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Optimal tool replacement for processes with low fraction defective

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Abstract

Tool wear is a frequent and natural part in many machining processes and is a systematic assignable cause. The fraction of defectives would rise as the tool deteriorates. When the fraction defective reaches a certain level, the tool must be replaced. To minimize the defective parts and the overall tool costs, the optimal tool replacement time needs to be determined. Process capability indices (PCIs) have been effectively used in the manufacturing industry to measure the fraction of defectives. Conventional methods of capability measurement become inaccurate since the process data is contaminated by the assignable cause variation. In order to determine the optimal tool replacement time to maintain maximum product quality, conventional capability calculation must be modified. Considering process capability changes dynamically, an estimator of C_{pmk} is investigated. We obtain an exact form of the sampling distribution in the presence of a systematic assignable cause. This study provides an effective management policy for optimal tool replacement under low fraction of defectives. To illustrate the application of this procedure, a case study involving the tool wear problem is presented.

Keywords: Quality management; Critical value; Process capability index; Replacement time; Tool wear

1. Introduction

In automated machines, tools occupy a prominent place in producing quality goods. The tool will wear gradually as the manufacturing process proceeds. For instance, the machining operation shapes a production part using, cutting, drilling, or grinding operations, and so on. While such wear is unavoidable, tools must be controlled to maintain product quality and efficient tool utilization. One important issue for tool wear control is the tool replacement policy. The tool should be replaced when product quality becomes worse. Process capability indices have been widely used in the manufacturing industry for measuring process quality, particularly, for processes with low fraction of defectives. In practice, a minimal capability requirement would be preset by the customers/engineers in order to maintain a low fraction of defectives. When the capability index fails to reach the prescribed minimum value, one could conclude that the process is incapable of reaching the

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desired production quality and the tool must be reset. In this study, we investigate an effective management policy based on process capability calculation for optimal tool replacement time with low fraction of defectives to meet manufacturing requirement.

In the manufacturing industry, process capability indices have been widely used to provide numerical measures on process reproduction capability, which are convenient and powerful tools for quality assurance and guidance for process improvement. Those indices are easy to understand and straightforward to apply in many industries such as automotive, semiconductor and IC assembly manufacturing industries. Among them, C_p and C_{pk} (see Kane, 1986) are the most extensively-used two in the manufacturing industry. Those indices have been defined explicitly as the following:

$$C_p = \frac{\text{USL} - \text{LSL}}{6\sigma}, \quad C_{pk} = \min\left\{\frac{\text{USL} - \mu}{3\sigma}, \frac{\mu - \text{LSL}}{3\sigma}\right\}, \quad C_{pm} = \frac{\text{USL} - \text{LSL}}{6\sqrt{\sigma^2 + (\mu - T)^2}},$$

$$C_{pmk} = \min\left\{\frac{\text{USL} - \mu}{3\sqrt{\sigma^2 + (\mu - T)^2}}, \frac{\mu - \text{LSL}}{3\sqrt{\sigma^2 + (\mu - T)^2}}\right\},$$

where T is the target value, μ is the process mean and σ is the standard deviation of the characteristic, USL and LSL are the upper and lower specification limits, respectively. On the topic of PCIs, several authors have presented the use and examined their associated properties with different degrees of completeness. Examples are Kushler and Hurley (1992), Rodriguez (1992), Kotz and Johnson (1993), Vännman and Kotz (1995), Bothe (1997), Spiring (1997), Kotz and Lovelace (1998), Palmer and Tsui (1999), Pearn and Shu (2003), Vännman and Hubele (2003), and references therein. Kotz and Johnson (2002) provided a compact survey for the development of PCIs with interpretations and comments on some 170 publications appeared during 1992–2000. Spiring et al. (2003) consolidated the research findings in the field of process capability analysis for the period 1990–2002.

To understand and correctly interpret process capability indices, the process under investigation must be free from any special or assignable cause (i.e., in-control). Unfortunately, such condition is hardly met in many industrial applications. For example, when the assignable cause is in the form of tool wear, the output values inherently will show a certain increasing or decreasing trend. The causes such as tool wear are responsible for inducing autocorrelation and are not physically removable from the process. As a result, processes with uncontrollable trend are quite common in practice, and process capability analysis becomes a difficult task for practitioners. Quality researchers see this fact, and several approaches have been suggested to deal with problems of assignable cause. Some approaches attempt to remove the variability associated with the systematic assignable cause. For instance, Montgomery (1985) proposed fitting the AR(1) time series model to the auto-correlated data. Yang and Hancock (1990) recommended that in computing the C_p index, the unbiased estimator of σ can be obtained as $\sigma/(1-\rho)^{1/2}$, where ρ is defined as the average correction factor. Time series modeling trend data had been also suggested by Alwan and Roberts (1988), who recommend using residuals in monitoring the process. Other approaches make the general assumption of linear degradation in the tool. For example, Long and De Coste (1988) investigated the procedure to remove the linearity by regressing on the means of the subgroups and then determined the process capability. Quesenberry (1988) also suggested that tool wear can be modeled over an interval of tool life by a regression model and assumes that the tool wear rate is known or a good estimate of it is available, and that the process mean can be adjusted after each batch without an error.

Most of the previous works reviewed above, however, did not consider a dynamic process capability over a cycle. By considering the process capability dynamic within a cycle, as well as from cycle to cycle, we could circumvent some of the problems encountered. Spiring (1991) has devised a modification of C_{pm} index for this dynamic process under the influence of systematic assignable causes. Pearn et al. (1992) proposed an index called C_{pmk}, which combines the merits of the three basic indices C_p, C_{pk}, and C_{pm}. In this paper, we consider capability index C_{pmk} for the dynamic process under the influence of systematic assignable cause. This study is divided into six sections beginning with introduction. Section 2 contains the concept of process capability measure when the process involves tool wear problem. In Section 3, a modified estimator of C_{pmk} is proposed and