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Controller performance analysis with LQG benchmark obtained under closed loop conditions

Ramesh Kadali, Biao Huang*

Department of Chemical and Materials Engineering, University of Alberta, Edmonton, Alberta T6G 2G6, Canada

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Abstract

This paper proposes a new method for obtaining a linear quadratic Gaussian (LQG) benchmark in terms of the variances of process input and output from closed-loop data, for assessing the controller performance. LQG benchmark has been proposed in the literature to assess controller performance since the LQG tradeoff curve represents the limit of performance in terms of input and output variances. However, an explicit parametric model is required to calculate the LQG benchmark. In this work, we propose a data driven subspace approach to calculate the LQG benchmark under closed-loop conditions with certain external excitations. The optimal LQG-benchmark variances are obtained directly from the subspace matrices corresponding to the deterministic inputs and the stochastic inputs, which are identified using closed-loop data with setpoint excitation. These variances are used for assessing the controller performance. The method proposed in this paper is applicable to both univariate and multivariate systems. Profit analysis for the implementation of feedforward control to the existing feedback-only control system is also analyzed under the optimal LQG performance framework. The proposed method is illustrated through a simulation example and an application on a pilot scale process. © 2002 ISA—The Instrumentation, Systems, and Automation Society.

Keywords: Controller performance assessment; LQG benchmark; Subspace identification; Subspace matrices; Nonparametric models; State space model; Closed-loop identification

1. Introduction

A typical industrial plant can contain thousands of controllers ranging from PI/PID (proportional, integral, and derivative) controllers to the more advanced model predictive controllers like dynamic matrix control (DMC) [1,2], generalized predictive controller (GPC) [3,4], quadratic dynamic matrix controller (QDMC) [5], etc. With a goal towards optimal performance, energy conservation, and cost effectiveness of the process operations in the industry, controller performance assessment has been receiving attention both from the industry and from the academia since the notable work of Harris [6]. Periodic tuning of the controllers becomes an important task of control engineers for obtaining optimal performance from the control systems. Controller performance assessment techniques are used as a tool to check the optimality of the current controller tuning parameters settings. Several benchmarks such as minimum variance control (MVC) [6–21], linear quadratic Gaussian (LQG) control [13,15], and designed controller performance versus achieved controller performance [22–24], etc., have been proposed for assessing the controller performance. Among these approaches, MVC benchmark is one of the popular benchmarks due to its nonintrusive nature for the univariate case and routine closed-

*Author to whom all correspondence should be addressed. Fax: (780)492-2881; *E-mail address:* bhuang @ualberta.ca

loop operating data can be used for the calculation of this benchmark. For the univariate application, only *a priori* knowledge of the process time delay is required for obtaining the MVC benchmark from routine operating data [7–9,15,12,25,6,17,] [20,21,26]. For the multivariate case, the calculations are more involved and require estimation of the unitary interactor matrix [13,10,11,12,14,16,] [27–29,19,20,30]. However, the MVC benchmark may not be a practical one for those control systems whose objective is not just minimizing process output variance but also keeping the input variablity (for example, valve movement) within some specified range to reduce upset to other processes, conserve energy, and lessen the equipment wear. The objective of such controllers may be expressed as minimizing a linear quadratic function of input and output variances. The LQG benchmark is a more appropriate benchmark for assessing the performance of such controllers. However, calculation of the LQG benchmark requires a complete knowledge of the process model [13,15], which is a demanding requirement or simply not possible in practice. An open-loop test for obtaining the process model may not always be feasible or may be expensive. The frequency domain approach was proposed by Kammer [31–33] for testing the LQ optimality for the performance assessment of a controller using closed-loop data with setpoint excitation. However, this approach does not give the quantitative values for the controller performance in terms of process input and output variances. In other words, it does not separate the nonoptimality/optimality with respect to process response (output) variance and process input variance. In this paper we propose subspace matrices based approach to obtain the LQG-benchmark variances of the process input and output to be used for the controller performance assessment. The required subspace matrices, those corresponding to the deterministic and stochastic inputs, are estimated from closed-loop data with setpoint excitation. The method proposed is applicable for both univariate and multivariate cases.

Subspace identification methods allow estimation of a state space model for the system directly from the process data. Certain subspace matrices, corresponding to the states, deterministic inputs, and stochastic inputs, are identified as an intermediate step in the subspace identification methods. Several approaches, such as N4SID (Numerical subspace state space identification), MOESP [MIMO (multi-input multi-output) output error state space model identification], and CVA (Canonical variate analysis), are popular for subspace identification using open-loop data. Subspace identification methods also exist for closed-loop data. Recently Van Overschee and De Moor [34] proposed a subspace identification method for the identification of the subspace matrices (all the three, corresponding to the states, deterministic input, and stochastic input) of the process using closed-loop data with the knowledge of the first N impulse response coefficients (Markov parameters for the multivariate systems) of the controller, where N is the maximum order of the state space model we want to identify. MOESP and CVA approaches were also used for the identification of a state space model using closed-loop data [35–37]. In addition to the setpoint excitation, the MOESP/CVA approach uses an external white-noise signal addition to the controller output to make it independent of the noise. The closed-loop state space model is first identified using the closed-loop data from which the open-loop state space matrices are retrieved. Ljung and McKelvey [38] presented a method for the identification of subspace matrices from closed-loop data using estimated predictors and state that their algorithm is an illustration of a ''feasible'' method rather than the ''best way'' of identifying systems operating in closed loop. The primary goal of all the above approaches is the identification of a state space model for the open-loop system.

Favoreel and co-workers [39–41] have recently proposed a method for the design of optimal LQG controllers directly from the subspace matrices, instead of using a state space model. Recent work by Kadali and Huang [42] allows identification of (only two of the subspace matrices, corresponding to) the deterministic subspace matrix and stochastic subspace matrix from closed-loop data without requiring any *a priori* knowledge of the controllers. This method requires set point excitation and is also extended to the case of measured disturbances [42]. These methods provide tools/means for the calculation of more practical controller performance benchmarks like LQG benchmark using closed-loop data. As will be shown later in this paper, the explicit process model is not required for obtaining the LQG benchmark.