Computers & Industrial Engineering 62 (2012) 1093–1108

Contents lists available at SciVerse ScienceDirect

Computers & Industrial Engineering

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

Neural networks for detecting cyclic behavior in autocorrelated process ☆

Ussanee Purintrapiban [a,*], H.W. Corley [b]

[a] Department of Production Engineering, King Mongkut's University of Technology Thonburi, 126 Pracha-utid Road, Bangmod, Toongkru, Bangkok 10140, Thailand
[b] Department of Industrial and Manufacturing Systems Engineering, University of Texas at Arlington, 420 Woolf Hall, 500 W. First Street, Arlington, TX 76019, United States

ARTICLE INFO

Article history:
Received 13 March 2011
Received in revised form 6 January 2012
Accepted 7 January 2012
Available online 14 January 2012

Keywords:
Neural networks
Pattern detection
Cyclical pattern
Autocorrelated data

ABSTRACT

In quality control area, cyclic behavior is one of the signals indicating an out-of-control situation in a manufacturing process. Neural network (NN)-based approaches have been proposed to detect the cyclical pattern in the data set collected from process. However, virtually all such proposed methods assume that the process data is independent and identically distributed when the process is under control. In other words, data from a manufacturing process is assumed uncorrelated. In this paper, a NN-based model for detecting the cyclical pattern in an autocorrelated process is proposed. After collecting the process data, this data set is preprocessed using the same information needed to calculate the fractal dimension of the data. It is then fed to a trained feedforward NN with a scaled conjugate gradient backpropagation training algorithm. An output of the model is the state of the process, i.e., whether the process is in-control or out-of-control with a particular cycle period. Such information can assist users of a manufacturing process to identify and remove the underlying causes of the out-of-control state. Our approach is thus suitable for automated manufacturing environment as a supplementary tool to traditional control charts. A Monte Carlo simulation was carried out to study performance of our proposed model. The results showed that the neural-based approach can quickly detect the cyclical pattern with better than 90% accuracy when the signal-to-noise ratio is greater than or equal 2.00. It performs well not only on autocorrelated data for a wide range of autoregressive coefficients, but also on uncorrelated data.

1. Introduction

Cyclic behavior is one of the signals indicating an out-of-control situation in a manufacturing process. These situations may be caused by the seasonal variations in incoming materials; in the recurring effects of temperature and humidity (cold morning start-up); in any daily or weekly chemical, mechanical, or psychological events; and in the periodic rotation of operators (Beneke, Leemis, Schlegel, & Foote, 1988). Identifying the presence of a cyclic pattern will assist users in the investigation of the causes underlying in the out-of-control state and hopefully lead to proper corrective actions.

To detect the cyclical pattern, there are generally two different approaches—the statistical-based approach and the neural network (NN)-based approach. The statistical-based approach is used by Sahrmann (1979), Al-Ghanim and Kamat (1995), Johnson and Counts (1979), Beneke et al. (1988), and Spurrier and Thombs (1990). Sahrmann (1979) presented a method that involved a Box–Jenkins model to estimate the amplitude of cycle data. Al-Ghanim and Kamat (1995) developed a methodology based on statistical correlation analysis. The others proposed control charts for detecting cycle so that the statistics are calculated, plotted, and used to give an out-of-control alarm when some statistic is beyond the prescribed control limits.

The NN-based approach was introduced to recognize control chart patterns (CCPs) in an automated environment by reason of automating control chart interpretation (Zorriassatine & Tannock, 1998). Studies on this issue can be divided into two categories—general-purpose and special-purpose CCP recognitions (CCPRs) (Hwarng, 1995a; Hwarng, 1995b). The first category utilizes NNs for recognizing multiple patterns on control chart. Related literature includes Perry, Spoerre, and Velasco (2001), Hassan, Baksh, Shaharoun, and Jamaluddin (2003), Al-Assaf (2004), Guh and Shiue (2005), Guh and Shiue (2010), and Gauri and Chakraborty (2009). Related works proposed in the late 1980s and the 1990s were reviewed in Zorriassatine and Tannock (1998). Although the general-purpose CCPR systems can effectively detect a cyclic pattern occurring in a process, previous work does not provide information about the cycle parameters of amplitude or period of cycle. Such information would be useful for identifying the root cause(s) of the out-of-control state and for determining corrective actions.

For a special-purpose CCPR, NNs have been adopted to identify certain details in a specific type of unnatural CCP. Hwarng (1995a), Hwarng (1997) suggested that this category is preferable for process with a particular type of unnatural behavior occurring

☆ This manuscript was processed by Area Editor H.-S. Jacob Tsao.
* Corresponding author. Tel.: +66 2 4709175; fax: +66 2 872 9081.
E-mail address: ussaneei.pur@kmutt.ac.th (U. Purintrapiban).

0360-8352/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
doi:10.1016/j.cie.2012.01.002

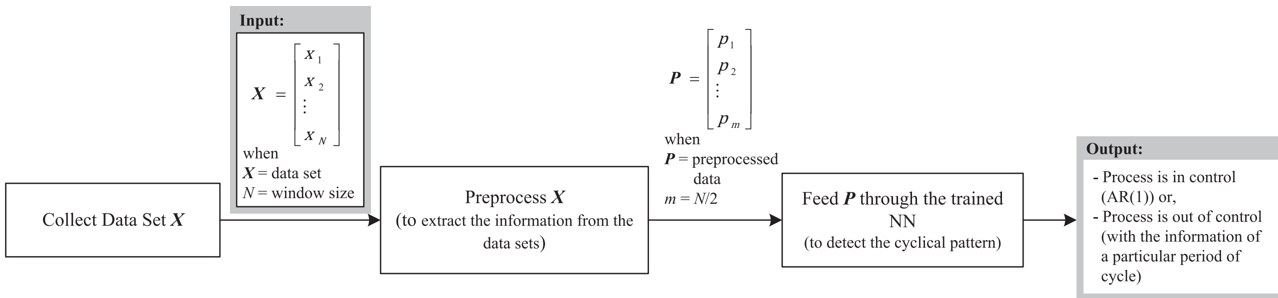

Fig. 1. Schematic diagram of NN for detecting cyclic behavior in autocorrelated process.

dominantly. Focused only on a cyclic pattern, Hwarng (1995a, 1997) presented CCPRs for identifying an amplitude value of a cyclic pattern at a fixed period value. Hwarng (1995b) additionally proposed a NN-based system to identify the period of a cycle. This system consisted of multiple multilayer perceptrons (MLP) with each perceptron corresponding to the cycle of a fixed period value. In this model, however, the false alarm rate tends to increase with the number of MLP. Purintrapiban, Kachitvichyanukul, and Ullah (2003) subsequently designed a single MLP NN for detecting the period value of a cycle at various amplitudes.

However, virtually all NN-based approaches in the literature apply only to independently and identically distributed (i.i.d.) process data. In other words, data collected from a manufacturing process are almost invariably assumed uncorrelated. Unfortunately, modern manufacturing processes frequently do not meet this requirement. For example, with feedback control method and sensor technologies, the collected data are serially correlated in time, i.e., autocorrelated (Castillo, 2002; Montgomery, 2009). Cheng and Cheng (2008), Guh (2008), Lu, Wu, Keng, and Chiu (2008), Noorossana, Farrokhi, and Saghaei (2003), and Shao and Chiu (1999) developed general-purpose CCPRs to deal with CCPs in the presence of autocorrelation. Still, even for an i.i.d. process, these CCPRs do not yield the required parameters of an individual pattern. Although the other studies are about special-purpose CCP recognizers as demonstrated in Chiu, Chen, and Lee (2001), Chiu, Shao, Lee, and Lee (2003), Cook and Chiu (1998), Hwarng (2004), Hwarng (2005), Pacella and Semeraro (2007), Yu and Xi (2008), and Zobel, Cook, and Nottingham (2004), they intended to detect a shift pattern in autocorrelated processes. The contribution of this paper is that we propose NN-based special-purpose CCP recognizer for a cyclic pattern in an autocorrelated process.

The paper is organized as follows. In Section 2, the details of the proposed system are described. Section 3 contains the description of the experiments, the performance measures, and the analysis of results. Our conclusions are discussed in Section 4.

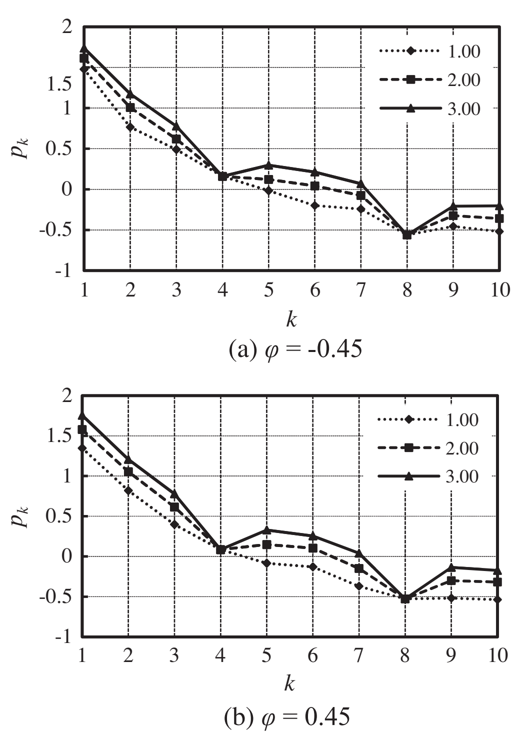

Fig. 2. Graphs of the preprocessed data sets (at period = 4 with various cycle amplitude).

2. NN for detecting cyclic behavior in autocorrelated process

A NN-based model is proposed to detect the cyclical pattern in an autocorrelated process. A schematic diagram of the NN model is presented in Fig. 1.

The input of the proposed model is a set of measurements of product characteristic from the given process. This data set is preprocessed using the same information as needed to calculate the fractal dimension of the process data as in Purintrapiban and Kachitvichyanukul (2003). The preprocessed data is then fed to a trained neural network. If the output of the network is a particular period of a cyclical pattern, the process should be studied and corrective actions taken to remove these unusual sources of the out-of-control situation. Otherwise the process can continue without change.

The following assumptions are made for our NN approach. First, the process under consideration produces a univariate product quality characteristic. Second, the data represent a stable AR(1) time series model with a specific autoregressive coefficient when the process is under control. Third, only one particular period of cycle is included in each set of time series data. Under these assumptions, our model consists of five major components: (1) pattern generation, (2) data preprocessing, (3) neural network architecture, (4) network training, and (5) detecting cyclic behavior. Each component is described in the following sections.

2.1. Pattern generation

We first describe how our simulated data set was generated to test our NN approach. The study assumes that the user intends to detect a cyclic pattern in manufacturing process that can be specified in a form similar to a data set generated by the pattern generator.

The AR(1) model selected to represent the autocorrelated process is:

$$Z_t = \mu + \phi(Z_{t-1} - \mu) + \varepsilon_t, t = 1, 2, \ldots, T, \tag{1}$$