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Fault-Tolerant Economic Model Predictive Control Using Empirical Models ⋆

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Abstract: In this work, we present a data-driven methodology to overcome actuator faults using a model-based feedback controller that optimizes process economics termed economic model predictive control (EMPC). Specifically, we utilize a moving horizon error detector that quantifies prediction errors and triggers updating the empirical model used for state predictions in the EMPC on-line using the most recent input/output data collected after the fault when significant prediction errors occur due to the loss of an actuator. The proposed approach is applied to a catalytic chemical reactor example where an actuator fault occurs, affecting the coolant temperature. The proposed scheme was able to reduce prediction errors caused by the actuator loss by replacing the model within the EMPC with a more accurate model, resulting in improved economic performance compared to not updating the model.

Keywords: nonlinear systems, on-line model identification, economic model predictive control, process control, optimization, fault-tolerance

1. INTRODUCTION

Recent technological developments in the chemical and petrochemical industry have led to the creation of complex process networks to increase operational efficiency and meet the increasing energy demand. One approach for maximizing the efficiency of process operation is by integrating process control and process economic optimization. Economic model predictive control (EMPC) is a recent model-based feedback control strategy that integrates process control with dynamic economic optimization of the plant. EMPC promotes optimal time-varying operation of the plant and can incorporate constraints that ensure closed-loop stability (e.g., Ellis et al. [2014], Amrit et al. [2011]). The first step in developing an EMPC is to establish a dynamic model representing the process dynamics, which can be accomplished either from first principles or, when modeling the underlying physico-chemical phenomena is difficult, through system identification. Various model identification methods have been developed to identify linear and nonlinear models from process data alone (e.g., Van Overschee and De Moor [1996]).

Subspace model identification (SMI) methods are non-iterative system identification methods that are capable of identifying multiple-input multiple-output (MIMO) models based on input/output data (Verhaegen and Dewilde [1992], Huang and Kadali [2008]). Well-recognized SMI methods include numerical algorithms for subspace state-space system identification (N4SID) (Van Overschee and De Moor [1996]), the Canonical Variate Algorithm (CVA) (Larimore [1990]), and the multi-variable output error state-space (MOESP) algorithm (Verhaegen and Dewilde [1992], Viberg [1995]). SMI methods have been widely used for industrial applications due to their reliability and numerical stability (Verhaegen and Dewilde [1992]). They have also been used to design model-based controllers such as model predictive control (MPC) and EMPC (Huang and Kadali [2008], Alanqar et al. [2015]).

A major problem that arises frequently in the chemical industry is actuator faults, in which authority over one or more actuators is lost. Detecting actuator faults and developing advanced fault-tolerant controllers for chemical process systems have been considered (Lao et al. [2013]). However, such work assumed the availability of a first-principles model to develop fault-tolerant control methodologies. To date, the development of fault-tolerant control strategies using empirical process models which are updated on-line has not been considered. In this work, we introduce a data-driven approach to overcome actuator faults in Lyapunov-based EMPC (LEMPC) based on linear empirical models. When actuator faults cause the prediction errors between the predicted states from the linear empirical model and the measured states to increase, model re-identification is triggered on-line by a moving horizon error detector if an error metric exceeds a pre-specified threshold. The proposed methodology is applied to a chemical process example to demonstrate the ability of the detector to indicate significant prediction errors when actuator faults occur and update the model on-line in order to obtain more accurate predictions.

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2. PRELIMINARIES

2.1 Notation

The operator $|\cdot|$ denotes the 2-norm of a vector. The symbol Ω_ρ represents a level set of a positive definite continuously differentiable scalar-valued function $V(x)$ ($\Omega_\rho := \{x \in R^n : V(x) \leq \rho\}$). A continuous function $\alpha : [0, a) \to [0, \infty)$ is a class $\mathcal{K}$ function if it is strictly increasing and is zero only when evaluated at zero. The symbol diag(a) designates a square diagonal matrix where the diagonal elements are the components of the vector a. $S(\Delta)$ signifies the class of piecewise-constant functions with sampling period $\Delta > 0$.

2.2 Class of Systems

We consider the following class of nonlinear systems:

$$\dot{x}(t) = f(x(t), u(t), w(t)) \tag{1}$$

where $x \in R^n$, $u \in R^m$, and $w \in R^l$ are the state vector of the system, manipulated input vector, and the disturbance vector, respectively. The disturbance vector is assumed to be bounded (i.e., $|w(t)| \leq \theta$ for all t). Physical limitations on actuation energy restrict the manipulated input to belong to $U := \{u \in R^m : u_i^{\min} \leq u_i \leq u_i^{\max},\ i = 1, \ldots, m\}$, where $u_i^{\min}$ and $u_i^{\max}$ denote lower and upper bounds on the components u_i, $i = 1, \ldots, m$, of u. The function f is assumed to be locally Lipschitz and the origin is taken to be an equilibrium of the nominal unforced system of Eq. 1 (i.e., $f(0, 0, 0) = 0$). We assume that measurements of the full state vector $x(t_k)$ are available at each sampling time $t_k = k\Delta$, $k = 0, 1, \ldots$.

We assume the existence of a locally Lipschitz feedback control law $h(x) \in U$ that can render the origin of the nominal ($w(t) \equiv 0$) closed-loop system of Eq. 1 locally asymptotically stable in the sense that there exists a continuously differentiable Lyapunov function $V : R^n \to R_+$ where the following inequalities hold (Khalil [2002]):

$$\alpha_1(|x|) \leq V(x) \leq \alpha_2(|x|), \tag{2a}$$

$$\frac{\partial V(x)}{\partial x} f(x, h(x), 0) \leq -\alpha_3(|x|), \tag{2b}$$

$$\left|\frac{\partial V(x)}{\partial x}\right| \leq \alpha_4(|x|) \tag{2c}$$

for all x in an open neighborhood D that includes the origin and $\alpha_j(\cdot)$, $j = 1, 2, 3, 4$, are class $\mathcal{K}$ functions. For various classes of nonlinear systems, stabilizing control laws have been developed that account for input constraints (Lin and Sontag [1991], Christofides and El-Farra [2005]). The stability region of the closed-loop system is defined to be a level set $\Omega_\rho \subset D$ where $\dot{V} < 0$.

In this work, we present an on-line model identification scheme to obtain empirical models that capture the evolution of the system of Eq. 1. The models obtained are linear time-invariant (LTI) state-space models of the form:

$$\dot{x}(t) = A_i x(t) + B_i u(t) \tag{3}$$

where the constant matrices $A_i \in R^{n \times n}$ and $B_i \in R^{n \times m}$ correspond to the $i - th$ model identification performed ($i = 1, \ldots, \tilde{M}$). We assume the existence of a set of stabilizing control laws $h_{L1}(x)$,$h_{L2}(x)$,…,$h_{L\tilde{M}}(x)$ designed based on the empirical models that can make the origin of the closed-loop system of Eq. 1 asymptotically stable and generate a continuously differentiable Lyapunov function $\hat{V} : R^n \to R_+$ where (Khalil [2002]):

$$\hat{\alpha}_1(|x|) \leq \hat{V}(x) \leq \hat{\alpha}_2(|x|), \tag{4a}$$

$$\frac{\partial \hat{V}(x)}{\partial x} f(x, h_{Li}(x), 0) \leq -\hat{\alpha}_{3_i}(|x|),\ i = 1, \ldots, \tilde{M} \tag{4b}$$

$$\left|\frac{\partial \hat{V}(x)}{\partial x}\right| \leq \hat{\alpha}_4(|x|) \tag{4c}$$

for all x in an open neighborhood D_{Li} that includes the origin in its interior. The functions $\hat{\alpha}_j(\cdot)$, $j = 1, 2, 4$ and $\hat{\alpha}_{3_i}$, $i = 1, \ldots, \tilde{M}$ are class $\mathcal{K}$ functions and the stability region of the system of Eq. 1 under the controller $h_{Li}(x)$ is defined as the level set $\Omega_{\hat{\rho}_i} \subset D_{Li}$, $i = 1, \ldots, \tilde{M}$.

2.3 Lyapunov-Based EMPC

The formulation of EMPC to be used in this work incorporates Lyapunov-based stability constraints based on the explicit stabilizing controller $h(x)$ (and thus is referred to as LEMPC (Ellis et al. [2014])) as follows:

$$\min_{u \in S(\Delta)} \int_{t_k}^{t_{k+N}} L_e(\tilde{x}(\tau), u(\tau))\, d\tau \tag{5a}$$

$$\text{s.t.} \quad \dot{\tilde{x}}(t) = f(\tilde{x}(t), u(t), 0) \tag{5b}$$

$$\tilde{x}(t_k) = x(t_k) \tag{5c}$$

$$u(t) \in U,\ \forall\, t \in [t_k, t_{k+N}) \tag{5d}$$

$$V(\tilde{x}(t)) \leq \rho_e,\ \forall\, t \in [t_k, t_{k+N}) \quad \text{if } x(t_k) \in \Omega_{\rho_e} \tag{5e}$$

$$\frac{\partial V(x(t_k))}{\partial x} f(x(t_k), u(t_k), 0) \leq \frac{\partial V(x(t_k))}{\partial x} f(x(t_k), h(x(t_k)), 0) \quad \text{if } x(t_k) \notin \Omega_{\rho_e} \tag{5f}$$

where the decision variables are the input trajectories over the prediction horizon $N\Delta$, which are implemented in a receding horizon fashion. Control actions are computed using process state predictions $\tilde{x}(t)$ from the dynamic model of the process (Eq. 5b) initiated from the state feedback measurement $x(t_k)$ at each sampling time (Eq. 5c). Input constraints are taken into consideration in the LEMPC design in Eq. 5d. The Mode 1 constraint (Eq. 5e) is activated when the state measurement is maintained within a subset of the stability region Ω_ρ that is referred to as Ω_{ρ_e}, and promotes time-varying process operation to maximize economics. When the closed-loop state exits Ω_{ρ_e}, the Mode 2 constraint (Eq. 5f) is activated to force the state back into Ω_{ρ_e} by computing control actions that decrease the Lyapunov function value. Ω_{ρ_e} is chosen to make Ω_ρ forward invariant in the presence of process disturbances.

3. EMPC USING ERROR-TRIGGERED ON-LINE MODEL IDENTIFICATION

The potential of EMPC for improving profits in the chemical process industries has motivated research in practical aspects of EMPC implementation, including the use of linear empirical models in EMPC (Alanqar et al. [2017]). However, all work on improving the practicality of EMPC