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Integrated Optimization Based on Transition Tracking Analysis for Batch Processes

Yan Qin*. Chunhui Zhao.*
Furong Gao**

* State Key Laboratory of Industrial Control Technology, Department of Control Science and Engineering, Zhejiang University, Hangzhou 310027 China (Correspoding author, email: chhzhao@zju.edu.cn).
** Department of Chemical and Biomolecular Engineering, The Hong Kong University of Science and Technology, Cleary Water Bay, Kowloon, Hong Kong, (e-mail: kefgao@ust.hk)

Abstract: Process optimization is an important issue for raising product quality and ensuring safety in batch processes and it is usually conducted at the point only when set-points are reached. In this work, process dynamic shift results from set-point tracking control, termed as transition tracking process, is detailedly analyzed in an integrated optimization framework, which also synthesizes the multi-stage characteristic of batch processes. Establishment of the regression relationship between process variables and quality indexes becomes possible and gradient directions are updated iteratively. The effacy of the proposed scheme is illustrated on the injection molding, which is a typical multi-stage batch process.

Keywords: multi-stage batch processes, quality optimization, process control, iterative learning control, model predictive control

1. INTRODUCTION

Batch and semi-batch processes play a significant role in the processing of a broad range of high-value-added products to meet the drastic competition market, such as specialty chemical products, semiconductor chips, plastics products. As a key factor of reducing production costs, improving product quality and meeting safety requirements, optimization technologies have been widely used in batch processes. In general, researchers in the field of automation refer to optimization operation by adjusting one or several key manipulated variables through some clever manner or on the basis of a process model (Bonvin, 1998). In practice, accurate mathematical process models are difficult to establish because of complicated physicochemical and mechanical characteristics. Thus, model-based optimization methods may not work effectively for the discrepancies between the simplified models and the real case.

In order to overcome the limitations, measurement-based optimization methods have been widely reported for batch processes. The essential relates to whether measurements are used on-line to drive the process towards the optimal strategy (Srinivasan et al., 2003). Bonvin et al. (2006) proposed an optimization scheme based on tracking appropriate reference through transforming the optimization problem into a control problem. It was an implicit model-based measurement optimization method had a close relationship with process knowledge or implicit model. Subsequently, model-free optimization methods have been developed in order to adjust process set-point just according to measurements. How to obtain accurate gradient information is an important issue to locate the optimum for model-free methods. DeHaan et al. (2005) gave an extremum-seeking control algorithm to accelerate the convergence rate of finite difference method. Further, Srinivasan et al. (2007) utilized physical equipment to get multi-variable gradient information directly. However, this algorithm relied on the strong assumption that several identical units were available, which was unrealistic for industrial process. Further, Kong et al. (2011) presented an optimization method whose gradient information can be obtained through stochastic perpetuation of the process variables without the limitation of physical equipment.

However, the above methods are implemented under the implicit precondition that the set-point signal can be reached quickly. In fact, for a huge number of batch processes, the set-point tracking process will last for many batches mainly because of the unsatisfied controller performances. These batches see a gradual shift of variables steady-state from one to another and this dynamic procedure mainly caused by set-point tracking control is termed as transition tracking process (TTP) in this paper. During the TTP, to some intermediate batches, the real values of process variables have not reached the set-point yet. However, it may not necessarily mean poor-quality products. Sometimes these intermediate batches very likely bring better quality indexes because the initial set-points may not be the best. Unfortunately, all previous work conduct optimization only when the set-points are reached, which, however, did not explore the TTP information. Thus, we can make use of TTP to further explore the relationships between process variables and quality indexes to obtain better optimization results, i.e. to find more reasonable set-points. In addition, the multi-stage is an important characteristic of the batch processes. Here, the multi-stage is defined as steps occurring in different processing units and performing different unit operations (Undey, Cinar, 2002). Different stages have obviously different effects on product quality and

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it is common that certain quality may be mainly affected by several key process variables in critical-to-quality stages (Lu, & Gao, 2006, Zhao, & Lu, 2014). Thus, stage based set-point adjustment may result in better quality control performance and less operation costs. To the best of the authors' knowledge, stage-based optimization method has not been explored.

Motivated by the aforementioned analysis, this paper devotes to develop an integrated optimization setting method by exploring TTP information and the multi-stage nature of batch processes. First, a process controller combing iterative learning control and model predictive control is designed to ensure every process variable in each batch run has a temporary steady-state during the TTP. And this makes it possible for the establishment of a regression relationship between process variables and quality indexes. Further, with the established regression relationship, a set-point iteration strategy is executed to obtain more accurate gradient information. Finally, the proposed method is validated in injection molding process.

2. METHODOLOGY

2.1 Optimization setting problem description

For batch processes, product quality is commonly available offline after batch completion. And during each batch run, quality variables are influenced by many factors (e.g. material characteristic, machine performance, controller performance). For batch processes, set-point values and controller performance are more concerned.

Consider batch processes that are subject to process variable constraints descried by

$$\begin{aligned} &\min_{(y_1^*,\cdots,y_p^*)} \ \boldsymbol{\gamma} = f(\mathbf{y}) \\ &s.t. \ \ y_{i\_\min} \le y_i^* \le y_{i\_\max} \quad i \in [1, p] \end{aligned} \tag{1}$$

The vectors $\boldsymbol{\gamma} \in \mathbb{R}^q$, $\mathbf{y} \in \mathbb{R}^p$ denote the quality variables and process variables, respectively. Function $f(\cdot)$ denotes an unknown regression function about $\mathbf{y}$ and $\boldsymbol{\gamma}$. Optimal process variables values $\mathbf{y}^*=(y_1^*,\ldots,y_p^*)$ are computed under the lower constrainst y_{i_min} and upper constrainst y_{i_max} with $f(\cdot)$. Process variables measurements are assumed to be sampled at every fixed time interval, whereas the elements of quality variables are only obtained after batch completion.

2.2 The idea of transition tracking process

In practice, process variables commonly can not arrive at the given set-points within a single batch. Naturally, the set-point tracking process results into a process state shift procedure, TTP, during which process variables are controlled to their set-points after certain batches. Injection molding, a typical batch process, is employed to better understand the TTP. In Fig. 1a, seven batches are needed for packing pressure to reach its set-point, 35bar. These batches constitute a TTP, during which packing pressure is controlled to approach its set-point as close as possible. Data information about corresponding quality index, weight, are plotted in Fig. 1b. From the TTP, we can easily discover a very important property that a smaller packing pressure results into a lighter part weight. And the lightest part weight is obtained in an intermediate batch, namely 2nd batch, rather than the 7th batch, where the packing pressure is 35bar. Thus, TTP may provide a guidance for process optimization.

In batch processes, usually, control actions are imposed on plants both along batch-wise and time-wise. It helps to eliminate tracking error and obtains faster response. However, if real values of process variables are continuously adjusted by controller along the time-wise direction, it will be difficult to distinguish the steady value for a process variable in each batch. Under this situation, the existing optimization methods take effect until entire process enters into a steady state. As a result, if we expect higher optimization efficiency, TTP should be considered properly into the optimization process.

2.3 An Integrated Quality Optimization Method

Subsequently, how to get and utilize the TTP information is a crucial issue. Here, we introduce an integrated optimization method, presented in Fig. 2, which consists of two major parts: lower process control part and upper optimum seeking part.

Lower process control part: A controller is designed to achieve batch-wise temporary reference tracking and time-wise error elimination. The temporary reference is automatically calculated according to controller performance and is a temporary target evolved batch to batch which finally equals to set-point at the end of a TTP. Thus, with the help of temporary reference, every process variable will enter into a steady-state within each batch.

Without loss of generality, assume K_η batches data are collected in the η^{th} TTP, note the process variables data matrix $\mathbf{Y}_\eta$ in the $\eta^{th}(\eta=1,2,\ldots)$ TTP is:

$$\mathbf{Y}_\eta = \begin{pmatrix} \mathbf{y}_1^\eta \\ \vdots \\ \mathbf{y}_{K_\eta}^\eta \end{pmatrix} = \begin{pmatrix} y_{1\_1}^\eta & y_{2\_1}^\eta \cdots & y_{p\_1}^\eta \\ \vdots & \ddots & \vdots \\ y_{1\_K_\eta}^\eta & y_{2\_K_\eta}^\eta \cdots & y_{p\_K_\eta}^\eta \end{pmatrix} \tag{2}$$

where $y_{i\_k}^\eta$ is the steady value of i^{th} process variable in the k^{th} batch during the η^{th} TTP.

Correspondingly, note quality variables obtained from offline assay in each batch during η^{th} TTP as $\boldsymbol{\varphi}_\eta$

$$\boldsymbol{\varphi}_\eta = \begin{pmatrix} \boldsymbol{\gamma}_1^\eta \\ \vdots \\ \boldsymbol{\gamma}_{K_\eta}^\eta \end{pmatrix} = \begin{pmatrix} \gamma_{1\_1}^\eta & \gamma_{2\_1}^\eta \cdots & \gamma_{q\_1}^\eta \\ \vdots & \ddots & \vdots \\ \gamma_{1\_K_\eta}^\eta & \gamma_{2\_K_\eta}^\eta \cdots & \gamma_{q\_K_\eta}^\eta \end{pmatrix} \tag{3}$$

Then, steady-values of process variables $\mathbf{Y}_\eta$ and the quality variables $\boldsymbol{\varphi}_\eta$ can be used to establish the local regression function $\Phi_\eta(\cdot)$ to substitute $f(\cdot)$ in a local region. Through analyzing data distribution, linear or nonlinear relationship can be identified.