Available online at www.sciencedirect.com
ScienceDirect
Computers & Industrial Engineering 52 (2007) 502–520
computers & industrial engineering
www.elsevier.com/locate/dsw

Using recurrent neural networks to detect changes in autocorrelated processes for quality monitoring

Massimo Pacella [a,*,1], Quirico Semeraro [b,2]

[a] Dipartimento di Ingegneria dell'Innovazione, Universita' degli Studi di Lecce, Via per Monteroni, 73100 Lecce, Italy
[b] Dipartimento di Meccanica, Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133 Milano, Italy

Received 17 January 2006; received in revised form 19 December 2006; accepted 23 March 2007
Available online 30 March 2007

Abstract

With the growing of automation in manufacturing, process quality characteristics are being measured at higher rates and data are more likely to be autocorrelated. A widely used approach for statistical process monitoring in the case of autocorrelated data is the residual chart. This chart requires that a suitable model has been identified for the time series of process observations before residuals can be obtained. In this work, a new neural-based procedure, which is alleviated from the need for building a time series model, is introduced for quality control in the case of serially correlated data. In particular, the Elman's recurrent neural network is proposed for manufacturing process quality control. Performance comparisons between the neural-based algorithm and several control charts are also presented in the paper in order to validate the approach. Different magnitudes of the process mean shift, under the presence of various levels of autocorrelation, are considered. The simulation results indicate that the neural-based procedure may perform better than other control charting schemes in several instances for both small and large shifts. Given the simplicity of the proposed neural network and its adaptability, this approach is proved from simulation experiments to be a feasible alternative for quality monitoring in the case of autocorrelated process data.

Keywords: Manufacturing; Quality monitoring; ARMA models; Recurrent neural network

1. Introduction

One of the major techniques of Statistical Process Control (SPC) is the control chart introduced by Shewhart. In its basics form, a control chart compares process observations (or a function of such observations) to a pair of control limits. Two fundamental assumptions for the development of a control chart are: (1) the distribution function underlying process data is normal and (2) process data are independently distributed.

* Corresponding author. Tel.: +39 0 832297253; fax: +39 0 832297279.
E-mail addresses: massimo.pacella@unile.it (M. Pacella), quirico.semeraro@polimi.it (Q. Semeraro).
[1] Dr. Pacella is an Assistant Professor in the Department of "Ingegneria dell'Innovazione" at the Universita' degli Studi di Lecce, Italy.
[2] Dr. Semeraro is a Professor in the Department of Mechanical Engineering and Dean of the Faculty of "Ingegneria Industriale" at the Politecnico di Milano, Italy. He is a Member of ASQ.

0360-8352/$ - see front matter
doi:10.1016/j.cie.2007.03.003

The most frequently reported effect on control charts of violating such assumptions is the erroneous assignment of the control limits. Alwan and Roberts (1995) considered a sample of 235 control chart applications and showed that about 85% displayed incorrect control limits. More than half of these displacements were due to violation of the independence assumption. Misplacement of control limits was due to serial correlation (i.e., autocorrelation) in the data.

Autocorrelated data are quite prevalent in process industries (Montgomery, 2000). Also in manufacturing, process data may present various types of temporal dependencies. Significant examples can be found in forging operations or extruding processes (Wardell, Moskowitz, & Plante, 1994). When data exhibits autocorrelation, control methods, which allow for violations of the independence assumption, must be used.

A common approach is to filter out autocorrelation by an autoregressive integrated moving average (ARIMA) model, following the techniques of Box et al. (Box, Jenkins, & Reinsel, 1994). If the time series model is accurate enough, the residuals (i.e., the prediction errors) are statistically uncorrelated to each other, and common control charts can be applied to them. However, time series modeling may be often awkward in actual applications (Zhang, 1998; Jiang, Tsui, & Woodall, 2000). For example, Stone and Taylor (1995) reported a few of industrial processes that exhibit temporal dependencies in their natural output, which were not adequately handled by the standard time series models.

In this work, autocorrelated data obtained from stationary processes are considered. Stationary processes are more commonly encountered in the manufacturing environment (Wardell et al., 1994; Zhang, 1998; Jiang et al., 2000). For statistical process monitoring, a stationary process, which has constant mean and constant variance, may undergo shifts in the mean and such shifts are to be detected as quickly as possible. The first order autoregressive first order moving average ARMA$(1,1)$ stationary model has been considered in the present research as reference test case (Box et al., 1994).

Witnessing the increasing capability of artificial neural networks (NNs) in modeling real systems, there is a great interest in NNs for quality monitoring. Among various models of NN, recurrent neural networks, exemplified by the Elman's NN (ENN), have been shown to be useful for time series modeling. The ENN employs feedback connections and addresses the temporal relationship of its inputs by maintaining an internal state (Elman, 1990). In this paper, the ENN is investigated for the problem of process monitoring in the case of autocorrelated data. Performance comparisons between the neural-based algorithm and several control charts are also presented in order to validate the approach. Different magnitudes of mean shift are considered under the presence of various levels of autocorrelation.

The paper is structured as follows. In Section 2, statistics-based control charts for autocorrelated data are reviewed. A few of neural-based control schemes are also analyzed. In Section 3, the stationary ARMA$(1,1)$ model, which is used as reference throughout the paper, is discussed. In Section 4, the ENN is presented, while in subsequent Section 5, the ENN training is discussed in the case of autocorrelated data. In Section 6, the performance are analyzed and compared to those of the major statistics-based control charts for autocorrelated data. Section 7 concludes the paper with a summary and remarks.

2. Review of control techniques

2.1. Statistics-based charting techniques

Three statistics-based charting techniques may be adopted to handle autocorrelation:

1. Time series model to fit the autocorrelated data combined to common Shewhart's control chart to monitor the residuals.
2. Control chart with adjusted control limits, which account for the autocorrelation of observations, to monitor process data.
3. Control chart of specialized statistics of the autocorrelated data.

The first technique was proposed by Alwan and Roberts (1988), which presented the use of time series modeling to signal assignable causes of variation by using the special-cause control (SCC) chart. The SCC chart is the Shewhart's chart of the residuals. The basic idea of the SCC chart is that if the common cause of the