



Production

ISSN: 0103-6513

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Associação Brasileira de Engenharia de
Produção
Brasil

Woodall, William H.
Current research on profile monitoring
Production, vol. 17, núm. 3, septiembre-diciembre, 2007, pp. 420-425
Associação Brasileira de Engenharia de Produção
São Paulo, Brasil

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Current research on profile monitoring

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Abstract

In many applications the quality of a process or product is best characterized and summarized by a functional relationship between a response variable and one or more explanatory variables. Profile monitoring is used to understand and to check the stability of this relationship over time. At each sampling stage one observes a collection of data points that can be represented by a curve (or profile). In some calibration applications, the profile can be represented adequately by a simple linear regression model, while in other applications more complicated models are needed. The purposes of this paper are to review recent research on the use of control charts to monitor process and product quality profiles and to encourage further research in this area.

Key words

Calibration, functional data analysis, linear regression, multivariate quality control, nonlinear regression, statistical process control, wavelets.

Atuais pesquisas em monitoramento de perfis

Resumo

Em muitas aplicações a qualidade de um processo ou de um produto é melhor caracterizada e descrita por uma relação funcional entre a variável resposta e uma ou mais variáveis explicativas. Monitoramento de perfis é usado para entender e checar a estabilidade desta relação ao longo do tempo. Cada vez que uma amostra é selecionada, uma coleção de pontos que pode ser representada por uma curva (ou perfil) é observada. Em algumas aplicações de calibração, o perfil pode ser representado adequadamente por um modelo de regressão linear simples, enquanto que em outras aplicações, modelos mais complicados serão necessários. Os objetivos deste artigo são: apresentar e resumir pesquisas recentes do uso de cartas de controle para monitorar perfis de processo e qualidade de produto e encorajar futuras pesquisas nesta área.

Palavras-chave

Calibração, análise de dados funcionais, regressão linear, controle de qualidade multivariada, regressão não linear, controle estatístico de processo, ondaletas.

INTRODUCTION

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. These cases appear to be increasingly common in practical applications. For each profile we assume that n ($n > 1$) values of a response variable (Y) are measured along with the corresponding values of one or more explanatory variables (the X 's). Except in the paper by Mosesova *et al.* (2007), it is assumed that each subgroup consists of a single profile. The reader is referred to Woodall *et al.* (2004) or Woodall (2007) for more detailed and comprehensive reviews of profile monitoring methods. This is a relatively new area of research, but it is growing rapidly.

Briefly summarizing, Woodall *et al.* (2004) highlighted the following important issues when monitoring profiles:

1. the usefulness of carefully distinguishing between Phase I and Phase II applications,
2. the decision regarding whether or not to include some between profile variation in common cause variation,
3. the use of methods capable of detecting any type of shift in the shape of the profile, and
4. the use of the simplest adequate profile model.

An effort has been made here not to cite references that were given in Woodall *et al.* (2004). In fact, roughly two-thirds of the fifty or so papers cited in this paper were published in 2006, were published or scheduled to appear in 2007, or are still under review.

Either parametric models or nonparametric methods can be used in both phases. In many cases of profile monitoring it is efficient to summarize the in-control shape of the profile with a parametric model and monitor for shifts in the parameters of this model. The control charts are based on the estimated parameters of the model from successive profile data observed over time. For nonparametric methods one can alternatively monitor metrics that reflect the discrepancies between observed profiles and a baseline profile established using historical Phase I data.

In some cases it is not clear what would be included under the heading of "profile monitoring". Under the definition of profile monitoring used in this paper, applications where times series data are collected on a number of individuals are not necessarily included unless, for instance, at each sampling time point one observes a time series with a differing time index. For example, an important quality of an automobile airbag is the pressure inside the bag as a function of the time since deployment. In this application one would have time series data collected each time an airbag is tested over time. Thus, this would qualify as a profile monitoring application.

The methods of Jiang *et al.* (2007), however, would not qualify as profile monitoring under the definition considered. In their application the data consist of times series for each of a number of customers. Changes in the shape of the customers' time series over time was of interest. Some might refer to the specified shape of the out-of-control shift of univariate time series data as a "profile", but this does not qualify under the definition used here. In addition, cases for which data are collected on multiple time series, which are possibly cross-correlated, are not necessarily included unless a model is used at each time period to represent the response variable. Thus, for example, the method of Brown *et al.* (2004) would not be included as a profile monitoring method, although it is a useful approach. In their application multiple time series data taken along the cross-section of paper during manufacture were broken into successive data segments. A stochastic model was fit to each segment and the estimated parameters were used as input into multivariate control chart methods. In this case, however, there is only one time index and there is no functional data analysis component to the problem.

USE OF SIMPLE LINEAR REGRESSION

Most of the work on profile monitoring has been for the case in which the profile can be adequately represented by a simple linear regression model. Calibration processes are often characterized by such linear functions. Chang and Gan (2006) proposed some Shewhart control charts for monitoring the slopes of relationships between two or more measurement processes in order to assure their accuracy. Monitoring of slopes of regression lines was also considered by Zhu and Lin (2007) in Phase I and in Phase II. Noorossana *et al.* (2004a) proposed a new method for monitoring simple linear regression profiles based on the multivariate control chart method of Healy (1987).

Mahmoud *et al.* (2007) and Zou, Zhang, and Wang (2006) considered change-point methods for detecting changes in the parameters of a simple linear regression model. These authors considered Phase I and Phase II applications, respectively. A self-starting method was proposed by Zou, Wang, and Tsung (2007), which avoids, to the extent possible, the distinction between Phase I and Phase II.

ISO 5725-6(1994) recommended a method for monitoring a linear calibration line based on the measurement of three standards at each time period. These standards are at low, medium and high values, respectively. The three deviations of the measured values from these standards are plotted simultaneously for each sample on a Shewhart-type control chart. Gupta *et al.* (2006) showed, however, that the use of control charts based on the estimated regression parameters is more effective in terms of run length performance. This

latter approach is also more interpretable, particularly as the number of standards measured at each time period increases. The NIST / SEMATECH *e-Handbook of Statistical Methods*, which is freely available online at <http://www.itl.nist.gov/div898/handbook/>, contains a discussion of the on-line methods recommended by ISO 5725-6 (1994).

A standard assumption in the monitoring of simple linear regression profiles is that the errors are independent and identically distributed, usually with an assumed normal distribution. Noorossana *et al.* (2007a, b) studied the effect of ignoring autocorrelation of the errors. Autocorrelated errors frequently occur within profile monitoring data because successive measurements are often made close in space and/or time. Noorossana *et al.* (2004b) studied the effect of non-normality of the error terms, using *t*-distributions as alternatives, on the performance of the EWMA/R method of Kang and Albin (2000).

OTHER PROFILE MODELING APPROACHES

In many applications the simple linear regression model is not sufficient to represent the shape of a profile, so more complicated methods are needed. Some of these models are discussed in this section.

Multiple and Polynomial Regression

Kazemzadeh *et al.* (2007a) and Mahmoud (2007) proposed Phase I methods for profiles represented by polynomial and multiple regression models, respectively. These authors each extended some of the simple linear regression profile methods. In particular, Kazemzadeh *et al.* (2007a) compared the *F*-statistic method of Mahmoud and Woodall (2004), the change-point method of Mahmoud *et al.* (2007), and a method based on T^2 statistics for detecting a step shift in the regression parameters. Mahmoud (2007), on the other hand, compared the *F*-statistic method of Mahmoud and Woodall (2004) with a T^2 -based method. Kazemzadeh *et al.* (2007b) considered the Phase II monitoring of polynomial regression profiles.

Zou, Wang, and Tsung (2007) also considered multiple regression models through a general linear model framework. The authors employed multivariate EWMA charts and considered diagnostic methods after an out-of-control signal, including a change-point approach. An example from semiconductor manufacturing was used as an illustration. A calibration example requiring multiple regression methods was the motivation of the work of Parker and Finley (2007).

Nonlinear Regression Models

Ding *et al.* (2006) used several types of data reduction methods for nonlinear profile data, in particular principal

component analysis and independent component analysis. These authors also studied methods for cluster analysis for profile data.

Williams, Birch, Woodall, and Ferry (2007) used the nonlinear regression approach of Williams, Woodall, and Birch (2007) to monitor dose-response profiles used in high-throughput screening, using illustrative data provided by DuPont. A four-parameter logistic regression model was used to represent the profiles. The focus in these papers was on monitoring the parameters of the nonlinear regression model. Only a couple of forms of nonlinear regression models have been studied thus far in this way.

Moguerza *et al.* (2007) used support vector machines to monitor the fitted curves themselves instead of monitoring the parameters of models fitting the curves. Their approach is contrasted with that of Williams, Woodall, and Birch (2007) using the same set of particleboard vertical density profile data.

Chen and Nembhard (2007) proposed a high-dimensional control chart approach to profile monitoring based on the adaptive Neyman test statistic for the coefficients of discrete Fourier transforms of profiles. They investigated the performance of their method for both linear and nonlinear profiles.

Mixed Models

In most linear models applied to profile data it is assumed that the errors are independent and identically distributed random variables. In some cases, however, the errors may be autocorrelated. This generalization was studied by Jensen *et al.* (2007) and Jensen and Birch (2007) for simple and nonlinear regression, respectively, using mixed models. Jensen and Birch (2007) showed that the use of mixed models could have significant advantages when nonlinear regression models are used.

Mosesova *et al.* (2007) also proposed a mixed model approach with an example from the automotive industry. Among other issues, these authors discussed the issue of curve registration, i.e., aligning the curves prior to analysis. This step is needed in some applications.

Use of Wavelets

Wavelets continue to be a popular way to represent profile data when simple models cannot adequately represent the shape of the profile. Reis and Saraiva (2006) used wavelets to represent the surface of paper. Zhou, Sun and Shi (2007), Jeong, Lu and Wang (2006), and Chicken and Pignatiello (2007) also proposed wavelet-based methods. Wavelet methods are usually recommended when the shape of the profiles is too complicated for linear and nonlinear models to work well. As pointed out by Woodall *et al.* (2004), however, one should keep in mind that monitoring only a subset of

the most significant wavelet coefficients based on in-control data can be dangerous in the sense that some out-of-control function changes will not be detectable.

OTHER APPLICATIONS

The profile monitoring framework includes applications in which numerous measurements of the same variable, e.g., a dimension such as thickness, are made at several locations on each manufactured part. Staudhammer, Maness, and Kozak (2007 a, b) proposed control charting methods for lumber manufacturing. In their application a laser was used to make dimensional measurements along each board at several locations. It was important to detect process faults which could result in boards not being the desired shape. In this application the key out-of-control shapes in the boards could be specified in advance. Schajer *et al.* (2004) described the measurement system used to obtain the lumber profile data.

Colosimo *et al.* (2007 b, d) proposed methods for monitoring dimensional requirements on manufactured items, with a focus on the monitoring of roundness. Colosimo *et al.* (2007a) considered the monitoring of more general shapes and surfaces. Colosimo *et al.* (2007c) compared a principal component approach to a method more commonly used in industry for profile monitoring described by Boeing (1998). The monitoring of shapes is a very promising area of research since the shape of manufactured items is very often an important aspect of quality. These researchers have shown that the standard methods for monitoring shape data are not as efficient as profile monitoring approaches. In some cases the current methods do not use all of the information in the data. For example, a standard metric for measuring roundness is the difference between the radii of the smallest circle containing the circular profile data and the largest circle falling within the profile data.

There have been two papers where the profiles correspond to infrared spectra. Marengo *et al.* (2005) considered an example involving organic pigments applied to cotton surfaces. Sahni *et al.* (2005), on the other hand, considered an example related to the shelf-life of a food product.

Wang and Tsung (2005) used profile monitoring methods to detect changes in a Q-Q plot which reflected the relationship between the current sample and a baseline sample. A closely related approach was proposed by Grimshaw and Alt (1997).

Jin (2004) proposed a very useful and relatively simple method in which the range of the independent X -variable is divided into p segments. A shift within a segment would be associated with a particular type of process fault. The recommendation was to use p -dimensional Hotelling's T^2 methods. This interesting approach is closely related to the approach proposed earlier by Young *et al.* (1999) who were monitoring the density profiles of particleboard. It is very reasonable to break the profile range up into subregions if process faults tend to affect a specific portion of the profile, as opposed to changing the profile over its entire range.

Several authors have discussed monitoring for "cycle-based signals." These signals are obtained using automated sensing during each repetitive operation of a manufacturing process. A common example is the tonnage signal (forming force) as measured by the strain gauge sensors installed on a forging press machine. Zhou *et al.* (2005) presented a method for the monitoring of such profiles when certain specified deviations in the shape of the profiles were known for some process faults. Their method was based on the approach of Healy (1987).

Finally, it was pointed out by Woodall (2006) that profile monitoring ideas could be applied in public health surveillance where the interest is in detecting clusters of increased disease rates over time. Thus, the approach of Zhou and Lawson (2007) would fall into the category of profile monitoring. In this application one can consider the incidence rate pattern to be a surface over the region of interest where the focus is to detect any increase over the in-control rate over any subregion.

CONCLUSIONS

Profile monitoring is very useful in an increasing number of practical applications. Much of the work in the past few years has focused on the use of more effective charting methods, the study of more general shapes of profiles, and the study of the effects of violations of assumptions. There are many promising research topics yet to be pursued given the broad range of profile shapes and possible models. There has been, to my knowledge, no discussion on assessing process capability with profile data. Some information and references have been given in this paper that should be helpful to those interested in research in profile monitoring or in its practical application.

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Acknowledgment

The author appreciates the cooperation of a number of authors in sharing their unpublished work.

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