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Closed-loop identification for plants under model predictive control

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A B S T R A C T

Model predictive controllers incorporate step response models for pairings of independent and dependent variables. Motivated by the fact that it may be time-consuming to conduct open-loop experiments to identify the step response models, the paper assesses the performance of closed-loop system identification on MPC-equipped plants, using both simulated and actual plant data. Pure feedback closed-loop system identification is shown to be effective for an identifiable simulated system and an industrial hydrogen production plant. The use of closed-loop system identification as a mechanism for monitoring model quality in MPC implementations may enhance the long-term sustainability of the implementation.

1. Introduction

Model predictive control (MPC) is a technology that has found wide acceptance in the petrochemical industry. MPC allows for improved plant efficiencies, enhanced product quality, and increased robustness to disturbances. Also, MPC allows for the satisfaction of known process operating constraints. MPC can bring many benefits without degrading the reliability of a process control system. In most implementations, the MPC is only loosely coupled to the underlying distributed control system (DCS), which means that the plant can run with or without the MPC being active.

Most oil refineries use MPC. In some implementations, there is one model predictive controller for each major unit operation. In other implementations, a single model predictive controller provides high-level set-points to the distributed control system for each unit operation.

MPC is also used at most industrial plants which produce hydrogen, carbon monoxide, and syngas. Steam methane reformer units produce a hydrogen-rich gas, known as reformate, from a hydrocarbon feed stock. The reformate is then cooled, separated, and purified to produce hydrogen, carbon monoxide, and syngas product streams. An MPC at hydrogen production plant has on the order of one to two dozen independent variables, and two to four dozen dependent variables. The independent variables may include a set-point for the flow rate of the hydrocarbon feed and a set-point for the flow of air to the reformer burner. Dependent variables include the rate of hydrogen production, the level of methane slip in the reformate, and the excess oxygen ratio for the burner.

MPC is widely used at Air Products (NYSE:APD), a leading industrial gases company. For 75 years, the company has provided atmospheric, process and specialty gases, and related equipment to manufacturing markets including metals, food and beverage, refining and petrochemical, and natural gas liquefaction. Air Products has over 50 years of experience designing, building, and operating more than 100 hydrogen facilities worldwide with hydrogen operations in 14 countries. Most of the hydrogen plants owned and operated by Air Products incorporate MPC. Also, the company provides a comprehensive range of services for customers who own and operate their own hydrogen plants (Services-and-Solutions, 2017).

In most implementations, model predictive controllers incorporate step response models for the relationship between each pairing of an independent and dependent variable. The step response models are used to solve a finite horizon optimal control problem which is typically formulated as a quadratic program with linear constraints.

To achieve the highest levels of performance with a model predictive controller, the step response models for the relationship between independent and dependent variables should be as accurate as possible. A variety of approaches are used to develop the step-response models. In some cases, simple first-principle models are used in conjunction with engineering know-how to provide an initial guess for the models in the absence of process data. A more sophisticated approach uses system identification techniques with actual plant operating data to produce the step-response model.

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Ideally, the step-response models should capture the true open-loop relationship between the independent and dependent variable. To make this more effective the ideal perturbations to the inputs should have the form of a pseudo random binary sequence (PRBS) (Koung & Macgregor, 1994) or constrained multisine input (Rivera et al., 2009). In practice, it may be costly and time-consuming to conduct open-loop experiments in a large petrochemical plant. It is also possible that the system is unstable under open-loop, in such case it would not be viable to perform an open-loop test. Thus, it may be necessary to perform system identification using closed-loop data produced with the distributed control system and/or the model predictive controller engaged.

The theory and technology for open-loop identification using deliberate system excitation is mature. Commercial MPC packages, including Aspen DMC and Invensys Connoisseur, incorporate methods for identification using the results of step tests. And while the theory of pure feedback closed-loop identification is mature, application of closed-loop identification in MPC implementations is rare.

There is important recent work on performing system identification on a closed-loop system under MPC by using additive external excitation. In one approach, a design-of-experiments approach is used to find the external excitation which will produce identifiability (Ebadat, Valenzuela, Rojas, & Wahlberg, 2017). In another approach, the MPC is designed specifically to ensure that an excitation signal will produce identifiability (González et al., 2014). Though these technologies are promising, they are likely years away from wide-spread adoption in industry. In the meantime, it is appropriate to assess the performance and potential applications of pure-feedback closed-loop system identification for systems under MPC.

An important motivation for performing pure-feedback closed-loop system identification is as a means for monitoring and maintaining the MPC implementation. As noted in a recent book, many MPC implementations fail due to gradual deterioration of MPC performance post-implementation (Lahiri, 2017). One major reason for the performance deterioration is degraded model quality (Lahiri, 2017; Yan, Harinath, & Dumont, 2009). In this paper, it is shown that closed-loop system identification may be used to monitor the quality of the MPC step-response models and triggering model updates when appropriate. Thus pure-feedback closed-loop system identification can be used, potentially in conjunction with other approaches for control performance monitoring (Mesbah, Bombois, Forgione, Hjalmarsson, & Hof, 2015), to enhance the sustainability of an MPC implementation.

Section 2 of this paper is a review of various closed-loop system identification approaches, which have been very well studied over the years by the academics and even applied in practice. Section 3 provides the results of simulation studies which were used to benchmark closed-loop system identification methods, as well as the results of pure-feedback closed-loop system identification when applied to data from a large-scale hydrogen production plant. Section 3.3 looks at the application of this system in a real-time practical setting to illustrate the value that could be gained from effective implementation of these approaches. Section 4 is a conclusion, with emphasis on recommendations and guidelines for future practitioners in this area.

2. Theory

Section 2.1 summarizes methods for identifying models using data from closed-loop experiments. Section 2.2 summarizes key results on the identifiability of closed-loop systems.

2.1. Closed-loop system identification approaches

As summarized in Esmaili, MacGregor, and Taylor (2000) and Huang and Shah (1997) most methods for identifying models using data from closed-loop experiments are variants of the following three approaches:

- (i) direct identification using prediction error methods to directly fit input/output models to the closed-loop data,
- (ii) indirect identification where a model is built between the output and the external variable exciting the process, and then the process model is calculated using prior knowledge of the controller equation,
- (iii) joint input/output identification where both the input and output variables are modeled as a function of the external exciting variable and the disturbance innovations, and then the process and disturbance models are extracted.

Details on all these approaches are given in Forssell and Ljung (1999), Lakshminarayanan et al. (2001) and Söderström and Stoica (1988). A series of two-step identification procedures was proposed as a variant of the joint identification approach (Huang & Shah, 1997; Van Den Hof & Schrama, 1993). In these approaches, the joint input/output identification problem is broken into two open-loop identification problems, the first problem is to fit a model to the input to yield an estimate of the closed-loop sensitivity function, and then, using this estimate to filter the input or output, the second problem is to identify the process model from the filtered data. By breaking up the identification problem into two open-loop problems, the two-step methods have suggested to be asymptotically unbiased. Direct identification, which is the more classical approach, gives asymptotically unbiased results, if adequate disturbance and transfer function model structures are used, and identified simultaneously (Gustavsson, Ljung, & Söderström, 1977; MacGregor & Fogal, 1995). Another motivation that is claimed for the two-step approach is that a disturbance model is not needed. This follows from Ljung (1999) which proved that open-loop identification will give an asymptotically unbiased estimate of the process model even if the disturbance model is inadequate, if the disturbance is stationary. However, with finite data sets and for disturbances that approach non-stationarity, the two-step approach can produce biased results, and provide estimates with larger variance.

The main distinction between the direct and two-step methods is how they diminish the effect of the feedback correlation in the closed-loop data. Both methods achieve this by filtering the data. In the direct method, both the input and output data are filtered with the inverse of the estimated disturbance model. In the two-step method, either the input data or the output data is filtered with the estimated closed-loop sensitivity function. Both the direct and two-step methods can be used to provide asymptotically unbiased results with parsimonious or non-parsimonious model structures, if the model structures contain the true process model and either the true disturbance model (direct method) or the true sensitivity function model (two-step method). Using the non-parsimonious model structure makes both methods easier to use in practice, at the expense of increasing the variance of the parameter estimates.

2.2. Identifiability

In the literature on system identification, a feedback system (as illustrated in Fig. 1) is deemed to be Closed-Loop Identifiable if the estimated parameters converge to their "true" values "in some stochastic sense" as the number of observation approaches infinity (Gustavsson et al. 1977). Typically, closed loop identification problems are significantly more complex than the open loop ones, since the system becomes less sensitive and requires more significant perturbations. There are several aspects that may affect the identifiability of a closed-loop system, such as the true model structure and model parameterization, and design of experiments. A practical manner to guarantee identifiability is to increase the number of controllers r (Gustavsson et al. 1977). To guarantee Strong System Identifiability (SSI) for a linear system with one or more linear controllers, the condition

$$r \geq \frac{n_y + n_u}{n_y + n_v} \tag{1}$$

should be satisfied, where r is the number of linear controllers, and n_y, n_u and n_v denotes the number of output, input and extra external