



Identification test design for multivariable model-based control: An industrial perspective



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ABSTRACT

The design of plant tests to generate data for identification of dynamic models is critically important for development of model-based process control systems. Multivariable process identification tests in industry continue to rely on uncorrelated input signals, even though investigations have shown the benefits of other input designs which lead to correlated, higher-amplitude input signals. This is partly due to difficulties in formulating and solving computationally tractable problems for identification test design. In this work, related results are summarized and extended. Connections between different designs that target D-optimality or integral controllability are established. Related concepts are illustrated through simulation case studies.

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1. Introduction

The majority of model-based control methods used in industry relies on an empirical linear dynamic model developed from data generated from a dedicated plant test. The natural framework for designing a plant test is design of experiments (DOE), in which a constrained optimization problem is formulated and solved to target aspects of the model that are important for ultimate use in the control system. Most frequently, however, standard errors in model parameters or predictions are simply considered to be indicators of model quality.

DOE is a vast and multifaceted area. However, in industrial practice, DOE for control-relevant model development is not performed routinely. Rather, uncorrelated test signals (such as multiple pseudo-random binary sequences (PRBS) signals) are typically applied to the process to be modeled, in either open- or closed-loop fashion, with the associated magnitudes set on the basis of constraints on inputs and outputs. The frequency range of the test signals is usually set based on rough knowledge of the open-loop process settling time and may be adaptively adjusted during the identification experiment.

The rationale for using uncorrelated input signals is that they are statistically optimal in a precise sense (namely D-optimal for identification of multivariable system parameters subject to input

constraints). However, uncorrelated input signals are generally not optimal when constraints other than simple input constraints must be satisfied during identification, such as output constraints, or when control-relevant criteria, such as integral controllability, must be satisfied by the identified model. In such cases, signals that may be very different from standard uncorrelated inputs may be optimal, especially for ill-conditioned systems, as shown by a number of investigations over the past two decades. However, appropriate alternatives to uncorrelated inputs have not found significant usage in practice, mainly due to practical difficulties in formulating tractable DOE problems for typically sized industrial systems. Further, the more tractable DOE formulations have been based on static models, with the dynamics treated as an afterthought in ad hoc fashion. Therefore, development of DOE formulations that address these industrial needs would increase the potential for DOE use in practice.

The intent of this work is to develop such formulations. Specifically, this paper

- Summarizes, extends, and examines control-relevance of constrained DOE for identification of steady-state multivariable models;
- Develops a control-relevant constrained DOE formulation that is computationally tractable, for identification of dynamic multivariable models; and
- Illustrates the resulting methods via computer simulation.

The rest of the paper is structured as follows. Background material and related literature are presented in Section 2, followed

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by a brief overview of industrial practice on identification test design in Section 3. Main results are presented in Sections 4 and 5 for the static and dynamic cases, respectively. Simulation-based case studies are shown in Section 6, followed by conclusions and recommendations in Section 7. More technical material is provided in Appendices.

2. Background

The performance of any model-based controller depends intrinsically on the accuracy of the plant model over the nominal operating range of the plant. In the process industry, Model Predictive Control (MPC) has become the preferred model-based scheme, in large part due to its ability to handle complex dynamics and constraints. In an MPC project, the plant test and subsequent model identification often consume more than 50% of the total project time (Darby & Nikolaou, 2012). In a plant test, process inputs that are expected to be used by the controller(s) are changed in a manner to sufficiently excite the outputs. The inputs include both manipulated variables (MVs) and measured disturbance variables (DVs); the outputs are the expected controlled variables (CVs). A range of testing approaches are used in practice, including both manual and automatic (computer-generated) test signal designs, most often in open loop but, increasingly, in closed loop. Most input testing continues to be based on spatially uncorrelated signals, where the term spatially uncorrelated implies negligible correlation between pairs of inputs at the same time instant. These signals can be implemented manually, one input at a time, or from computer-generated random sequences. Automatic testing approaches and improved identification techniques have been major focus areas for the MPC vendors over the last 10–15 years as a means of reducing the cost and effort involved in model development, especially since a model (or portions of a model), must be re-identified when there are changes to the process, such as a process revamp or a significant change in a product specification. Today, automatic testing products – both open- and closed-loop approaches – are available. Table 1 provides a current summary of offerings of major MPC technology providers.

As mentioned earlier, the natural framework for posing the input design problem is via (optimal) design of experiments (DOE), as traditionally done in regression problems (Box, Hunter, & Hunter 2005; Fedorov, 1972; Fedorov & Hackl, 1997; Montgomery, 2001; Pukelsheim, 1993; Silvey, 1980). The objectives of DOE are at the discretion of the designer and may be the accuracy of the model parameters themselves or control-relevant characteristics of the model (Gevers, 2005; Hjalmarsson, 2005). DOE problems for the identification of dynamic models are usually difficult to solve (involving non-convex optimization) and most investigations have been limited to SISO or 2×2 MIMO problems. While not necessarily cast as a DOE problem, control-relevant testing and identification of multivariable systems has been an active research area over the last two decades, although only a few of these developments have found usage in industrial practice.

Table 1
Commercially available software for multivariable input test generation.

Product	Company	Type of automatic test
Connoisseur	Invensys	Open loop
DeltaV Predict	Emerson	Open loop
DMCplus SmartStep	AspenTech	Closed loop
INCA Test	IPCOS	Open loop
Profit Stepper	Honeywell	Open or closed loop
SMOC QuestPro	Shell	Open or closed loop
Tai-Ji	Tai-Ji Control or Matrikon	Open or closed loop

A particular challenge of a multivariable system, unlike the SISO case, is that accurate estimation of the individual transfer function elements in a transfer matrix may not be sufficient to guarantee robust closed-loop stability. For a MIMO system, the distribution of model errors among the individual transfer function elements is of greater importance. Control-relevant identification focuses on properties of the identified model that are important for the resulting model-based controller. One such property, which this article will consider further, is integral controllability (IC) (Garcia & Morari, 1985) a condition that enables tuning of multivariable controllers with integral action for robust closed-loop stability. The IC condition is an eigenvalue inequality that couples the plant steady-state gain matrix \mathbf{G} and the inverse of the controlled system's steady-state model $\hat{\mathbf{G}}$ as, explained in Eq. (13) below. This coupling underscores the importance of accurate identification of the plant inverse gain matrix (see, e.g., Li & Lee, 1996).

In an analysis of DOE for identification of a static (steady-state) model, Koug and MacGregor (1993, 1994) showed that higher-amplitude, correlated inputs, designed on the basis of uncorrelated, orthogonally rotated inputs, facilitate the identification of models that satisfy IC when compared to traditional uncorrelated binary sequences, particularly for ill-conditioned systems. The design rule of Koug–MacGregor sets the magnitudes of the rotated inputs in inverse proportion to the singular values of the steady-state gain matrix. Insightful geometric reasoning for the 2×2 case was used as motivation to extend the results to the static $n \times n$ case. Even though the preceding DOE results were developed for the static case, a number of case studies have shown that a rotated input design can be successfully applied to the identification of dynamic models by designing random binary inputs of appropriate magnitude and frequency content (Ashari & Mevel, 2011; Bruwer & MacGregor, 2006; Conner & Seborg, 2005; Galvanin, Macchietto, & Bezzo, 2007; Koug & MacGregor, 1993, 1994; Misra & Nikolaou, 2003; Micchi & Pannocchia, 2008; Tosukhowong & Lee, 2008).

Motivated by the idea of transforming uncorrelated signals, but not limiting the transformation matrix to orthogonal rotations, Zhan, Li, and Georgakis (2006) developed a D-optimal, constrained design for the static case, which incorporated uncertainty of the gain elements, to arrive at the optimal transformation matrix. The result was extended by Li and Georgakis (2008) to include, as constraints, dynamic predictions of the outputs (at user-selected time instances) based on the current dynamic model. However, IC was not explicitly considered in these investigations. Bruwer and MacGregor (2006) used rotated inputs as the basis for designing experiments, subject to input/output constraints, where the magnitudes (non-binary) were optimally chosen from the vertices of the feasible constraint region.

For the case of a $n \times n$ linear system with constant (frequency-independent) left right rotation matrices in the SVD of its transfer matrix, Featherstone and Braatz (1998) showed that design of IC-relevant experiments for identification of a dynamic model to be used in an SVD controller (Hovd, Braatz, & Skogestad, 1997) reduces to D-optimal design (which may include possible constraints). Their proposed approach decouples input–output maps, and consequently the eigenvalue inequalities into a series of far more manageable scalar inequalities. This approach naturally leads to the use of orthogonally rotated inputs as the basis for experiment design.

Uncorrelated rotated inputs result in highly correlated actual inputs when applied to ill-conditioned plants, and in uncorrelated outputs in general. This observation serves as a motivation for closed-loop experiments with uncorrelated excitation of the controller setpoints. Several authors (Anderson & Kummel, 1992; Koug & MacGregor, 1993; Micchi & Pannocchia, 2008) have shown that such closed-loop testing results in increased estimation accuracy of the weaker directions (i.e., singular vectors corresponding to small

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