# Computers & Industrial Engineering 75 (2014) 187-199

Contents lists available at ScienceDirect

# **Computers & Industrial Engineering**

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



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#### ARTICLE INFO

Article history: Received 21 November 2013 Received in revised form 26 March 2014 Accepted 30 May 2014 Available online 26 June 2014

Keywords: Exponentially weighted moving average filter Hotelling T<sup>2</sup> chart Statistical process control Profile analysis Real-time monitoring

## ABSTRACT

A statistical process control (SPC) framework is proposed to detect potential changes of a wave profile on a real-time basis. In regular profile monitoring, change detection takes place when a complete profile is generated. In this study, the detection of a potential profile change takes place before the entire information on the profile of interest is fully available. The main research goal is to make a correct process decision as soon as possible. A real-world example of condensation-water-temperature profile monitoring was used to demonstrate the proposed framework. A simulation study was also conducted. The simulation results confirm that the proposed framework is capable of detecting profile changes without having to wait for the entire profile to be generated.

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#### 1. Introduction

Profile monitoring has drawn much attention in the field of Quality Engineering in recent years. A profile is a relationship between a response variable and explanatory variable(s) (Woodall, 2007). Usually, the explanatory variable can be either time or space. If there are two spatial explanatory variables, the response is a surface. In this study, only one explanatory variable over time is considered for a response with oscillating patterns. In profile analysis, a decision about the quality of a profile is usually made at the end of the period when a profile is completely generated. Most of the research conducted in the field of profile monitoring is based on this approach. In this study, a new approach is proposed to detect profile changes based on real-time data feed before the entire profile is generated. The goal is to detect a possible deviation from a normal profile pattern as soon as possible.

It would be extremely beneficiary to detect an irregular profile before the entire profile is generated. In manufacturing, if profile changes related to a process status can be detected as soon as possible, product costs can be reduced through defect preventions. For example, Chang, Tsai, Lin, Chou, and Lin (2012) studied the strategy of implementing SPC in a curing process in which the condensation-water-temperature profile is considered here. Fig. 1(a)-(k) contain the progression of a water temperature profile during the curing process. In a separate work, the authors aimed to detect whether the curing process is in control or not based on the information provided in Fig. 1(k) while this research focuses on monitoring the same process but using partial information provided by Fig. 1(a)-(j). If an abnormal profile be detected during earlier stages, process adjustments can be made to maintain product quality. The goal of this study is to provide a method to detect an out-of-control profile as soon and as accurate as possible. However, the practice of engineering process control (EPC) (del Castillo, 2002) is not in the scope of this study.

# 2. Background

## 2.1. Current profile monitoring methods

Profile monitoring is the use of control charts for cases in which the quality of a process or product can be characterized by a functional relationship between a response variable and one or more explanatory variables (Woodall, 2007). In terms of modeling approaches for profile monitoring, Woodall (2007) specifies two categories of profile, linear and nonlinear profile. A review of the most conducted current research will be summarized in the following sub sections. The main purpose of this review is to show that none of current research in profile monitoring has considered



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Fig. 1. Completion of a condensation-water-temperature profile.

wave profiles. In addition, none of the current research attempts to provide a decision before a profile is fully generated.

## 2.1.1. Methods in linear profile monitoring

Methods dealing with linear profiles can be found in many studies. Kang and Albin (2000) proposed two methods to detect abnormal profiles. First, they monitored slope and intercept parameters using the Hotelling's  $T^2$  control chart. Second, they used exponential weighted moving average (EWMA) and R chart to monitor average residuals between sample profiles and reference profile. Another model parameters monitoring methods can be found in Kim, Mahmoud, and Woodall (2003), Zou, Tsung, and Wang (2007), Mahmoud (2008), and, Zhu and Lin's (2010) study. Kim et al. (2003) monitored slope, intercept, and the variance of deviation between samples and regression line simultaneously by their proposed three univariate exponentially weighted moving average (EWMA) charts. Zou et al. (2007) proposed a multivariate exponentially weighted moving average monitoring scheme for linear profiles. Mahmoud (2008) monitored multiple linear regression model's parameters, intercept, slope, and variance, from the multiple linear profiles. Zhu and Lin (2010) proposed a Shewhart control chart for monitoring slopes of linear profiles from the truncated vertical density profiles problem (Walker & Wright, 2002).

Above mentioned methods dealing with linear profiles used the control charting approach. Mahmoud, Parker, Woodall, and Hawkins (2006) proposed a change-point approach based on the

segmented regression technique for testing the constancy of regression parameters in a linear profile data set. Hosseinifard, Abdollahian, and Zeephongsekul (2011) proposed a feed-forward neural network to detect and classify step shifts in linear profiles. More details regarding linear profiles monitoring methods can be found in Noorossana (2011).

# 2.1.2. Methods in nonlinear profile monitoring

To monitor the nonlinear profiles, Woodall (2007) categorized approaches into four types: (1) applying multiple and polynomial regression (Kazemzadeh, Noorossana, & Amiri, 2008; Mahmoud, 2008; Zou et al., 2007); (2) applying nonlinear regression models (Chang & Yadama, 2010; Chen & Nembhard, 2011; Ding, Zeng, & Zhou, 2006; Shiau, Huang, Lin, & Tsai, 2009; Williams, Woodall, & Birch, 2007); (3) use of mixed models (Abdel-Salam, Birch, & Jensen, 2013; Jensen & Birch, 2009; Jensen, Birch, & Woodall, 2008; Qiu, Zou, & Wang, 2010); and (4) use of wavelets (Chicken, Pignatiello, & Simpson, 2009; Reis & Saraiva, 2006; Zhou, Sun, & Shi, 2006). In this section, we will update recent developed methods according to these categories. Also, we will briefly introduce some represented approaches. Detail of other approaches to monitor the process stability can be found in Noorossana (2011).

Kazemzadeh et al. (2008) developed three methods for monitoring polynomial profiles in Phase I. These three methods are called the Change Point approach, F-approach and, the Hotelling Download English Version:

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