Nonlinear Analysis: Hybrid Systems 28 (2018) 75–86

Contents lists available at ScienceDirect

Nonlinear Analysis: Hybrid Systems

journal homepage: www.elsevier.com/locate/nahs

Model predictive control of batch processes based on two-dimensional integration frame

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ARTICLE INFO

Article history:
Received 2 February 2017
Accepted 6 November 2017

Keywords:
Batch process
Integrated model predictive control
Model identification
Dynamic R-parameter
Iterative learning control

ABSTRACT

A novel integrated model predictive control (MPC) strategy for batch processes is proposed in this paper. Both batch-axis and time-axis information are integrated into a two-dimensional control frame. The control law is obtained through the solution of a MPC optimization with time-varying prediction horizon, which leads to superior tracking performance and robustness against disturbance and uncertainty. Moreover, both model identification and dynamic R-parameter are employed to compensate the model-plant mismatch and make zero-error tracking possible. Next, the convergence analysis and tracking performance of the proposed integrated model predictive learning control system are described and proved strictly. Lastly, the effectiveness of the proposed method is verified by an example.

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1. Introduction

Batch processes provide the flexibility required for multipurpose facilities and have been widely applied to the manufacture of low-volume, high-value and products, such as specialty chemicals, pharmaceuticals, food and consumer products [1]. However, most traditional control techniques are not suitable for batch processes for its strong nonlinearity, inherent dynamic nature and discontinuous operations. Therefore, the optimization and control of batch processes remains to be challenging in modern industrial control.

Batch processes have the characteristic of repetition, and thus iterative learning control (ILC) can be used in the optimization control of batch processes [2–4]. After its initial development for industrial robot [5], ILC has been increasingly practiced for batch processes with repetitive natures to realize perfect tracking and control optimization [6,7]. Xiong and Zhang presented a batch-to-batch iterative optimal control method based on recurrent neural network models to solve the model prediction errors problem [8]. Lee et al. proposed the optimal iterative learning algorithm based on linear time-varying models for the temperature control of batch processes [9,10]. In above mentioned results, only the batch-to-batch control is taken into account and it is difficult to guarantee the performance of the batch process when the real-time uncertainties and disturbances exist. Therefore, an integrated control system is required for the maximization benefit of batch processes, in which the information of time-axis and batch-axis are processed synchronously. Rogers first employed two-dimensional (2D) theory to solve the above-mentioned problem [11]. Li et al. presented an ILC strategy for 2D time-invariant linear repetitive systems with fixed time delays [12]. Chin et al. proposed a two-stage iterative learning control technique by using the real-time feedback information to modify the ILC parameters for independent disturbance rejection [13]. For piecewise affine batch processes, Liu et al. proposed a 2D closed-loop ILC method for robust tracking of the set-point profile against

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https://doi.org/10.1016/j.nahs.2017.11.002
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uncertainties and disturbances [14]. Liu et al. also proposed robust PI based set-point learning control for batch process with time-varying uncertainties and load disturbances [15]. Chen et al. combined the model predictive control (MPC) with the ILC based on 2-D theory for linear batch processes [16]. To guarantee robust convergence along both time and batch directions, a 2D ILC scheme which integrates feedback control with feedforward control was developed by Gao et al. for robust tracking of desired trajectory [17]. For multi-phase batch processes, Wang et al. proposed a iterative learning model predictive control scheme to reject the uncertain disturbances in time-axis [18]. Duran et al. presented a iterative learning modeling method and used it to control batch fermentation process [19]. Based on data-driven model, predictive quality control strategy for batch process was proposed by Aumi [20]. Lu et al. proposed natural gradient method based model-free optimization to control the quality of batch process [21]. Recently, Wang et al. presented an average dwell time based optimal ILC for multi-phase batch processes [22]. Su et al. adopted Just-In-Time-Learning modeling and based on that, an extended prediction self-adaptive control was proposed [23]. B. Corbett proposed a subspace identification methods for data-driven modeling and quality control of batch processes [24].

However, most 2D controllers proposed in the references assume that the batch processes are described by linear differential equations or can be locally linearized for the feasibility of proof and analysis. How to extend the traditional 2D controllers to a more general 2D control frame for batch process with strong nonlinearity remains to be a problem.

Inspired by MPC with time-varying prediction horizon and iterative learning control (ILC), a novel 2D control frame for batch process with strong nonlinearity is proposed in this paper, combining batch-axis discrete information and time-axis continuous information through the cost function of time-varying MPC strategy. The new integrated control system not only created a feedback controller in time-axis with iterative learning convergence in batch-axis, but also improved the accuracy of the model through online parameter modification. Furthermore, the convergence and tracking performance of such nonlinear 2D control system are given rigorous description and proof for the first time. Lastly, simulation examples illustrated the effectiveness of the strategy.

The paper is structured as follows. Section 2 gives the description of batch processes discussed in this paper. Section 3 proposes the integrated MPC system with model identification and convergence and tracking performance analysis is presented in Section 4, followed by the simulation example given in Section 5. In the end, the conclusion is given in Section 6.

2. System description

A batch process is a reaction process repeatedly conducting a given task over a limited duration of time. The discussed nonlinear batch process in this paper can be described by the following discrete-time state-space representation.

$$\begin{cases} x_k(t+1) = f(x_k(t), u_k(t), t) \\ y_k(t) = g(x_k(t), t) \\ x_k(0) = x_0, t = 1, 2, \ldots, T;\ k = 1, 2, \ldots \end{cases} \tag{1}$$

where t and k denote time step and cycle index, respectively. $x_k(t) \in R^n$, $u_k(t) \in R^m$ and $y_k(t) \in R^l$ are, respectively, the state, the control input and the batch process output at time t in kth cycle, and x_0 is the initial state of each cycle. $f(\cdot, \cdot, \cdot) : R^n \times R^m \times R^+ \to R^n$ and $g(\cdot, \cdot) : R^n \times R^+ \to R^l$ represent the dynamic characteristics of system, T is the duration of each batch.

3. Integrated MPC strategy with model identification

The formulation of the proposed integrated MPC strategy with model identification is depicted in Fig. 1, where $u_k(t|t)$ and $y_k(t+1)$ are the real time control signal and corresponding output within the kth batch. P_t is the time-varying prediction horizon of the integrated MPC controller. Based on the information of previous batch input and real-time feedback, the MPC optimizer can calculate an input sequence $\mathbf{U}_k(t|t)$ by solving an optimization problem online. The control signal $u_k(t|t)$, which is the first component of $\mathbf{U}_k(t|t)$, is sent to the process. Then the $\mathbf{U}_k(t+1|t+1)$ is recalculated as the previous instant with shrinking prediction horizon. The step is implemented repeatedly until the end of current batch. At next batch, this whole procedure is repeated to let the output trajectory asymptotically converge towards the reference trajectory while disturbances and uncertainties are compensated in real time.

3.1. Model identification with online updated parameter algorithm

Neuro-fuzzy model (NFM) [25] is employed to identify the proposed batch process in this paper. The NFM is described by the function $\hat{\mathbf{Y}}_k = \Phi(\mathbf{U}_k)\mathbf{W}_k$, where $\mathbf{W}_k = [w_1(k), w_2(k), \ldots, w_N(k)]^T$ are model adjustable parameters, and $\Phi(\mathbf{U}_k)$ is a matrix decided by $\mathbf{U}_k$. It is evident that $\mathbf{U}_k$ is the variable of function $\Phi(\cdot)$. More specificity, $\hat{\mathbf{Y}}_k = \Phi(\mathbf{U}_k)\mathbf{W}_k$ can be written as

$$\begin{aligned} \hat{\mathbf{Y}}_k &= \sum_{i=1}^{N} \hat{\alpha}_i \cdot f_i(\mathbf{U}_k) \\ &= (f_1(\mathbf{U}_k), f_2(\mathbf{U}_k), \ldots, f_N(\mathbf{U}_k)) \cdot \left(\hat{\alpha}_1, \hat{\alpha}_2, \ldots, \hat{\alpha}_N\right)^T \\ &= \Phi(\mathbf{U}_k) \cdot \mathbf{W}_k \end{aligned}$$

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