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Integrating Iterative Learning Estimation with Optimal Control for Batch Productivity Enhancement

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Abstract: Optimal control has wide applications for the control of batch and semi-batch processes to develop an optimum control input policy by extremizing a performance measure. The deployment of optimal control relies heavily on the accuracy of the process models being used for computation of the optimal profile. Often, the process models do not replicate the plants due to various shortcomings such as assumptions made during model formulations, poor first principles knowledge and limited range of experimental data due to short process development cycles. Moreover, scale-up of the processes from lab to manufacturing scale renders the developed models obsolete. The estimated model parameters can significantly differ from their nominal values which calls for the development of a strategy that updates process models so as to achieve an improved and tight control of batch processes. In this paper, we propose a novel methodology based on iterative learning to gradually update models using on-line measurement data at the end of each successive batch run by minimizing the error between plant and model data. In the proposed methodology, we further integrate Iterative Learning Estimation (ILE) with optimal control to update the optimal control input profile with the advent of measurement after each successive batch run. An important aspect of this integration is to ensure that model updates between batch runs generate feasible optimal control trajectories. Simulations are performed for the temperature control of a batch reactor system to validate the proposed methodology.

Keywords: Iterative Learning, Batch Control, Optimal Control, Model-based Control, Optimization, Parameter Estimation

1. INTRODUCTION

Batch processes play a key role in a large number of industries focusing on high value products ranging from traditional polymerization to emerging pharmaceuticals, fine and specialty chemicals, and semi-conductor manufacturing. In spite of such large applications of batch processes, the development of control theory has lagged continuous processes owing to the peculiar complexities of the batch processes. One of the important characteristics of the batch processes is their dynamic operation where the process variable relationships change over the complete batch run. The process dynamics can be highly non-linear with sharp discontinuities owing to the presence of multiple phases/stages during the operation of batch processes. Secondly, most batch processes correspond to a fixed duration of operation which implies that any control strategy needs to be implemented in a shrinking time horizon which is a daunting task due to reduced controllability (Soni and Parker, 2004). These characteristics make the performance control of the batch processes difficult and challenging. Grade transitions between continuous processes such as polymerization have similar characteristics of batch processes and pose a similar set of problems related to optimal control.

Given the deployment of batch processes for the production of high value products, there has been a growing concern in the industry regarding the final product quality which drives profit margins in the high end industries. Process optimization is deployed as a technique to reduce production costs, improve product quality, reduce product variability and for scale up from lab to industrial scale. Therefore, optimal control has been widely used to obtain an input policy which will maximize or minimize a performance measure. Optimal control algorithms rely heavily on the accuracy of the process models and the optimum input trajectories have been found to be highly sensitive to the model uncertainties and disturbances. While the objective function for a typical control problem has to be extremized which crucially depend on model fidelity, an often ignored aspect of the optimal control problem is the need to honor constraints on the optimal control trajectory. Since these trajectories are also inferred at optimum values based on the process models, the ability to honor these constraints in a batch run is critically dependent on the model fidelity.

Development of highly accurate models is a formidable task owing to the complexities of the batch processes and availability of frugal data. Precise estimation of model parameters is an arduous task, and parameters estimated

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at lab scale generally fail to replicate the output performance at the industrial scale. Computation of optimal input profiles is also affected by uncertainty in the initial conditions, variations across batch and inaccurate measurements. These result in the sub-optimal output profiles, thus making it difficult to achieve the performance objective or a track reference output trajectory. Therefore, it is important to modify the optimal control profile to account for uncertainty.

However, there are many processes where optimal control profiles are obtained offline based on the process models. But, as discussed above, it is imperative to perform an online computation and update of optimal control by taking advantage of the measurement data. In the past, many approaches have been suggested for the on-line update of optimal control profile so as to handle uncertainty. These have been mainly categorized into two approaches, viz. Robust and Measurement based optimization. Robust optimization is performed when measurement data is absent, by considering several possible values of the parameters while the Measurement based optimization takes the advantage of measurements to adjust the optimal profile accounting for parameter uncertainties and disturbances (Srinivasan *et al.*, 2003a). In this paper, an on-line update of the optimal input control policy is attempted using iterative learning of the batch process data refining the model using measurements from each successive batch run.

Iterative learning has been widely established as an emerging technique for the control of repetitive processes. Batch processes fall into this regime and iterative learning have been used to control the input batch trajectories to ensure that the output follows a reference output trajectory. Iterative Learning Control (ILC) algorithm is based on interbatch learning concept by minimizing the error between the reference and the plant output trajectory. The input trajectory is updated, using the error information, after each batch run so as to achieve convergence. A detailed review of ILC has been performed by Lee and Lee (2007) and Wang *et al.* (2009). However, one of the limitations of ILC is that the optimal reference output trajectories are computed using the process models, and thus relies heavily on the fidelity of the process models. As already discussed, process models suffer from many shortcomings and hence, there exists a strong reason to refine the reference trajectories so as to enhance the overall performance of the system.

For control, ILC algorithm updates an initially chosen input policy which reduces the error between the reference output trajectory and measured output trajectory. The specification of the reference trajectory could sometimes pose limitations on the tracking ability of ILC. For e.g., various path or input constraints could make it difficult to achieve perfect tracking of reference trajectories. On the other hand, the reference trajectory specified based on an initial approximate model could lead to infeasibility and/or sub-optimal objective function value when the resultant control policy is applied on plant due to model-plant mismatch. It is therefore appropriate to explore the potential of refining the model between batch runs with a view to eventually push the batch closer to optimal operation.

In this paper, we exploit the dual nature of estimation and control and propose Iterative Learning Estimation (ILE) methodology to recursively update the model parameters and reference trajectories so as to achieve feasible and optimal batch operation. While the ILC approach has been proven for the fixed reference trajectory, in this work we have used the traditional time optimal control methods along with Iterative Learning Estimation to progressively improve the batch operation.

The rest of the paper is organized in the following manner. In Section 2, the theory of ILE methodology and its dual relationship with ILC is presented. Section 3 puts forth the aspects of integration of ILE and optimal control methods used to update model parameters and establish optimal control input trajectory. Section 4 discusses about the case study performed for the optimal temperature control of series reactions in the batch reactor. Results which validate the proposed integrated approach are presented in Section 5 followed by conclusions.

2. ITERATIVE LEARNING METHODOLOGY

We begin this section with a brief discussion of the established Iterative Learning Control (ILC) approach. We then proceed to present the dual relationship between Iterative Learning Estimation (ILE) and ILC and develop the formulation of Iterative Learning Estimation (ILE).

2.1 Duality of ILE and ILC

We briefly present the ILC methodology first. Consider a general representation of a system as:

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

$$y = g(x, u, \theta) \tag{2}$$

where $x_{n\times 1}$, $u_{p\times 1}$, $\theta_{q\times 1}$ and $y_{r\times 1}$ represents the vector of state variables, input variables, parameter values and output variables respectively.

Consider a batch run of N sampling instants which can be represented as:

$$Y^k = G_p U^k \tag{3}$$

where G_p is the matrix $(Np \times Nr)$ defining the input-output relationship, Y^k is the system output vector of size $Nr \times 1$ and U^k is input process vector of size $Np \times 1$. These vectors can be represented as follows:

$$Y^k = \begin{bmatrix} y^k(1) & y^k(2) & \cdots & y^k(N) \end{bmatrix}^T \tag{4}$$

$$U^k = \begin{bmatrix} u^k(0) & u^k(1) & \cdots & u^k(N-1) \end{bmatrix}^T \tag{5}$$

Here, k represents the batch index.

The reference output trajectory can be represented as follows:

$$Y^{ref} = \begin{bmatrix} y_r(1) & y_r(2) & \cdots & y_r(N) \end{bmatrix}^T \tag{6}$$

For the k^{th} batch run, the error between the reference output trajectory and plant output is defined as follows:

$$\|e^k\| = \|Y^{ref} - Y^k\| \tag{7}$$

The control errors are then minimized to update the input trajectory:

$$\min_{u(k)} \|e^k\| \tag{8}$$