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Comprehensive economic index prediction based operating optimality assessment and nonoptimal cause identification for multimode processes

Yan Liu[a], *Fuli Wang*[a,b,*], *Yuqing Chang*[a,b], *Ruicheng Ma*[c]

[a] *College of Information Science & Engineering, Northeastern University, Shenyang 110819, China*
[b] *State Key Laboratory of Synthetical Automation for Process Industries (Northeastern University), Shenyang 110819, China*
[c] *School of Mathematics, Liaoning University, Shenyang 110036, China*

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ABSTRACT

For many multimode processes, the process operating performance may deteriorate with time from optimal state due to process disturbances, noise, and other uncertainties, and it is important to develop an effective operating optimality assessment method; however, it has not yet been paid sufficient attention and few researches have been reported in this area so far. In this study, a novel comprehensive economic index (CEI) prediction based operating optimality assessment and nonoptimal cause identification method is proposed for continuous multimode processes. The assessment strategies are formulated for both stable and transitional mode on account of their different process characteristics. In stable mode, the CEI is predicted by some common methods and then the optimality index is constructed based on the predicted CEI. In transitional mode, the CEI of a transition is predicted by the weighted average of the CEIs of the similar historical transitions, and then the optimality index is calculated for online assessment of the transitional mode. When the operating performance is nonoptimal, the responsible cause variables can be identified by the proposed nonoptimal cause identification method. Finally, the feasibility and efficiency of the proposed strategies are demonstrated through the Tennessee Eastman (TE) process.

1. Introduction

In industrial processes, the process operating optimality is a crucial problem that has attracted tremendous attention from both academia and industrial areas for the past decades (Camponogara and Scherer, 2011; Shen et al., 2014). However, because of the disturbance, noise, and other uncertain causes, industrial processes are not likely to be maintained all the time on the optimal point given by optimization approach, which discounts the benefits of preliminary designs for process optimization and results in the degraded operating behaviors. Therefore, it is crucial to achieve the online operating optimality assessment for the industrial processes.

Additionally, due to load change, feedstock variation and parameter drift, etc., many industrial processes, including both continuous and batch processes, have the multimode characteristic (Zhang et al., 2013; Yu and Qin, 2008; Tan et al., 2012; Wang et al., 2012). For example, the Tennessee Eastman (TE) process is a continuous multimode process and simulates a chemical production process with four kinds of reactants A, C, D, E and an inert gas B to produce two kinds of liquid products G and H. To get different product, the operating conditions should be adjusted accordingly, which causes different stable modes, and the adjustment process from one stable mode to another can be considered as the transitional process. As another example, i.e. injection-molding process, which is a batch process and a polymer processing technique.

* *Corresponding author at*: College of Information Science & Engineering, Northeastern University, 3 Lane 11, Wenhua Road, Heping District, Shenyang, Liaoning 110819, China. Tel.: +86 024 83687434; fax: +86 024 23890912.
E-mail address: wangfuli@mail.neu.edu.cn (F. Wang).
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The entire production will go through four stages: injection, packing-holding, plastication, and cooling. The process characteristics within each stage are relatively stable and can be considered as stable modes, while the process between two stages is considered as transitional mode. In this study, only continuous multimode process is considered.

The stable mode is the main process which occupies the most production time to yield high productivity, and the good operating performance of a stable mode is the guarantee for the improvement of the comprehensive economic index (CEI). Owing to the unstable production conditions, however, the transitional process usually produces the substandard products, which may affect the CEI. If nonoptimal transitional mode can be evaluated timely and accurately, managers and operators can take appropriate action to adjust and improve the transition process, which can shorten the transition duration, reduce scrap rates and economic losses. In short, both stable and transitional mode are the indispensable parts of a multimode process, and the online operating optimality assessment for multimode processes is meaningful for further production operating adjustment and process performance improvement.

Nowadays, the operating performance assessment for multimode processes mainly focus on safety. Operating safety assessment is to ensure production safety, human health and avoid environmental pollution, etc., and some methods have been applied to this aspect recently (Ye et al., 2009; Lin et al., 2013). In particular, multimode process monitoring (Wang et al., 2012; Yu and Qin, 2009; Haghani et al., 2014; Zhang and Li, 2013), as a kind of effective means to ensure the process operating safety, is also considered to belong to the scope of safety assessment. By way of comparison, the purpose of operating safety assessment or process monitoring is to distinguish between safe and unsafe, or normal and fault, whereas operating optimality assessment is to answer “whether the operating performance is optimal or nonoptimal under normal operating conditions”. Therefore, process operating optimality assessment is above the level of operating safety and makes a deeper understanding and mastering with the process operating performance for the operators and managers. Through operating optimality assessment, they can propose reference suggestions for further operating adjustment and performance improvement. However, to the best of the authors’ knowledge, few works have been reported on operating optimality assessment for multimode industrial processes. Recently, Ye et al. proposed a probabilistic framework of operating safety and optimality assessment for continuous multimode industrial processes (Ye et al., 2009). They used a Gaussian mixture model (GMM) to characterize multiple stable modes and constructed the safety and optimality indices (SI and OI) in each mode respectively. Then, a hierarchical-level classification method was presented to divide these indices into different performance levels, and margin analysis on each level was introduced. Nevertheless, they only considered the operating performance assessment for stable modes and neglected that for transitional modes which objectively exist in multimode processes. In addition, when the operating performance is nonoptimal, only experience-based qualitative analysis is provided rather than a general quantitative analysis. That is to say, an automatic nonoptimal cause identification method has not been explored.

It is true that the operating optimality assessment for stable and transitional modes as well as the nonoptimal cause identification is the core part of operating performance assessment for multimode process, but considering the integrity of the method, some issues have to be addressed and are listed as follows:

(i) Offline mode identification for modeling data
The common treatment for this issue is to assume that the offline modeling data for stable and transitional modes can be separated with the help of the expert knowledge and process information before modeling. Encouragingly, some automatic mode identification algorithms have been developed in recently years (Tan et al., 2012; Wang et al., 2012).

(ii) Online mode identification for online application
The online mode identification is to determine the mode type of the current process and then select the right model for online implementation. To try each mode in turn is an alternative way, but it is time-consuming work and only suitable for the processes with a small number of modes. Wang et al. (2012) proposed the mode transformation probability-based online mode identification method which can save online computing time and enhance real-time performance of online mode identification.

In this paper, only the existing methods of offline and online mode identification are used and the main efforts are focused on the online operating optimality assessment and nonoptimal cause identification for both stable and transitional modes. It is widely accepted that the process operating optimality is closely associated with the CEI which may be one of the important production indices, such as costs, profits, total revenue and production efficiency, etc. or the weighted integration of several production indices. If the CEI approaches to or reaches the history optimal level, we believe that the process operating performance is optimal. Thus, it is suitable to evaluate the process operating performance based on CEI. However, CEI is difficultly achieved online and usually determined by offline statistical analysis, which may introduce a large delay and discount the timeliness of online implementation, so the easy-measured variables can be used to predict the CEI for online assessment. To predict the quality in the stable mode, various data-driven prediction methods have been developed and applied to the industrial processes (Liu et al., 2011; Wang, 2011; Ding et al., 2011; Wang et al., 2010). Then, the online assessment method for stable mode is proposed based on the predicted CEI.

Because of the dynamics of transitional modes, the CEI of a transition is derived from the accumulation effects of the whole transition. That is to say, in transitional mode assessment, the whole transition information should be used in CEI prediction, and multiway partial least squares or other prediction algorithms for batch processes are seemed to be a choice to develop the prediction model. Nevertheless, the characteristics of the transitional mode limit the application of those algorithms in CEI prediction. On the one hand, because the transitional modes do not play the primary role in the continuous industrial processes compared with the stable modes, it is difficult to collect adequate transition data to develop the model, which affects the accuracy and reliability of the prediction model. On the other hand, transitions usually have uneven-length durations within the same kind of transitional mode, and the durations of nonoptimal transitions may be much longer than those of optimal ones, which causes the prediction algorithms for batch processes difficult to be applied to transitional process. Basing on the fact that the transitions with similar operating performance usually have the similar transition trajectories, the CEI of the new transition can be predicted by the weighted average CEI of the similar transitions. Therefore, the CEI prediction method based on the similar transition trajectories is given for transitional mode, and the process operating performance of the transitional mode is evaluated on account of the predicted CEI. The proposed CEI prediction method for transitional mode can easily achieve the purpose of CEI prediction for online transition and do not need to synchronize the transitions with different lengths no matter for offline or online.

Also, when the process operating performance is nonoptimal, the contribution-based nonoptimal cause identification methods for both stable and transitional mode are proposed for identifying the responsible cause variables. The idea of the proposed nonoptimal cause identification is similar to that of the contribution plots based fault diagnosis method (Peng et al., 2013; Liu et al., 2013). Then, the managers and operators can take appropriate operating adjustment strategies by combining their experience and the results of nonoptimal cause identification for production improvement. The schematic diagram of proposed method is shown as Fig. 1.

The rest of this paper is organized as follows. First, some preparatory theoretical supports are framed by revisiting to the existing offline and online mode identification algorithms. Subsequently, the prediction models for each of the stable modes are established and the optimality index based on the predicted CEI is calculated for online operating optimality assessment. In Section 4, the online assessment strategy for transitional mode is developed, where the CEI is predicted based on the similar transition trajectories. For nonoptimal operating performance, the nonoptimal cause identification