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Model predictive control with closed-loop re-identification

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ABSTRACT

In this work, we address the problem of handling plant-model mismatch by designing a subspace identification based MPC framework that includes model monitoring and closed-loop identification components. In contrast to performance monitoring based approaches, the validity of the underlying model is monitored by proposing two indexes that compare model predictions with measured past output. In the event that the model monitoring threshold is breached, a new model is identified using an adapted closed-loop subspace identification method. To retain the knowledge of the nominal system dynamics, the proposed approach uses the past training data and current input, output and set-point as the training data for re-identification. A model validity mechanism then checks if the new model predictions are better than the existing model, and if they are then the new model is utilized within the MPC. The effectiveness of the proposed method is illustrated through simulations on a nonlinear polymerization reactor.

1. Introduction

The operation of chemical plants faces numerous challenges such as inherent nonlinearity, complex variable interactions and process constraints. The most common control method that can handle these challenges is model predictive control (MPC). In several industrial applications of MPC, a linear model is used, in part due to the simplicity of developing linear models and in part due to the computational ease with using linear models. In order to handle the resultant plant-model mismatch, robust MPCs and offset-free MPC approaches have been developed.

In robust MPC approaches, the control action is computed to handle the worst case effect of the uncertainty (Rawlings and Mayne, 2009; Mayne et al., 2006). These include Lyapunov-based MPC which enables explicit characterization of the region from where stability of the closed loop system under MPC controller is achievable in the presence of constraints and uncertainty (Mahmood and Mhaskar, 2014). In another approach, the so-called offset-free MPC, the nominal model is integrated with augmented disturbance states to eliminate offset in set-point tracking (Pannocchia and Rawlings, 2003; Wallace et al., 2016).

While these approaches are often able to eliminate uncertainty at steady state operation, the closed-loop performance certainly stands to improve if a better model is utilized in the control design. To determine if the closed-loop system is behaving as expected, existing approaches have focused on the area of control performance monitoring. In this direction, numerous MPC performance assessment methods are proposed to monitor the closed-loop performance by comparing the controller with a benchmark (Huang and Shah, 2012; Shah et al., 2002; Chilin et al., 2012). Most of these methods focus on tuning of the controller parameters to remedy the performance degradation. In model predictive approaches, where the control action is more directly dependent on the underlying model, there exists the necessity of explicitly monitoring model validity.

There exist some results on MPC with re-identification (IMPC) where model validity is accounted for by requiring excitation constraints to ensure that the model parameters remain identifiable (Genceli and Nikolaou, 1996). In this approach, identification is performed at every time step. Furthermore, the approach requires finding the right trade-off between the inevitable performance deterioration (due to excitation conditions) and the possibility of loss of model validity. In Potts et al. (2014) MPC Relevant Identification (MRI) was extended to Enhanced Multi-step Prediction Error Method (EMPEM). In Heirung et al. (2012) single input single output IMPC was extended to improve performance of the output regulation by not disturbing the plant when the model is deemed to have an acceptable precision. Acceptable precision is quantified through bounds on the variance of parameter estimates and parameter convergence rate in the MPC cost function.

In particular, in this method, autoregressive models with exogenous inputs are used and recursive weighted least-squares algorithm is utilized to estimate model parameters. In order to solve the trade-off between control performance and persistence

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of excitation, in a recent contribution (Patwardhan and Goapluni, 2014; Bustos et al., 2016) maximizing the MPC objective function is used instead of minimization to maximize signal variance and address the feasibility and stability of MPC with re-identification. In another direction, in Badwe et al. (2009), plant-model mismatch is detected by partial correlation analysis in order to determine the correlation between model residual of each output and each manipulated variable with effect of disturbance and other manipulated variables removed. This correlation may be significant in the presence of plant-model mismatch. In Badwe et al. (2010) model-plant mismatch is quantified by comparison of actual and achieved control quality. Note that in theses studies it is assumed that sufficient set-point excitation is available in order to calculate the plant-model mismatch. In the proposed approach, the set point excitation is not necessary for the monitoring aspect. Furthermore, in these approaches, the original training data is not retained in the new model identification, and these methods are designed to address situations where the system is changed significantly and previous data are not at all representative of the plant in question. In situations where plant model mismatch arises due to change in operating condition (with the possibility of reverting back to the nominal plant operation), it becomes useful to merge old and new plant data in the re-identification step.

Motivated by the above considerations, in this work we address the problem of plant model mismatch by developing a model monitoring and closed-loop re-identification based MPC design. The rest of the manuscript is organized as follows: First, the general mathematical description for the systems considered in this work, and a representative formulation for linear model predictive control are presented. Then the proposed approach for closed-loop re-identification of plant is explained. The efficacy of the proposed method is illustrated through formulations and implementations for a nonlinear polymerization continuous stirred-tank reactor (CSTR) with input rate of change constraints and measurement noise. Finally, concluding remarks are presented.

2. Preliminaries

In this section, a brief description of the general class of processes that are considered in this study is provided. Then, the orthogonal projection based subspace identification and a representative MPC formulation is presented.

2.1. Problem statement

Consider a general multi-input multi-output (MIMO) controllable system, with $y \in \mathbb{R}^{n_y}$ denoting the measured outputs, and $u \in \mathbb{R}^{n_u}$ denoting the vector of constrained control (manipulated) input variables, taking values in a nonempty convex subset $\mathcal{U} \subset \mathbb{R}^{n_u}$, where $\mathcal{U} = \{u \in \mathbb{R}^{n_u} \mid u_{\min} \leq u \leq u_{\max}\}$, $u_{\min} \in \mathbb{R}^{n_u}$ and $u_{\max} \in \mathbb{R}^{n_u}$ denote the lower and upper bounds of the input variables. In keeping with the discrete implementation of MPC, u is piecewise constant and defined over an arbitrary sampling instance k as:

$$u(t) = u(k), \quad k\Delta t \leq t < (k+1)\Delta t$$

where Δt is the sampling time and x_k and y_k denote state and output at the kth sample time. We consider the case where the MPC is implemented based on a linear (identified) model, identified using subspace identification techniques, and address the problem of monitoring model quality online, and triggering re-identification as appropriate, to maintain model validity and closed-loop performance.

2.1.1. Subspace identification

In this section the conventional state space subspace identification method is reviewed (Van Overschee and De Moor, 1994; Huang and Kadali, 2008; Zhao and Qin, 2014). In the subspace identification approach, the goal is to determine the system matrices for a discrete linear time invariant model of the following form:

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{1}$$

$$y_k = Cx_k + Du_k + v_k \tag{2}$$

where $x \in \mathbb{R}^{n_x}$ denotes the vector of state variables, $y \in \mathbb{R}^{n_y}$ denotes the vector of measured outputs, $w \in \mathbb{R}^{n_x}$ and $v \in \mathbb{R}^{n_y}$ are zero mean, white vectors of process noise and measurement noise with the following covariance matrices:

$$E\left[\begin{pmatrix} w_i \\ v_j \end{pmatrix}\begin{pmatrix} w_i^T & v_j^T \end{pmatrix}\right] = \begin{pmatrix} Q & S \\ S^T & R \end{pmatrix}\delta_{ij} \tag{3}$$

where $Q \in \mathbb{R}^{n_x \times n_x}$, $S \in \mathbb{R}^{n_x \times n_y}$ and $R \in \mathbb{R}^{n_y \times n_y}$ are covariance matrices, and, δ_{ij} is the Kronecker delta function. To identify the system matrices, Hankel matrices are first constructed by stacking the process variables as follows:

$$U_p = U_{1|i} = \begin{bmatrix} u_1 & u_2 & \dots & u_j \\ u_2 & u_3 & \dots & u_{j+1} \\ \dots & \dots & \dots & \dots \\ u_i & u_{i+1} & \dots & u_{i+j-1} \end{bmatrix} \tag{4}$$

$$U_f = U_{i+1|2i} = \begin{bmatrix} u_{i+1} & u_{i+2} & \dots & u_{i+j} \\ u_{i+2} & u_{i+3} & \dots & u_{i+j+1} \\ \dots & \dots & \dots & \dots \\ u_{2i} & u_{2i+1} & \dots & u_{2i+j-1} \end{bmatrix} \tag{5}$$

where U_p and U_f denote the past and future input Hankel matrices. i is a user-specified parameter that limits the order of the system (n) (which in itself is a user-specified parameter). Similar block-Hankel matrices are made for output, process and measurement noises $Y_p, Y_f, V_p, V_f \in \mathbb{R}^{in_y \times j}$ and $W_p, W_f \in \mathbb{R}^{in_x \times j}$ are defined in the similar way. The state sequences are defined as follows:

$$X_p = \begin{bmatrix} x_1 & x_2 & \dots & x_j \end{bmatrix} \tag{6}$$

$$X_f = \begin{bmatrix} x_{i+1} & x_{i+2} & \dots & x_{i+j} \end{bmatrix} \tag{7}$$

furthermore with:

$$\Psi_p = \begin{bmatrix} Y_p \\ U_p \end{bmatrix} \tag{8}$$

$$\Psi_f = \begin{bmatrix} Y_f \\ U_f \end{bmatrix} \tag{9}$$

The orthogonal projection of row space of matrix A onto row space of matrix B, (A/B) is defined as:

$$\frac{A}{B} = AB^{\dagger}B \tag{10}$$

where the superscript $\dagger$ stands for pseudo-inverse. By recursive substitution into the state space model Eqs. (1) and (2), it is straightforward to show:

$$Y_f = \Gamma_i X_f + \Phi_i^d U_f + \Phi_i^s W_f + V_f \tag{11}$$

$$Y_p = \Gamma_i X_p + \Phi_i^d U_p + \Phi_i^s W_p + V_p \tag{12}$$

$$X_f = A^i X_p + \Delta_i^d U_p + \Delta_i^s W_p \tag{13}$$