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A demerit-fuzzy rating system, monitoring scheme and classification for manufacturing processes

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ABSTRACT

For monitoring online manufacturing processes, the proportion of weights imposed on each type of product's defects (nonconformities or demerits) has a profoundly effective impact on control charts' performance. Apparently, the demerit-chart approach is superior than the widely-used *c*-chart scheme, because it allows us to place relative precise weights (real numbers) on defects according to their distinctly inferior degrees affecting the product quality so that the abnormal variations of processes can be literally exposed. However, in many applications, the seriousness of defects is evaluated partially or entirely by the inspectors' perceptive judgement or knowledge, so with the precise-weight assignment, the demerit rating mechanism is considered to be somewhat constrained and subjective which inevitably leads to the targeted manufacturing process with limited and possibly biased information for online surveillance. To cope with the drawback, a demerit-fuzzy rating system and monitoring scheme is proposed in this paper. We first incorporate fuzzy weights (fuzzy numbers) to properly reflect the severity measures of defects which are categorized linguistically. Then, based on properties of fuzzy set theory and proposed approaches for fuzzy-number ranking, we develop the demerit-fuzzy charting scheme which is capable of discriminating process conditions into multi-intermittent statuses between in-control and out-of-control. This approach improves the traditional process control techniques with the binary-classification restraint for the process conditions. Finally, the proposed demerit-fuzzy rating system, monitoring scheme, and classification is elucidated by an application in garment industry to monitor textile-stitching nonconformities conditions.

1. Introduction

Intensified competition in the global marketplace has made organizations around the world realize that their survival highly depends on whether their provided products or services meet or surpass customer's expectations. In general, they must ensure that their products are produced by a stable and repeatable process; that is, outcomes of critical-to-quality (CTQ) characteristics of the products have small variability around their nominal dimensions. The statistical process control (SPC), a powerful collection of problem-solving tools, is useful for process variability reduction and achieving the process stability and capability (Chen, Chang, & Chiu, 2008; Kaya & Kahraman, 2011). Among them, the control charts are commonly used to keep continuing records of the CTQ characteristics. Their merits lie in the ability of online monitoring to scrutinize the process shifts and to indicate the abnormal conditions (Evans & Lindsay, 2011; Peng, Chen, Yu, Zhou, & Sun, 2008). Thus, Kaya and Kahraman (2011) claimed that it is the best to first use control charts to check if a process is in statistical control before it is further analyzed with process capability analysis (PCA).

For many applications, functions of their product's CTQ characteristics, such as appearance, color, sensory types, among others, are always partially or fully assessed by the inspectors' visual or perceived impression mainly due to difficulty of being measured numerically and accurately (Kanagawa, Tamaki, & Ohta, 1993; Raz & Wang, 1990; Wang & Raz, 1990; Yanger & Filev, 1993). In such cases, based on the number of defects found on the CTQ characteristics, each inspected item is placed into either a conforming or nonconforming group, where the readings are called attribute data. For controlling and monitoring this type of data, Woodall (1997) compiled comprehensive contemporary articles and shed new light on the future research. The *c*-chart is suitably used for controlling a single type of defect in the inspection unit because

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it counts each defect affecting equally on the product as well as the process. Though the c-chart is usually used in monitoring the wafer defects in IC manufacturing, Hsieh, Tong, and Wang (2007) pointed that it results in more false alarming signals.

Especially, in modern advanced processes, it is found that the types of defects observed from the inspected unit are not always of equal degrees of seriousness. While some defects are slightly minor, others can be moderate or very severe. Hence, the better way is to categorize different types of defects according to their inferior grade impacting on the product's quality performance. Jones, Woodall, and Conerly (1999) and Chen (2005) provided a linguistic classification scheme for some types of defects such as "class A defects-very serious", "class B defects-serious", "class C defects-moderately serious", and "class D defects-not serious". This scheme also proportionally rates each class with a precise weight for manifesting its grouped defects impairing on the product's quality. The calculation of a demerit statistic which sums the weighted defect results for each class is similar to the c statistic, except the latter has only one classification of defects. It can be noted that the proportion of weights given on each type of product defect has a significantly effective impact on the control charts performance for monitoring online manufacturing processes (Chen, 2005; Jones et al., 1999). Ostensibly, the demerit chart is more effective than the c-chart, because it permits the arrangement of a relative precise-weight (real number), according to different severity degrees of defects, where the abnormal problems of processes can be exactly revealed.

Although the traditional demerit chart inherits the excellent weighting scheme in line with severity degrees of defects, it suffers certain limitation when the expert's knowledge is inevitably incorporated into the linguistic classification of defects (Alipour & Noorossana, 2010; Perrone, Zinno, & Noto LA Diega, 2001), where the weighting rate for each classification is a fuzzy number (Chen, 2005, 1968, 1975a, 1975b, 1975c). In other words, the crisp-weight defect assignment for the chart is somewhat constrained and subjective, which leads to the targeted manufacturing process with limited and possibly biased information for online surveillance. The similar view can be referred to researches by Kanagawa et al. (1993), Filzmoser and Viertl (2004), Viertl and Hareter (2004), Cheng (2005), Gülbay and Kahraman (2006, 2007) and Shu and Wu (2010, 2011). Chen (2005) established a fuzzy demerit control chart with a ranking method using α-cuts. However, the approach significantly increases the risk of losing fuzziness information residing in the raw data which could possibly lead to misclassification of the manufacturing process condition (Chen, 2005; Guo, Zhao, & Cheng, 2008; Shu & Wu, 2011). To fulfill the voids, in this paper, we propose a new demerit-fuzzy rating mechanism and monitoring scheme for the online manufacturing processes, which can efficiently classify a process into four statuses: in-control, rather in-control, rather out-of-control, and out-of-control in order to offer an economic consideration to avoid unnecessary adjustment to the current process if the set-up cost is large and/or intolerable.

This paper is organized as follows. Section 2 briefly reviews the construction of the traditional demerit chart. The fuzzy set theory and properties used in this paper are introduced in Section 3. In order to adequately reflect the seriousness measures of defects which are categorized linguistically, we develop a demerit-fuzzy rating mechanism by carrying out the fuzzy-weight defects assignment in Section 4. Section 5 is used to present the construction of membership functions of upper and lower control limits based on the resolution identity property. In Section 6, for realizing the process situations, a new fuzzy-number ranking method developed from Yu and Dat's (2014) approach is used to identify the relationships between each demerit-fuzzy sample with the fuzzy-upper and fuzzy-lower control limits. It improves the restraints of binary classifications of the process conditions used by the traditional demerit chart. The proposed demerit-fuzzy chart is elucidated in Section 7 with an application in garment industry to monitor stitching defects because the quality of stitching is one of the key factors to determine the quality of garments (Wong, Yuen, Fan, Chan, & Fung, 2009). Some concluding remarks make up the last section.

2. Precise-weighting demerit chart

We now briefly review the construction of a crisp-weighting demerit chart which was first proposed by Dodge (1928) and reviewed by Chen (2005). Let D be the demerit statistic, defined as a precise-weighted sum of q categories of defects for each sample. Suppose that, in any sample, the occurrence of defects within each category is well modeled by a Poisson distribution with mean defects λ_k $(k = \overline{1,q})$, where their corresponding precise weights are w_k. All samples are mutually independent. In this case, the mean (Chang, Chen, Chen, & Huang, 2008) and variance of the demerit statistic D (Chen, 2005) are given by

$$\mathbb{E}(D) = \sum_{k=1}^{q} w_k \lambda_k \quad \text{and} \quad \mathrm{Var}(D) = \sum_{k=1}^{q} w_k^2 \lambda_k \tag{1}$$

In general, the precise-weighting demerit chart adopts the center line (CL), the usual upper (UCL) and lower control limits (LCL), where

$$\begin{aligned} UCL &= \sum_{k=1}^{q} w_k \lambda_k + K\sqrt{\sum_{k=1}^{q} w_k^2 \lambda_k} \\ CL &= \sum_{k=1}^{q} w_k \lambda_k \\ LCL &= \max\left\{ \sum_{k=1}^{q} w_k \lambda_k - K\sqrt{\sum_{k=1}^{q} w_k^2 \lambda_k}, 0 \right\} \end{aligned} \tag{2}$$

where K is the number of standard deviation units (also called *sigma*) that are allowed as tolerance. It is actually the distance between the center line to a control limit, and is usually assigned with a value of 3 to avoid false alarms (Chen, 2005; Montgomery, 2009; Nembhard & Nembhard, 2000). Thus, $K = 3$ is used in this study.

In practice, the parameters λ_k $(k = \overline{1,q})$ are unknown. Therefore, they must be estimated from preliminary samples taken from the underlying process that is thought to be in control. These estimates are usually well estimated based on more than 20 drawn samples. Suppose that s samples have been collected, where each sample contains n products or service. From practitioners' visual inspection on their CTQ characteristics, q different classes of defects are categorized. d_{ijk} is denoted as a number of defects within defect class k for the jth observation in sample i, where $i = \overline{1,s}; j = \overline{1,n}$ and $k = \overline{1,q}$. Fig. 3 displays defects data from an inspected process.

Therefore, from the observed sample ith, the total number of defects in class k is

$$d_{i\cdot k} = \sum_{j=1}^{n} d_{ijk} \tag{3}$$

For all s samples, the total number $(d_{\cdot\cdot k})$ and its average $(\bar{d}_{\cdot\cdot k})$ of defects in class k are respectively given by

$$d_{\cdot\cdot k} = \sum_{i=1}^{s}\sum_{j=1}^{n} d_{ijk} = \sum_{i=1}^{s} d_{i\cdot k} \tag{4}$$

$$\bar{d}_{\cdot\cdot k} = \frac{d_{\cdot\cdot k}}{s} = \frac{1}{s}\sum_{i=1}^{s}\sum_{j=1}^{n} d_{ijk} \tag{5}$$