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A time series model coefficients monitoring approach for controlled processes

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ABSTRACT

Statistical process monitoring (SPM) has been adopted widely in manufacturing industry. Traditional SPM techniques such as principal component analysis (PCA) and partial least square (PLS) are applied to monitor a stationary process. When applied to a process with a feedback and/or feedforward controller, there are some monitoring challenges needed to be addressed, such as nonstationarity of process data and false alarm. To deal with these problems, a statistical online process monitoring scheme is presented in this paper. The proposed method consists of two phase: on-line time series model building and process monitoring via SPM. In the model building phase, a process with a controller is represented by a time series model, and a recursive extended least square (RELS) algorithm is used to identify the coefficients of this model. Furthermore, it is proved that the coefficients are stationary even if the process input/output data are non-stationary. In the process monitoring phase, the changes in process input-output relations or disturbance dynamics can be detected by applying SPM on the model coefficients. The validity and effectiveness of the proposed approach are illustrated by three examples in industrial processes, i.e., a semiconductor manufacturing process, a DC motor process and a benchmark Tennessee Eastman process.

1. Introduction

The increasing demands for safe operation of industrial plants continue to gain attention of research in process monitoring. Various feedback/feedforward regulations such as proportional integral derivative (PID) controllers and model predictive controllers are applied in industrial manufacturing processes to compensate the unknown disturbances and changes. The controller will bring the output back to target even though there are trivial sustained changes in process input-output relation or patterned disturbance. However, when the trivial changes become some kind of faults which cannot be handled by the controller, the process will be unstable immediately. Therefore, it is crucial to develop an approach to monitor the process changes which initially can be handled by the process controllers.

Statistical process monitoring (SPM) is a powerful technology in many industries to detect and identify changes and faults, which makes use of the input-output process data to monitor the process. Such methods as principal component analysis (PCA) and partial least square (PLS) are mostly frequently employed as key tools of SPM. One of a drawback of PCA and PLS is that the variables being monitored must be stationary. Thus the issue of nonstationarity must be addressed when joint monitoring schemes are considered. Various tools are adopted to handle the nonstationarity of the process data, which includes independent component analysis (ICA) (Lee et al., 2006), external analysis

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(Ge et al., 2014), subspace separation (Zhang et al., 2013), and multi-model method such as Gaussian Mixture Model (GMM) (Yu and Qin, 2008), co-integration testing method (Chen et al., 2009), Bayesian Regulation (Ge and Song, 2010), Hidden Markov model (Yu, 2010), and mode clustering (Tong et al., 2013), etc. Most of the above results are based on the assumption that there are limited process modes and the process is operated in a steady condition for each mode. In many processes, patterned special cause events occur frequently, so that there are non-Gaussian disturbances, which will make the output non-stationary when no control action is taken. If a feedback/feedforward controller is applied, the process outputs may be stationary, but the inputs become necessarily non-stationary and varying since it keeps compensating the disturbances and the changes. This is recognized by Castillo (2002), Box and Paniagua (2007). In addition, the process setpoint, which is the target of the process output, sometimes will be time-varying owing to process requirements. Thus servo-control will be adopted for the output to follow the varying setpoints. Both the controlled output and the manipulative actions can be non-stationary with the change of the setpoint. Since in these cases it is hard to identify a single mode and distinguish the normal and abnormal input/output data, the methods mentioned above cannot give a satisfactory monitoring result. Therefore, there are some technical challenges needed to be solved in order to monitor such a controlled process with non-stationary input and/or output data.

It is pointed out by Woodall et al. (2004) that the assignable causes of variation corresponding to unusual and preventable events will cause a change in parameters of the underlying model. In recent years, several researchers have studied on the model building and parameter monitoring of the different models. Ge et al. combined statistical local approach into subspace model identification technique and monitored the change of model parameters (Ge et al., 2010). Runger et al. (2007)used process-oriented basis representation to express multivariate quality vectors as linear combination of fault patterns and monitor estimated coefficients of the linear relationship. Fan et al. (2013) applied the sum of sine functions to model the nonlinear profiles and the vector of parameter estimates by Hotelling T^2 and metric control charts. Colosimo et al. (2008) proposed a spatial autoregressive model for bidimensional system with Hotelling T^2 chart. However, most of their work focused on constructing models related to the quality vectors and explanatory variables which do not consider process controllers, patterned disturbance and varying setpoint.

For a controlled process, the closed loop response of the controlled variables can always be expressed as autoregressive moving average (ARMA) time series (Pan and Castillo, 2001; Box et al., 1994) or auto-regressive moving average exogenous (ARMAX) time series with the setpoint changes as the exogenous variables. Hence, the coefficients of the time series model would remain unchanged in normal condition. If there is a change in the process input–output relation or the patterned disturbances, the coefficients of this time series model will exhibit a sustained change. As far as we know, the coefficients monitoring of a time series model of a controlled process have rarely been discussed in the literature.

In this paper, ARMA or ARMAX models for controlled process are set up. There are many methods available for identification of the coefficients of closed loop time series model. In this paper, recursive extended least square (RELS) algorithm (Yang et al., 1996) is applied to estimate the coefficients of

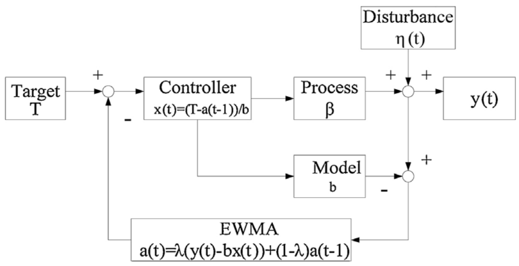

Fig. 1 – The structure of EWMA Run-to-run control.

ARMA and ARMAX model. And the estimated coefficients are proved to be a stationary time series even with non-stationary disturbances and changed setpoint. Thus, the detection of coefficients' changes can be accomplished by various traditional SPM methods which can be applied on stationary data. This converts the problem of monitoring non-stationary data into a simple problem of monitoring only stationary coefficients. In our approach, PCA or dynamic PCA (Yin et al., 2014) is adopted to monitor the coefficients of time series model.

The rest of this paper is organized as follows. Section 2 will explain our motivation by presenting the problems through two different examples. Section 3 will introduce our methodology including the definition of variables, closed loop time series model constructing, a recursive extended least square (RELS) algorithm to estimate the coefficient, and application of PCA on the model coefficients. In this section, the stationarity of the coefficients of time series model is proved. The effectiveness of our approach is demonstrated in Section 4 by three examples including a semiconductor manufacturing process, a DC motor process and a benchmark Tennessee Eastman process. The last section gives our conclusions.

2. Motivation

In this section, two examples are discussed. One is a batch semiconductor manufacturing process under an exponentially weighted moving average (EWMA) run-to-run controller. The other is a DC motor process with a PI controller.

2.1. *Case 1: A batch process with EWMA controller*

In recent years, run-to-run (RtR) control technology has been widely adopted in the batch process such as semiconductor manufacturing processes (Qin, 2006). It is a form of discrete process control in which the product recipe with respect to a particular process is modified between machine runs to minimize process drift, shift, and variability. EWMA algorithm is the most widely used estimation algorithm for RtR control. The structure of the EWMA RtR control is shown in Fig. 1.

Let us assume that the input-output relationship for a batch manufacturing process (Qin, 2006):

$$y(t) = \alpha + \beta x(t) + \eta(t) \quad (1)$$

where $y(t)$ and $x(t)$ are the output and input; and $\eta(t)$ is the process disturbance at the tth run; β is the true gain, α is the actual intercept of process. Given a model gain b, a EWMA algorithm is used to update the estimate of the intercept as:

$$a(t) = \lambda(y(t) - bx(t)) + (1 - \lambda)a(t - 1) \quad (2)$$