Control Engineering Practice 22 (2014) 194–204

Contents lists available at ScienceDirect

Control Engineering Practice

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

Modeling and monitoring of nonlinear multi-mode processes

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ARTICLE INFO

Article history:
Received 9 August 2012
Accepted 6 April 2013
Available online 29 May 2013

Keywords:
Multi-mode processes modeling
Monitoring
Subspace separation

ABSTRACT

In this paper, a new subspace separation method is proposed and a new modeling and monitoring approach in multi-mode processes based on subspace separation is proposed. The existing modeling methods have the following disadvantages: (1) different monitoring models are built in view of each different mode, which needs each mode to be able to offer fully complete modeling reference data. (2) The connection between each mode is ignored, which could be useful in process modeling and monitoring. The proposed method has the following advantages: (1) the common subspace is extracted and the monitoring performance of multi-mode processes is significantly improved. (2) New subspace separation is used to establish an integrated monitoring system, which would simplify the monitoring model structure and enhance its reliability. (3) The direct relationship of input dataset and output dataset is considered in the multi-mode processes, which is crucial for the complex industry process. Experiment results show effectiveness of the proposed method.

1. Introduction

With the development of technology of melting, electro-fused magnesia furnace (EFMF) has already gotten extensive application in the industry. EFMF refining technology can enhance the quality and increase the production variety. The working conditions of the EFMF are changed frequently and have complex characteristics such as strong nonlinearity and multiple modes (Zhang, Chai, & Li, 2012). In order to ensure the safety and quality of products in the complex industry process, the monitoring of the process performance has become a key issue (Rashid & Yu, 2012a, 2012b; Yu, 2012b). Data-based multivariate monitoring methods (Ge & Song, 2008; Karra & Karim, 2009; Mahadevan & Shah, 2009) such as principal component analysis (PCA) (Zhang & Ma, 2011; Zhang, Li, & Teng, 2012), partial least squares (PLS) (Zhang, Zhang, & Li, 2011; Zhang, Zhou, Qin, & Chai, 2010) and independent component analysis (ICA) (Kano, Tanaka, Hasebe, Hashimoto, & Ohno, 2003; Zhang, 2009; Zhang & Zhang, 2010) have been widely used to establish a relationship between process measurement and process output. Accurate process modeling and monitoring can avoid cumbersome and enhance its reliability. However, those methods are not available for multi-mode processes monitoring. How to model and monitor efficiently the multi-mode processes is a challenging problem (Choi, Morris, & Lee, 2008).

Considering that the mode multiplicity is an inherent nature of multi-mode processes, various strategies have been reported and can be put into process monitoring (Dunia & Qin, 1998). To solve the multi-mode problem, subPLS modeling algorithm has been developed (Yang & Gao, 1999, 2000), recursive or adaptive PCA method (Li, Yue, Valle-Cervantes, & Qin, 2000), model library based methods (Tenenhaus & Vinzi, 2005), localized discriminant analysis method (Hoskuldsson & Svinning, 2006), multi-block partial least squares (MBPLS) (Alcala & Qin, 2009; Camacho & Pico, 2006; Maiti, Srivastava, Bhushan, & Wangikar, 2009; Qin, Valle, & Piovoso, 2001; Undey & Cinar, 2002; Undey, Ertunc, & Cinar, 2003; Zhang et al., 2010), localized Fisher discriminant analysis (Yu, 2011), Gaussian mixture model approach (Yu, 2012a), and multi-mode statistical analysis method (Zhang et al., 2012) have been proposed. MPLS uses process variables over the entire modes, which reveals well the time correlations throughout the cycle and thus shows efficiency for analysis of cumulative effects on process. However, if the data are handled in a single matrix for multiple modes, the connection from one mode to another tends to be ignored. It is commonly accepted that more underlying information can be explored by dividing the data into meaningful blocks or by the types of variables in multi-mode processes and multiple specific models are built instead of single modeling of all data. The effect of each block can be seen clearly and thus more comprehensive process understanding and process analysis can be expected (Qin, 2003; Reinikainen & Hoskuldsson, 2007; Wang, Tan, & Peng, 2012; Zhao, Wang, & Zhang, 2009). One is to build the variable correlation model within each mode under the influence of other modes by MBPLS. Compared with MPLS, the advantage of MBPLS is mainly to allow easier modeling based on

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http://dx.doi.org/10.1016/j.conengprac.2013.04.007

both the roles of each smaller meaningful block and the integrated contribution of all blocks. Zhang et al. (2010) has made a comprehensive review of multi-block algorithms and reported the super scores of MBPLS are identical to the scores of regular MPLS and thus achieved the same process monitoring performance. Zhang et al. (2012) has presented a multi-mode statistical analysis method to reduce the complexity of fast process analysis, which revealed that which part of process variation was responsible for process variations and which part of process variation was dominated in each mode. For multi-mode processes, how the effects of process dynamics on process monitoring with the modes change is an interesting issue. The multi-mode processes model should be built in a quite different way from the conventional process modeling methods. The key point or most concerned is how to capture process dynamics along with mode alternation and process evolvement. This also requires the attention to the difference in different modes.

In this work, a new multi-mode processes modeling and monitoring approach based on a new subspace separation method is proposed to extract the inherent process-related features across multiple data sets in the electro-fused magnesia furnace (EFMF). From the process-concerned viewpoint, each different mode can be separated into two subspaces, called common and specific subspaces. In the common subspace, the process variability stays invariable from one mode to another, thus revealing the same contributions to process features. That is, they explain the same part of process variability. In the specific subspace, the process variability is more specific, revealing different effects on process modeling in each different mode. That is, they explain different parts of process characteristics in a complementary way. It should be noted that here the proposed multi-mode processes modeling and monitoring method focuses on two neighboring modes for multi-mode processes analysis and monitoring. The purposes of multi-mode modeling and monitoring are: explore the subspaces in two neighboring modes and give more meaningful information about the mode behaviors. In comparison with the conventional multi-mode processes modeling and monitoring methods, the separation of the common and specific subspaces is the major difference. In addition, the direct relationship of input dataset and output dataset is reflected in the proposed method, which is crucial for the complex industry process. Experiment results show effectiveness of the proposed method.

The paper is organized as follows. New multi-mode processes modeling and monitoring approach based on a new subspace separation method is proposed in Section 2. Process description, experiment results and discussion are presented in Section 3. Finally, conclusions are given in Section 4.

2. Modeling and monitoring multi-mode processes

2.1. Multi-mode processes modeling

Different modes have different characteristics and reveal different effects on multi-mode processes. Only focusing on the process variables is insufficient for the multi-mode modeling and monitoring. In this research, it is considered that some features may not change from one mode to another. That is, part of the potential mode variations will stay consistent between two modes and reveal the same process characteristics. Instead of isolating the effects of single mode on processes, it is necessary to gain a detailed process-concerned insight into the potential mode characteristics from the multi-mode viewpoint, which can provide important information of the changing process characteristics from one mode to another. The key is how to separate the two different types of process variation.

The notations used in the proposed method are listed in Table 1.

Table 1
Important notations used in the proposed method.

Notation	Description
m	Operation mode
$M_m (m=1,2)$	The number of samples
n	The number of variables
d	The dimension of common subspace
$\mathbf{X}_m$	multi-mode input dataset
$\mathbf{Y}_m$	multi-mode output dataset
$\mathbf{x}_i$	Sample point of input dataset
$\mathbf{y}_i$	Sample point of output dataset
$\mathbf{\Phi}$	Nonlinear mapping
$\mathbf{\Phi}(\mathbf{x}_i)$	Nonlinear mapping of sample point
$\mathbf{\Phi}(\mathbf{x}_j)$	Neighboring point
$\mathbf{\Phi}(\mathbf{X}_g)$	Common subspace dataset
$\mathbf{\Phi}(\mathbf{x}_{g,i})$	Data point of common subspace
k	Field number of $\mathbf{\Phi}(\mathbf{x}_i)$
$\mathbf{W}$	Weight vector in the proposed method
$e(W)$	Error of construct weight matrix $\mathbf{W}$
$e(z)$	Loss function
$\mathbf{t}$	Score vector of $\mathbf{\Phi}(\mathbf{X}_g)$
$\mathbf{w}$	Load vector of $\mathbf{\Phi}(\mathbf{X}_g)$
$\mathbf{u}$	Score vector of $\mathbf{Y}$
$\mathbf{c}$	Load vector of $\mathbf{Y}$
$\mathbf{M}$	$(I-W)^T(I-W)$
Var	Variance
ρ	Correlation coefficient
cov	Covariance
tr	Trace of the matrix
$\mathbf{\Phi}(\mathbf{X}_{s,m})\quad(m=1,2)$	Specific subspace dataset

It can be classified into two modes based on process characteristics in the EFMF multi-mode processes, where input dataset $\mathbf{X}_m = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\} \in \mathbf{R}^{M_m \times n} \quad (m=1,2)$ and output dataset $\mathbf{Y}_m = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n\} \in \mathbf{R}^{M_m \times n} \quad (m=1,2)$ are obtained, where the subscripts m denotes different operation modes, M_m denotes the number of samples for different modes, n denotes the number of variables for the industrial process monitoring, $M=M_1+M_2$ is the total length of two modes. Standardize the dataset of two modes. We first map $\mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{bmatrix}^T$ into a feature space $\mathbf{\Phi}(\mathbf{X}) = [\mathbf{\Phi}(\mathbf{x}_1), \mathbf{\Phi}(\mathbf{x}_2), \ldots, \mathbf{\Phi}(\mathbf{x}_v)] \in \mathbf{R}^M$ via a nonlinear mapping $\mathbf{\Phi}: \mathbf{R}^n \to \mathbf{F}$ (feature space). Then a low-dimensional embedding $\mathbf{\Phi}(\mathbf{X}_g) = [\mathbf{\Phi}(\mathbf{x}_{g,1}), \ \mathbf{\Phi}(\mathbf{x}_{g,2}), \ldots, \mathbf{\Phi}(\mathbf{x}_{g,v})] \in \mathbf{R}^d$ $(d<M)$ will be extracted, which can explore the intrinsic structure hidden in the high-dimensional dataset $\mathbf{\Phi}(\mathbf{X})$. The subscript v is the dimension of the feature space and it can be arbitrarily great. Here, $\mathbf{\Phi}(\mathbf{X}_{g,i}) \in R^{d \times 1}$ is a low-dimensional coordinate of $\mathbf{\Phi}(\mathbf{x}_i) \in \mathbf{R}^{M \times 1}$. In this section, new modeling method based on subspace separation is proposed for multi-mode processes. Some same variable correlation exists in the relationships between two modes. In the space of two modes we can find out a common subspace, where the underlying process-relevant variations stay invariable, showing the common contribution to multi-mode processes. Better monitoring performance of each mode is obtained by multiple modeling method, but the correlations of each modes are neglected. In the proposed approach, the multi-mode processes are separated correctly since the correlations of two modes are considered. Their differences are shown in Figs. 1 and 2.

The common subspace of two modes can be extracted by the proposed method. The specific subspace may be quite different, revealing quite different process characteristics. In the research, the specific subspace can be used as the purpose of process monitoring and the subspace extraction algorithm can be used as the basic modeling method. Different potential characteristics information is contained in each subspace. The two subspaces give