possible to derive several measures of control performance. Further guidelines for controlled variable selection from a partial gain concept are provided in Skogestad and Postlethwaite (2005). However, a limitation of this partially controlled plant analysis is that it is a steady-state evaluation and does not address the dynamics of the system. In addition, two of the important considerations when selecting

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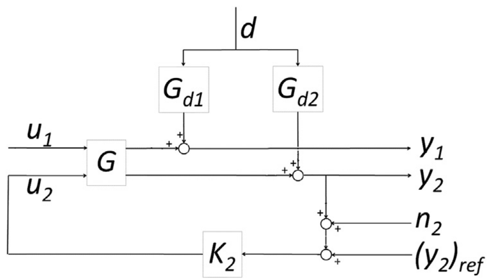

Fig. 1. Partially control plant block flow diagram.

secondary controlled variables are ease of measurement and controllability and a purely steady-state based analysis cannot address these issues.

A new method for secondary controlled variables selection has recently been published by Yelchuru and Skogestad (2013). In this method, the objective is the selection of a set of secondary controlled variables or a linear combination of secondary controlled variables that minimizes the 'state drift' of the plant. This method of secondary controlled variable selection, as applied by the authors, was limited to only steady-state analysis. However, the method itself could be applied to dynamic systems. This method also does not directly account for the servo nor regulatory control performance of the supervisory control layer, which can be drastically affected by the secondary controlled variables. Another method for system stabilization is proposed by Alonso and Ydstie (2001) which connects thermodynamics and the passivity theory of control. This method, however, does not consider the control performance of a primary control loop. Although the process may be stabilized, the economic/primary controlled variable performance may not be satisfactory.

In this paper, a new method of secondary controlled variable selection has been developed that considers the servo and regulatory control performance of the closed loop system directly and optimizes the regulatory control performance as measured by the scaled integral absolute error (IAE). Additionally, issues related to loop interactions are addressed by relative gain array (RGA) constraints on the supervisory and regulatory control layers. This method consists of three stages as summarized below.

- A priori analysis

  ○ This stage comprises of formulation and implementation of a subset selection constraint. This subset selection constraint is an integer constraint that is used to determine if a manipulated variable can be used for control of a candidate controlled variable. Servo and regulatory control performance criteria, as well as process insight, can be used to formulate this constraint.

- Set selection

  ○ A new objective function is formulated for selection of the secondary controlled variables. This new objective function is sum of scaled integral absolute errors (IAEs) of the primary controlled variable loops with secondary controlled variables used as manipulated variables. The IAEs are scaled according to the economic importance of the associated primary controlled variable. In this way, the impact of the control performance on the economic performance is 'approximately' captured in a single objective function.
  ○ Loop interactions are included within the framework. An RGA analysis is included within the formulation to ensure minimal loop interactions exist within the regulatory and supervisory control layers.
  ○ An approach by which the subset selection constraint may be implemented within a branch and bound algorithm is discussed. In addition, methodologies by which this constraint may be used for pruning of supernodes (nodes with a large set of possible solutions) within a branch and bound algorithm are also discussed.

- A posteriori analysis

  ○ Evaluation of the controllability of the system at off-design operating conditions.
  ○ Evaluation of the dynamic performance of the secondary controlled variables within the nonlinear process model.

2. Secondary controlled variable selection

In the proceeding sections, a more in-depth discussion of each of the three stages is provided.

2.1. A priori analysis

The a priori analysis is divided into four steps: identification of a candidate set of secondary controlled variables and disturbances, generation of a subset selection constraint, identification of input–output models, and calculating and scaling of the IAE of the cascaded primary control loop.

2.1.1. Identification of a candidate set of secondary controlled variables and disturbances

For the identification of the candidate set of secondary controlled variables, process insight is required. It is at this stage that one must decide which controlled variables will be considered for further analysis and this decision is best made with process insight. While it is possible to screen a large number of candidate variables by using the proposed three stage method, inclusion of certain candidate variables may not add any value. At this stage, only those variables that are obviously not candidate secondary controlled variables are excluded from the candidate set. Applying process insight in this manner simplifies and accelerates the entire procedure of secondary controlled variable selection; however, it is not required. Likewise, identification of disturbances to the process also requires process insight. The disturbances here do not necessarily need to be the same as those that were considered during primary controlled variable selection. The disturbances considered during primary controlled variable selection are related to higher level operations and disturbances. At this level, it is of more concern to reject local disturbances and not allow them to propagate through the process, eventually affecting the primary controlled variables and/or making the process unstable. Unlike the generation of a candidate set of secondary controlled variables, which does not necessarily require process insight, the proposed procedure for secondary controlled variable selection requires the identification of process disturbances, therefore requiring a degree of process insight.

2.1.2. Subset selection constraint

Here, a subset selection constraint is defined. First, a linear process model, as defined in Eq. (1), must be identified. Here, G_{p2}, G_{d2}, u, d, and y_2 are the process and disturbance gain matrices, input variables, disturbance variables, and secondary controlled variables, respectively. It is also important to note that the gain matrices are scaled in the manner defined by Skogestad (2004), i.e. based upon optimal variation of input and output variables. Let Q be a set of n_{cv} vectors of length n_u. Here, n_{cv} is the number of candidate secondary controlled variables and n_u is the number of manipulated variables. If the jth element of the ith set is a logical 1, the corresponding pairing of the ith input to the jth output is feasible; otherwise,