Available online at www.sciencedirect.com
ScienceDirect
Applied Mathematics and Computation 188 (2007) 262–270
APPLIED MATHEMATICS AND COMPUTATION
www.elsevier.com/locate/amc

Monitoring high-yields processes with defects count in nonconforming items by artificial neural network

Babak Abbasi, Seyed Taghi Akhavan Niaki *

Department of Industrial Engineering, Sharif University of Technology P.O. Box 11365-9414 Azadi Avenue, Tehran, Iran

Abstract

In high-yields process monitoring, the Geometric distribution is particularly useful to control the cumulative counts of conforming (CCC) items. However, in some instances the number of defects on a nonconforming observation is also of important application and must be monitored. For the latter case, the use of the generalized Poisson distribution and hence simultaneously implementation of two control charts (CCC & C charts) is recommended in the literature. In this paper, we propose an artificial neural network approach to monitor high-yields processes in which not only the cumulative counts of conforming items but also the number of defects on nonconforming items is monitored. In order to demonstrate the application of the proposed network and to evaluate the performance of the proposed methodology we present two numerical examples and compare the results with the ones obtained from the application of two separate control charts (CCC & C charts).

Keywords: High-yields processes; Generalized Poisson model; Statistical process control; Artificial neural network

1. Introduction

Traditional attribute control charts, such as *p* and *c* charts, are not suitable in automated high-yield manufacturing and continuous production processes. Although there are some procedures to improve the performance of *p* chart when the proportion of nonconforming is low Acosta-Mejia [1], these procedures are not applicable to the cases of continuous inspection or when the defect rate is very low Woodall [17]. For such a process, the quality level is usually at parts per million (ppm), or almost zero defects, so that even for a sample size of thousands, usually no nonconforming item is observed. For these processes, Goh, Kaminsky et al., Glushkovsky, Xie and Goh, Nelson [8,12,7,19,20,14] recommend applying the cumulative count of conforming (CCC) chart. In this chart, which is based on the geometric distribution, we count the cumulative conforming items until the first nonconforming item is observed.

* Corresponding author.
E-mail addresses: b_abbasi@mehr.sharif.edu (B. Abbasi), Niaki@Sharif.edu (S.T. Akhavan Niaki).

0096-3003/$ - see front matter
doi:10.1016/j.amc.2006.09.114

In high-quality processes, there are many instances such that when we observe a nonconforming item, the number of defects in the nonconforming item is of an important use too. As an example, we may refer to Xie and Goh [18] who present a real example of computer hard disks manufacturing process. For these situations, He et al. [11] show that the generalized Poisson distribution (GPD) is very useful and fits these processes very well, especially when the ratio of the sample variance to the sample mean is significantly larger than one. This is the case in high quality processes (see Lambert, Xie and Goh, Collica et al. [13,18,4] for more details of over desperation processes). He et al. [11] present control charts based on Generalized Poisson distribution for high quality process with number of defects in nonconforming item. They recommend the application of two control charts simultaneously to monitor the interval between two nonconforming items (the CCC chart) and the number of defects on the nonconforming item (the C chart). We note that when we apply two separate univariate control charts for multivariate cases simultaneously, the determination of type one error becomes a problem. Another serious problem arises in situations in which both deterioration on the cumulative counts of conforming and improvement on the number of defects on the nonconforming item occur at the same time such that the overall out-of-control condition cannot be detected.

In this paper, we present an artificial neural network (ANN) based approach to monitor high-yields processes. We design the network such that it not only controls both the interval between two nonconforming items and the number of defects on the nonconforming item simultaneously, but will also be able to detect different magnitudes of mean-shifts. To do this, first in Section 2 we briefly explain the procedure proposed by He et al. [11]. Then in Section 3, we explain the fundamentals of neural network, the Perseptron neural networks, and the training process. In Section 4, we introduce neural network modeling applied for high-yield process monitoring. We present two simulation examples to illustrate the proposed method and to compare its performance with He et al.'s [11] procedure in Section 5. Conclusion and recommendations for future research will come in Section 6.

2. High-yields process monitoring based on simultaneous CCC & C charts

When the data from a high-yields process is coming from a generalized Poisson model, He et al. [11] propose a procedure using two simultaneous control charts. In the generalized Poisson distribution (GPD), we assume that the overall probability of finding x defects in a product is

$$P_x(\theta,\lambda)=\frac{\theta(\theta+x\lambda)^{x-1}\,\mathrm{e}^{-\theta-x\lambda}}{x!},\quad x=0,1,2\ldots,\quad \lambda\geqslant 0 \tag{1}$$

in which the probability of nonconforming, (p), is equal to $1-\mathrm{e}^{-\theta}$. If θ increases, the defective rate of the process increases and vise-versa. Hence, θ shows the defective rate of the process. For the parameter λ, on one hand, we can see that when λ is small; there will be some small but frequent non-zero counts. On the other hand, when λ increases, we will observe larger but less frequent non-zero counts. Therefore, we can interpret λ as the size of non-zero count. Using these interoperations, He et al. [11] apply two separate control charts to monitor parameters of a GPD. They use a geometric chart (CCC chart) to monitor parameter θ and apply a chart to control λ. For the CCC chart, after defining the probability of false alarm rate, α_{ccc}, the control limits are

$$\mathrm{UCL}_{\mathrm{ccc}}=\frac{\ln(\frac{\alpha_{\mathrm{ccc}}}{2})}{\ln(1-p)},\quad \mathrm{CL}_{\mathrm{ccc}}=\frac{\ln(0.5)}{\ln(1-p)},\quad \text{and}\quad LCL_{\mathrm{ccc}}=\frac{\ln(1-\frac{\alpha_{\mathrm{ccc}}}{2})}{\ln(1-p)}. \tag{2}$$

Then we monitor the parameter θ by plotting the cumulative conforming counts on this chart.

For the C chart, noting that the non-conformities only occur under the condition that the product is nonconforming, we obtain the control limits by conditioning, i.e.:P(k non-conformities/non-conforming) = $P(x=k/x>0)=\frac{\theta(\theta+k\lambda)^{k-1}\,\mathrm{e}^{-\theta-k\lambda}}{k!(1-\mathrm{e}^{-\theta})}, k=0,1,2,\ldots$. This is called zero-truncated generalized Poisson distribution [5] and the mean and variance of this distribution are

$$\begin{aligned}&E(X)=\theta(1-\lambda)^{-1}(1-\mathrm{e}^{-\theta})^{-1},\\&\mathrm{Var}(X)=\left[\theta(1-\lambda)^{-3}+\theta^2(1-\lambda)^{-2}\right](1-\mathrm{e}^{-\theta})^{-1}-\theta^2(1-\lambda)^{-2}(1-\mathrm{e}^{-\theta})^{-2}.\end{aligned} \tag{3}$$