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Autocovariance-based plant-model mismatch estimation for linear model predictive control ☆

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HIGHLIGHTS

- An autocovariance-based plant-model mismatch estimation approach is proposed.
- Explicit relations between closed-loop data statistics and mismatch are established.
- Changing of constraint active sets in the MPCs are considered in the approach.
- Estimates are very close to their true values in the case study.

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ABSTRACT

In this paper, we present autocovariance-based estimation as a novel methodology for determining plant-model mismatch for multiple-input, multiple-output systems operating under model predictive control. Considering discrete-time, linear time invariant systems under reasonable assumptions, we derive explicit expressions of the autocovariances of the system inputs and outputs as functions of the plant-model mismatch. We then formulate the mismatch estimation problem as a global optimization aimed at minimizing the discrepancy between the theoretical autocovariance estimates and the corresponding values computed from historical closed-loop operating data. Practical considerations related to implementing these ideas are discussed, and the results are illustrated with a chemical process case study.

1. Introduction

Model predictive control (MPC) has become the de-facto advanced control approach in the process industries [1,2], with a large number of working applications reported already more than a decade ago [3]. MPC offers distinct advantages over other model-based control techniques, in that it can naturally handle state, input, and output constraints, account for interactions between variables, and deal with non-square systems. MPC performance, however depends strongly on the accuracy of the system model. The identification of such models for large industrial plants involves significant time and effort, and model accuracy tends to degrade in time due to the natural evolution of the physical system that they represent. In the chemical industry, phenomena such as corrosion, catalyst deactivation, and fouling will inevitably cause a drift of the process dynamic characteristics over time, leading to a mismatch between the model prediction and the actual plant states. Commercial MPC is typically used in conjunction with a (nonlinear) real-time optimization (RTO) scheme which utilizes additional degrees of freedom to meet plant-level economic objectives; a linear (LP) or quadratic (QP) programming-based optimizer is sometimes used between the RTO and MPC in a cascade [4,5]. Thus, model mismatch may impact not only control performance within the MPC loop but also the calculations of input and output targets, possibly leading to calculation of infeasible or suboptimal setpoints. This is significant because the ability to execute setpoint changes based on plant- and unit-level objectives is often a primary economic justification for implementation of MPC. As a result, maintenance and updating of the MPC model should be conducted regularly; owing to the cost involved, it is desirable that the nature and magnitude of such plant-model mismatch be estimated from plant data, prior to initiating a model re-identification effort.

The problem of plant-model mismatch has been addressed in the literature from the perspective of quantifying the (degradation of) closed-loop control performance. The general approach consists of defining a performance metric, which is then compared to

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a reference value derived either from theoretical considerations or from data that correspond to a "golden" [6] period of optimal operation. Here, we recall the minimum variance benchmark [7], linear quadratic Gaussian benchmark, and the covariance benchmark [6]. MPC-specific benchmarking was also proposed, using the value of the controller objective function as the performance metric [8–10]. Another type of metrics are statistics calculated from process data. Techniques such as principal component analysis (PCA) and partial least squares (PLS) are first used to project the process data onto a smaller set of latent variables, which are then used to define and compute performance metrics. The Q statistic and Hotelling's T^2 statistic are two widely-used metrics in this context [11]. Although the above listed approaches can detect a problem with the control performance, they provide limited diagnostic information.

Further efforts have focused on identifying the *source* of performance degradation. Control charts [12], derived from statistical process control, can serve to identify variables that contribute most to the controller performance degradation. Moreover, a study of the correlation between process variables can provide information about each individual submodel of a MIMO system. For example, the partial correlation between the model prediction error and the manipulated variables of the plant has been used to detect the input/output pairs where mismatch is present [13,14]. Kaw et al. [15] proposed using a frequency domain analysis combined with external set-point changes to estimate plant-model mismatch in the internal model control (IMC) framework for single-input, single-output (SISO) systems. This approach uses a "plant-model ratio (PMR)" defined as the ratio between the plant and model frequency response functions. The idea is that mismatches in gains, time constants and time delays result in characteristic signatures in the PMR and can be used to narrow down the source of error. Limitations include the need for sufficient external excitation and inability to distinguish between mismatches in individual parameters. Botelho et al. [16] also considered the closed-loop case, computing the nominal outputs from a plant under no mismatch via the closed loop sensitivity function, and then using e.g. the variance as a benchmark against which to compare plant output variance. In doing so, the authors were able to detect problematic input–output channels; they also indicate the ability to discriminate between the effects of modeling error and unmeasured disturbances by considering the distributions of the nominal outputs and nominal output errors.

Estimating the *magnitude* of the plant-model mismatch for specific parameters has received comparatively little attention in the literature. Ji et al. [17] proposed a frequency domain approach, wherein sinusoidal excitations at different frequencies are imposed on the plant and the MPC model simultaneously. The difference between the frequency response of the plant and the model is used for mismatch estimation. Bachnas et al. [18] describe an iterative closed loop identification scheme for MPC using a state space realization of an orthogonal basis function (OBF) based model, chosen for its desirable adaptivity properties. New expansion coefficients of the OBFs are identified from closed loop excitations by minimizing the one-step ahead prediction error. In our previous work [19], we proposed a new approach for the estimation of plant-model mismatch in the case of MPC, based on finding the plant mismatch values that minimize the discrepancy between the autocovariance of the plant inputs and outputs predicted using the plant model, and the autocovariance obtained from operating data.

In this contribution, we provide a general formulation of the autocovariance-based plant-model mismatch estimation problem for MIMO systems. Based on a set of reasonable assumptions concerning the active set of the MPC controller, we develop our results for the case of linear MPC with input constraints. Our approach is predicated on deriving expressions for the autocovariance matrices of the plant inputs and outputs as explicit functions of the magnitude of mismatch in the coefficients of the step response plant model in the case where the active set of MPC does not change during the operation. Then, we formulate the problem of mismatch estimation in terms of an optimization problem, showing that the mismatch between the plant and the model used in the controller is a global minimizer of the discrepancy between the aforementioned autocovariance matrices, and the corresponding autocovariances computed using data from the closed-loop operation of the plant.

The paper is organized as follows: we begin with a description of the class of systems and controllers considered. The explicit relation between autocovariance matrices and plant-model mismatch is established in the third section. In the fourth section, we present the optimization problem associated with computing the plant-model discrepancy from plant data for both cases where MPC has a fixed or changing active set. We illustrate these ideas with a chemical process example, and close with conclusions and an account of potential future directions for research.

2. Preliminaries

2.1. Problem statement

We consider a feedback control loop with a linear discrete-time MPC controller. The block diagram of the feedback system is shown in Fig. 1. The plant has F outputs and G inputs, denoted by $\mathbf{y}(t) \in \mathcal{R}^F$ and $\mathbf{u}(t) \in \mathcal{R}^G$, respectively. The model in the MPC captures the plant dynamics relating the outputs to the inputs; however, mismatches inevitably exist between this model and the behavior of the plant. We discuss mismatch representations used in this work below.

2.1.1. Mismatch representation for non-parametric models

Non-parametric models for input/output systems include step response and impulse response models. They are commonly used in MPC applications since they can represent a wide range of input/output behaviors, but the number of coefficients needed to define the model is usually very large. Finite step response models have the form

$$\hat{\mathbf{y}}(k) = \sum_{i=1}^{N-1} \hat{\mathbf{S}}_i \Delta\mathbf{u}(k-i) + \hat{\mathbf{S}}_N \mathbf{u}(k-N) \tag{1}$$

where N is the model horizon, $\hat{\mathbf{S}}_i$ are the step response model coefficient matrices and $\Delta\mathbf{u}(k)$ are changes in inputs, defined as

$$\Delta\mathbf{u}(k) = \mathbf{u}(k) - \mathbf{u}(k-1). \tag{2}$$

The corresponding plant dynamics can be expressed in the same form as

$$\mathbf{y}(k) = \sum_{i=1}^{N-1} \mathbf{S}_i \Delta\mathbf{u}(k-i) + \mathbf{S}_N \mathbf{u}(k-N) \tag{3}$$

where $\mathbf{S}_i$ are the step response model coefficient matrices for the true plant dynamics. The mismatch between the coefficient matrices in the two models can be represented as

$$\delta\mathbf{S}_i = \mathbf{S}_i - \hat{\mathbf{S}}_i. \tag{4}$$

2.1.2. Mismatch representation for parametric models

Of the class of parametric models, we focus on transfer function models in this work, and represent the transfer function matrix of a MIMO system as:

$$\hat{G}_{fg} = f(\hat{K}_{fg}, \hat{\tau}_{fg}, \hat{\theta}_{fg}) \tag{5}$$