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Quality-based supplier selection and evaluation using fuzzy data

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ABSTRACT

Since fuzzy quality data are ubiquitous in the real world, under this fuzzy environment, the supplier selection and evaluation on the basis of the quality criterion is proposed in this paper. The C_{pk} index has been the most popular one used to evaluate the quality of supplier's products. Using fuzzy data collected from $q \geqslant 2$ possible suppliers' products, fuzzy estimates of q suppliers' capability indices C_{pki} $(i = 1, 2, \ldots, q)$ are obtained according to the form of resolution identity that is a well-known theorem in fuzzy sets theory. Certain optimization problems are formulated and solved to obtain α-level sets for the purpose of constructing the membership functions of fuzzy estimates of C_{pki}. These membership functions are sorted by using a fuzzy ranking method to choose the preferable suppliers. Finally, a numerical example is illustrated to present the possible application by incorporating fuzzy data into the quality-based supplier selection and evaluation.

1. Introduction

Nowadays rising customers' expectations as well as increasing the product quality are becoming an important strategic priority in the pretty competitive global business environment. Manufacturers must produce the correct products at the accurate time and deliver them promptly to customers to sustain their competitive advantage in the marketplace (Hensler, 1994; Hutt & Speh, 2006). Manufacturers increasingly purchase components from suppliers or hire contract manufacturers to produce necessary parts, and they assemble these parts to deliver finished products to customers. In the automotive industry, the cost of components and parts purchased from outside vendors have increased up to 50% of their revenues (Weber, Current, & Benton, 1991). The high technology firms spend more than 80% of total product costs on purchasing materials and services (Burton, 1988; Carr & Pearson, 1999). Obviously, the quality of parts obtained from suppliers determines the quality of the finished products produced by manufacturers as well as the customers' satisfaction and loyalty. Therefore, the evaluation of supplier performance and selection of suppliers are becoming major challenges faced by the manufacturing and purchasing managers (ASQC, 1981).

Assessing a group of suppliers and selecting one or more of them are a complex task because various criteria must be considered in the decision-making process such as quality, cost, goodwill, service, delivery time, and environmental impact (Humphreys, Wong, & Chan, 2003). According to research conducted by Dickson (1966), quality and delivery are two of the most demanded items by component suppliers. Twenty five years after Dickson's research, Weber et al. (1991) still considered quality to be of "extreme importance" and delivery to be of "considerable importance". According to Weber's research on the Just-In-Time (JIT) model, the importance of quality and delivery remains the same. Pearson and Ellram (1995) surveyed 210 members of the National Association of Purchasing Management (NAPM), who were randomly selected from the listings of electronic firms in the two-digit SIC code 38, and they indicated that quality is the most important criterion in the selection and evaluation of suppliers for both the small and large electronic firms that were surveyed. Moreover, according to the survey of current and potential outsourcing end-users by the Outsourcing Institute (2003), the top 10 factors in vendor selection are commitment to quality, price, reference/reputation, flexible contract terms, scope of resources, additional value-added capability, cultural match, existing relationship, location, and others. Quality is still the most important factor for selecting the preferred suppliers. Furthermore, Olhager and Selldin (2004) investigated the strategies and practices in the supply chain management using the sample of 128 Swedish manufacturing firms, and concluded that many aspects are important when companies choose supply chain partners, but quality is the most important criterion. In other words, based on the above works, quality can be seen as a fundamental factor for supplier evaluation among various criteria.

Quality affects the productivity and business performance in both industrial and customers' organizations. Much evidence

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suggests that high quality has a positive impact upon significantly increasing profitability, through lowering operating costs and improving market share (Garvin, 1988; Maani, 1989; Phillips, Chang, & Buzzell, 1983; Voehl, Jackson, & Ashton, 1994). Kane (1986) stated that the quantification of the process mean and variation is central to understanding the quality of the components produced from a manufacturing process. This fact brings a issue of quality-based supplier selection and evaluation by process capability indices (PCIs) into the main focus of this research.

The first PCI appearing in the literature was the precision index and it was proposed by Juran (1974) and Kane (1986) and defined as

$$C_p = \frac{USL - LSL}{6\sigma}, \tag{1}$$

where USL stands for the upper specification limit, LSL stands for the lower specification limit, and σ stands for the process standard deviation. The index C_p measures process precision (consistency of quality). However, it does not consider whether the process is centered. By considering the magnitude of process variance as well as the location of process mean, the C_{pk} index is defined as

$$C_{pk} = \min\left\{\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\}, \tag{2}$$

which has been the most popular one used in the manufacturing industry (Kane, 1986; Kotz & Lovelace, 1998). Montgomery (2005) recommended some minimum capability requirements for performing the manufacturing processes under some certain designated quality conditions. For example, $C_{pk} \geqslant 1.33$ is for the existing processes, and $C_{pk} \geqslant 1.50$ is for the new processes. On the other hand, $C_{pk} \geqslant 1.50$ is also for the existing processes on safety, strength, or critical parameter, and $C_{pk} \geqslant 1.67$ is for the new processes on safety, strength, or critical parameter. Finley (1992) also found that the required values on all critical supplier processes are 1.33 or higher, and the C_{pk} values of 1.67 or higher are preferred. Many companies have recently adopted criteria for evaluating their processes that include more stringent process capability. Motorola's "Six Sigma" program essentially requires the process capability to be at least 2.0 to conform the possible 1.5σ process shift (Harry, 1988).

The supplier certifications in the manuals of ISO 9000 and QS-9000 include a detailed procedure in evaluating supplier's products on the basis of the most well-known C_{pk} index. For a purchasing contract, a minimum value of C_{pk} is usually specified. If the prescribed minimum C_{pk} fails to be met, then the supplier is verified to be incapable. Otherwise, the supplier is evaluated to be capable. Naturally, we can investigate the supplier selection and evaluation for the case with $q \geqslant 2$ candidate suppliers' products by using the C_{pk} index.

Let P_i be the products population of ith supplier with the mean μ_i and variance σ_i^2 where $i = 1, 2, \ldots, q$. The capability index C_{pki} indicated the quality of the ith supplier's products can be defined as

$$C_{pki} = \min\left\{\frac{USL - \mu_i}{3\sigma_i}, \frac{\mu_i - LSL}{3\sigma_i}\right\} \tag{3}$$

for $i = 1, \ldots, q$.

Conceptually, in evaluating a group of suppliers and further selecting one or more of them, the assessment requires knowledge of μ_i and σ_i obtained from each supplier's products in Eq. (3). However, the μ_i and σ_i are usually unknown. In this case, to assess the appropriate suppliers, sample data must be collected from suppliers in order to estimate C_{pki}. Let $x_{i1}, x_{i2}, \ldots, x_{in_i}$ be independent random samples from P_i for $i = 1, 2, \ldots, q$. Generally, the underlying data obtained from the output responses of each supplier's products are always assumed to be real numbers. Such a situation, Pearn, Kotz, and Johnson (1992), Pearn and Shu (2003) and Prasad and Calis (1999) have used the statistical point estimate $\hat{c}_{pki}$ on C_{pki} by

$$\hat{c}_{pki} = \min\left\{\frac{USL - \bar{x}_i}{3s_i}, \frac{\bar{x}_i - LSL}{3s_i}\right\}, \tag{4}$$

where the mean μ_i in Eq. (3) is substituted by the sample mean $\bar{x}_i$

$$\bar{x}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} x_{ij}$$

and the standard deviation σ_i in Eq. (3) is substituted by the sample standard deviation s_i

$$s_i = \left[\frac{1}{n_i - 1}\sum_{j=1}^{n_i}(x_{ij} - \bar{x}_i)^2\right]^{1/2}$$

for $i = 1, 2, \ldots, q$.

However, in the practical situations, data collected from the key quality characteristic of suppliers' products are often somewhat imprecise (fuzzy). For example, the data may be given by color intensity of pictures or by the readings on an analogue measurement equipment, as in the studies of Filzmoser and Viertl (2004) and Viertl and Hareter (2004). In addition, the imprecise data may be given by scarce sample data, e.g., the observations made with coarse scales, linguistic data, or data collected with vague and incomplete knowledge, as discussed by Gulbay and Kahraman (2007) and Sugano (2006). Lee (2001) and Hong (2004) indicated that the measurements partly carried out by the decision-makers subjective determination can also be seen to be fuzzy numbers. In their studies, the estimation of C_{pk} index was proposed using fuzzy data.

In this paper, we study the quality-based supplier selection and evaluation using fuzzy data, which was not seriously treated by the researchers. The paper is organized as follows. In Section 2, we introduce the basic properties of fuzzy numbers. In Section 3, we discuss the fuzzy estimate of C_{pki} by considering fuzzy quality data collected from suppliers. Using the form of resolution identity theorem, the membership function of the fuzzy estimate of C_{pki} for each supplier is obtained. In order to compute the membership degrees, some optimization problems are formulated. In Section 4, we provide computational methods to solve the optimization problems. In Section 5, to select the preferable suppliers, a ranking method proposed by Yuan (1991) is extended to sort the membership functions of fuzzy estimates of suppliers' C_{pki} indices. Finally, we summarize our proposed method in a step-by-step procedure. An application of light emitting diodes (LEDs) is illustrated as an example.

2. Fuzzy numbers

The fuzzy subset $\tilde{a}$ of $\mathbb{R}$ is defined by a function $\xi_{\tilde{a}} : \mathbb{R} \to [0, 1]$, which is called the *membership function*. The α-level set of $\tilde{a}$, denoted by $\tilde{a}_\alpha$, is defined as $\tilde{a}_\alpha = \{x \in \mathbb{R} : \xi_{\tilde{a}}(x) \geqslant \alpha\}$ for all $\alpha \in (0,1]$. The 0-level set $\tilde{a}_0$ is defined as the closure of the set $\{x \in \mathbb{R} : \xi_{\tilde{a}}(x) > 0\}$, i.e., $\tilde{a}_0 = \mathrm{cl}(\{x \in \mathbb{R} : \xi_{\tilde{a}}(x) > 0\}) = \mathrm{cl}(\bigcup_{\alpha>0}\tilde{a}_\alpha)$.

Definition 2.1. The fuzzy subset $\tilde{a}$ of $\mathbb{R}$ is said to be a *fuzzy number*, if the following conditions are satisfied:

(i) $\tilde{a}$ is normal, i.e., there exists an $x \in \mathbb{R}$ such that $\xi_{\tilde{a}}(x) = 1$.
(ii) $\xi_{\tilde{a}}$ is quasi-concave, i.e., $\xi_{\tilde{a}}(tx + (1-t)y) \geqslant \min\{\xi_{\tilde{a}}(x), \xi_{\tilde{a}}(y)\}$ for $t \in [0, 1]$.
(iii) $\xi_{\tilde{a}}$ is upper semicontinuous, i.e., $\{x \in \mathbb{R} : \xi_{\tilde{a}}(x) \geqslant \alpha\}$ is a closed subset of $\mathbb{R}$ for each $\alpha \in (0,1]$.
(iv) The 0-level set $\tilde{a}_0$ is a closed and bounded subset of $\mathbb{R}$.