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Just-in-Time-Learning based Extended Prediction Self-Adaptive Control for batch processes☆

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ABSTRACT

This article presents a new Extended Prediction Self-Adaptive Control (EPSAC) algorithm based on the Just-in-Time Learning (JITL) method. In the proposed JITL-based EPSAC design, linearization of the process model is achieved by a set of local state-space models, each of which can be independently and simultaneously identified by the JITL method along the base trajectory. For the end-product quality control for a simulated semi-batch pH-shift reactive crystallization process where shrinking prediction and control horizons are essential, the proposed EPSAC algorithm not only simplifies the control weight tuning but also provides better and more robust closed-loop control performance than its previous counterpart.

1. Introduction

With the stringent specifications on product quality and higher competition in the process industry, the development of nonlinear model predictive control (NMPC) is of interest to both academic and industrial sectors. The major advantage of NMPC lies in its capability of handling nonlinearities and time-varying characteristics inherent in the process dynamics in addition to addressing constraints and bounds imposed on both state and manipulated variables by performing the real-time dynamic optimization [1,2]. Various NMPC design methods have been developed using different techniques to deal with process nonlinearity, including successive linearization [3], neural networks [4], robust control [5,6], multiple models [7–10] and hybrid models [11].

Among various NMPC design methods reported in the literature, Extended Prediction Self-Adaptive Control (EPSAC) and its variants adopt the approach of iterative optimization based on a predefined input trajectory. [12–15]. In the EPSAC design framework, the model prediction consists of a base and an optimized term. The base term is computed from a nominal process model using the current values of input variables obtained from the predefined base input trajectory and the corresponding output variables, while the optimized term is computed from a finite step or impulse response model obtained along this trajectory. In this manner, the nonlinear process model can be directly used in the form of an input–output algorithm without any linearization [13,16,17].

A potential drawback of previous EPSAC methods is the incorporation of a convolution model in the formulation of the control algorithms. Since model parameters are obtained by introducing a step change to the current input value specified by the base input trajectory, the predicted outputs at sampling instants further away from the current sampling instant become less accurate due to process nonlinearity, leading to inevitable modeling error that degrades the achievable closed-loop performance. To alleviate the abovementioned limitation, the aim of this paper is to develop a new EPSAC algorithm using a set of local state-space models identified by the Just-in-Time Learning (JITL) method [18,19] along the base trajectory. To evaluate the performance of proposed design for batch process control, simulation results of implementing the JITL-based EPSAC to a semi-batch pH-shift reactive crystallization process are presented and discussed in detail.

2. Conventional EPSAC algorithm

NMPC refers to predictive control schemes based on nonlinear models and/or a nonlinear cost function and nonlinear constraints,

☆ The proposed EPSAC algorithm was partially demonstrated at the 2012 AIChE Annual Meeting in Pittsburgh, U.S.

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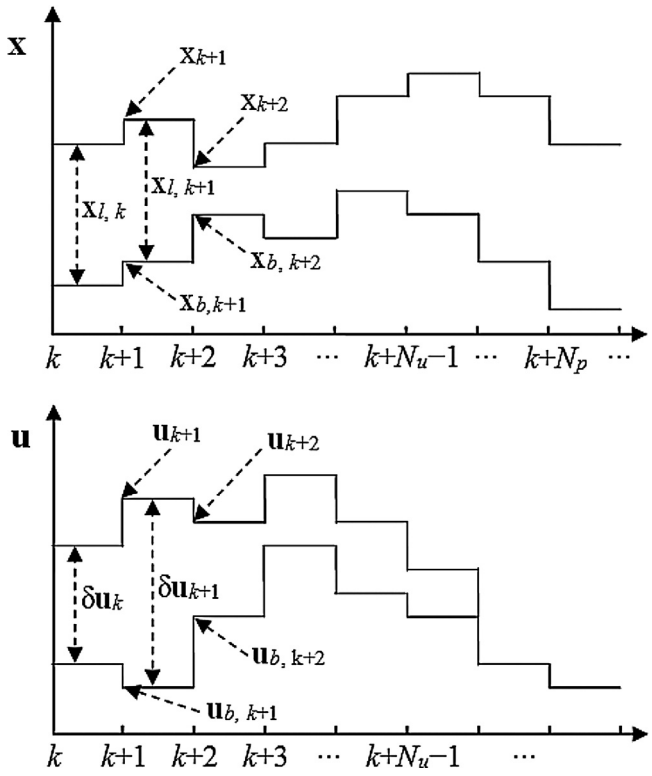

Fig. 1. The variables decomposition in the EPSAC method.

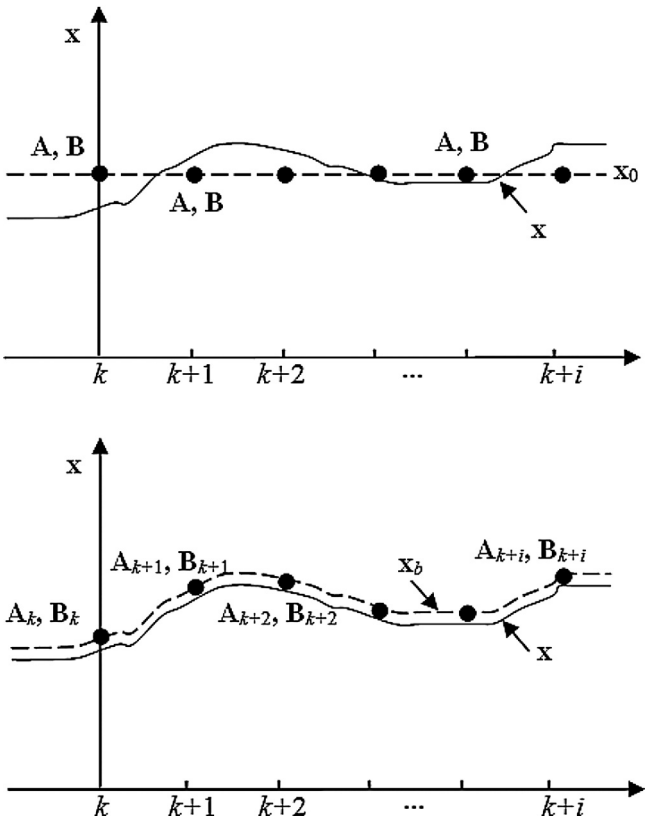

Fig. 2. Modeling of nonlinear processes using one local state-space model (top) and multiple state-space models (bottom).

whose optimal problem to be solved online at every sampling instant is [15]

$$\min_{\boldsymbol{u}_k,\ldots,\boldsymbol{u}_{k+Nu-1}} \quad J(\boldsymbol{x},\boldsymbol{u}) \tag{1}$$

subject to

$$x_{k+i} = f(\boldsymbol{x}_{k+i-1}, u_{k+i-1}) + \boldsymbol{w}_{k+i}, \quad i = 1,\ldots,N_u,\ldots,N_p \tag{2}$$

$$\boldsymbol{d}_{k+i} = \boldsymbol{d}_{k+i-1} + \boldsymbol{\xi}_{k+i} \tag{3}$$

$$\boldsymbol{y}_{k+i} = g(\boldsymbol{x}_{k+i}, \boldsymbol{u}_{k+i}) + \boldsymbol{d}_{k+i} + \boldsymbol{v}_{k+i} \tag{4}$$

$$h(\boldsymbol{x}_{k+i}, \boldsymbol{u}_{k+i}) \le \boldsymbol{0} \tag{5}$$

where J is the objective function, N_u is the control horizon, N_p is the prediction horizon, $\mathbf{x}_k$, $\mathbf{u}_k$, $\mathbf{y}_k$, and $\mathbf{d}_k$ are the vectors of n_x system state variables, n_u inputs, n_y measured variables, and n_y unmeasured disturbances at the kth sampling instant, respectively, and $\mathbf{w}_k$, $\boldsymbol{\xi}_k$, and $\mathbf{v}_k$ are the vectors of noise on the state variables, unmeasured disturbances, and the measured variables, respectively. The system dynamics are described by the vector function f, the measurement equations by the vector function g, and the linear and nonlinear constraints for the system are described by the vector function h.

In the EPSAC strategy, future response can be expressed as the cumulative result of two effects: (1) a base response that accounts for the effect of past control, a base future control scenario, and the effect of future disturbances; and (2) an optimizing response that accounts for the effect of the optimizing future control actions [14], as schematically illustrated in Fig. 1. The future sequences of the input variables $\mathbf{u}_{k+i}$ are considered as the sum of the base input $\mathbf{u}_{b,\,k+i}$ and future incremental control actions $\delta\mathbf{u}_{k+i}$:

$$u_{k+i} = \boldsymbol{u}_{b,\,k+i} + \delta\boldsymbol{u}_{k+i}, \quad i = 0, 1,\ldots, N_u - 1 \tag{6}$$

where $\delta\mathbf{u}_{k+i} = \mathbf{0}$ for $i \ge N_u$. Then the future trajectories of process variables can also be considered as the cumulative result of these two effects:

$$\mathbf{x}_{k+i} = \boldsymbol{x}_{b,\,k+i} + \boldsymbol{x}_{l,\,k+i}, \quad i = 1, 2,\ldots, N_p \tag{7}$$

where $\mathbf{x}_{b,\,k+i}$ is calculated using the nominal model of Eq. (2) and the predetermined sequence of $\mathbf{u}_{b,k+i}$. On the other hand, $\mathbf{x}_{l,\,k+i}$ is obtained by implementing impulse inputs $\{\delta\mathbf{u}_k,\ \delta\mathbf{u}_{k+1},\ldots,\ \delta\mathbf{u}_{k+i-1}\}$. A similar decomposition into the sum of two parts is also applied to the nonlinear constraints of Eq. (5) to arrive at a quadratic program (QP) problem, where the soft constraint approach is used to provide a numerical convergence of QP optimizer [15,20].

The key idea of EPSAC is to predict nonlinear process variables by iterative optimization with respect to future trajectories so that they converge to the same nonlinear optimal solution [14,15,21]. The conventional EPSAC algorithms use convolution models, such as finite step or impulse models, to predict process outputs around the future trajectories ($\mathbf{x}_b$ and $\mathbf{u}_b$, see Fig. 1) in order to calculate the optimized term $\mathbf{x}_{l,\,k+i}$ in Eq. (7) from $\delta\mathbf{u}_{k+i}$ in Eq. (6).

The superposition principle underlying the predictive schemes given in Eqs. (6) and (7), which is employed by previous EPSAC designs, becomes unreliable and hence inaccurate for long prediction horizons in the presence of nonlinear process dynamics and time-varying process characteristics. To partially address this shortcoming brought about by using the convolution models in the EPSAC design, complicated weights in the objective function have been designed and fine-tuned to improve the end product quality control of a batch crystallization process [15].