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Improvement in quality and productivity of an assembled product: A riskless approach

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ABSTRACT

In this paper, to show the importance of improvement on savings of costs in a riskless sense, the quality loss and manufacturing cost functions are employed to allocate the components tolerances of an assembled product simultaneous with taking appropriate improvement operations. The use of improvement operations reduces the variability of the process while increasing the production costs. To apply improvement operations in a riskless sense, which actually does not impose additional costs to the producers, we take advantages of the trade-off between improvement costs and tolerance costs. Therefore, a series of algorithms are proposed for simultaneous selection of tolerances and improvement operations so as to minimize the total cost. The use of our approach helps considerably save large amounts of computer time by pruning many unnecessary evaluations. It is shown that proper choices of both improvement operations and tolerances have an important impact to enhance productivity and quality.

1. Introduction

Improvement in quality has always been a challenging issue for companies as it usually incurs additional costs to the producers. In this regard, one of their main concerns is to choose improvement operations so as to manufacture higher quality products with substantial cost savings. It is practically shown that productivity does indeed increase as quality improves (Deming, 2000; Roland, Christine, & Peter, 2002; Shewhart, 1980).

In order to improve the quality of a product, its deviation from its nominal value that occurs due to noise factors needs to be reduced. Offline quality control is one of the major counteractions for this purpose that can be implemented in three stages, namely: system design, parameter design and tolerance design. Among these stages, tolerance analysis is a valuable tool for reducing manufacturing cost by improving producibility. Tolerance analysis of assemblies of manufactured parts is an essential part of successful product development. In the recent decade, many authors have presented different useful methods of selecting design tolerances by employing manufacturing cost function or quality loss function and/or a combination of both. Manufacturing cost (MC) is defined as all costs associated with production of a part and quality loss (QL) is the costs related to the deviation of a characteristic of a part from its nominal value.

Gerth and Hancock (2000) developed a tolerancing-based method for improving complex, multiple process systems that contain a large number of variables. Feng, Wang, and Wang (2001) proposed a stochastic integer programming (SIP) approach for simultaneous selection of tolerances and suppliers based on quality loss function and process capability indices. Peng, Jiang, and Liu (2008) used a combined model to balance manufacturing cost and quality loss to achieve the concurrent optimal allocation of design and process tolerances to each component for mechanical assemblies involving interrelated dimension chains. Wu, Dantan, Etienne, Siadat, and Martin (2009) considered the nonlinearly constrained tolerance allocation problems to minimize the ratio between the sum of the manufacturing costs and the risk (probability of the respect of geometrical requirements). Muthu, Dhanalakshmi, and Sankaranarayanasamy (2009) applied two Meta-heuristics techniques, i.e. genetic algorithm and particle swarm, to allocate tolerances to components by considering both manufacturing cost and quality loss functions so as to minimize the total cost. They further concluded that the results obtained by these techniques outperform the results obtained by classical optimization approach in terms of reduction in total cost for overrunning clutch assembly problem. Rao, Rao, Janardhana, and Vundavilli (2011) proposed a concurrent approach to determine tolerances at the minimum total cost using three evolutionary methods, i.e. genetic algorithm, differential evolution, and particle

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swarm optimization. Chen, Li, and Yu (2013) constructed optimal tolerances based upon assembly deformation and quality loss with an application in aircraft industry. Walter and Wartzack (2013) developed an optimization methodology for the tolerance-cost-optimization of a system in motion by considering two main characteristics of systems in motion during its use. Liu, Jin, Liu, and Xie (2013) used an analytical method in a model including two kinds of constraints, i.e. assembly tolerance constraint and process accuracy constraints, to obtain optimal tolerances based on manufacturing cost and quality loss. Geetha, Ravindran, SivaKumar, and Islam (2015) applied a genetic algorithm to determine the best product sequence of the scheduling and to allocate components tolerances based on three elements namely: manufacturing cost, quality loss and the machine idle time cost. However, none of these authors considered the impact of improvement on productivity. Furthermore, in all these studies a fixed relationship between standard deviation and tolerance is assumed, which actually indicates a fixed value for process capability index.

In quality engineering, parameter design is used to achieve the desired level of quality and economic tolerance design is used to allocate optimal tolerances to components so as to minimize the total cost. However, it is worth thinking of more productivity during allocation of the tolerances to the components by taking some improvement operations. The question could be "will improvement in quality of some component(s) reduce the total cost more than before?". In this regard, Moradinaftchali, Xiaoguang, and Lixin (2015) have introduced a new approach for allocating the tolerance to a component which results in the minimum total cost by taking improvement operations. Through their method, the fixed relationship between standard deviation and tolerance of the component is first relaxed and then other sources of variability for applying improvement operations are entered into the total cost model. This is because manufacturing cost function only reflects the cost incurred to the producer by tightening the natural tolerance based upon controlling a few sources of variability and not all tangible sources. This study aims to develop the model proposed by Moradinaftchali et al. (2015) for an assembled product with m assembly components and to introduce a riskless approach for taking improvement operations simultaneous with appropriate choices of tolerances which result in the minimum total cost. Here, the term "riskless" signifies that taking improvement operations should not incur additional costs to the producers. To overcome the difficulties of simultaneous choices of improvement operations and tolerances, a series of algorithms are proposed that help considerably save large amounts of computer time by pruning too many unnecessary evaluations.

In this paper, to enhance the readability, the descriptions of the notations are addressed in Table 1. In the next section the assumptions made in this paper and a description of the problem are presented. Section 3 develops the model and provides a series of algorithms for the problem described in Section 2. An example for purposes of illustration is presented in Section 4. Section 5 provides conclusion of this study.

2. Assumptions and problem description

2.1. Assumptions and background

In order to introduce our method, some assumptions need to be established to construct the model. However, such assumptions are not concrete and hence using different assumptions will require appropriate alternatives for variables and parameters defined in the model. Throughout this paper, normality of the quality characteristic is accepted since researches show that products with quality characteristics following normal distributions result in less failures, lower warranty costs, lower quality loss, and higher customer satisfaction (Taguchi, 1985; Taguchi, Elsayea, & Hsiang, 1989).

Let X_i be a nominal-the-best (N-type) quality characteristic of component i for a normally distributed process with mean, μ_i, and variance, σ_i^2, for which the process mean and design target are equal and both centered within the upper and lower specification limits. We can then define the expected quality loss and process capability index of the quality characteristic X_i as

$$E(L(X_i)) = E(k_i(X_i-\mu_i)^2) = k_i\sigma_i^2, \tag{1}$$

$$C_{Pi} = \frac{\Delta_i}{3\sigma_i}. \tag{2}$$

It is further assumed that the functional relationship between manufacturing cost and tolerance of the component can be given by an exponential/reciprocal power function (Michael & Siddall, 1982) as

$$MC_i = A_{i0} + \frac{b_i e^{-c_i\Delta_i}}{\Delta_i^{a_i}}. \tag{3}$$

The fixed cost, A_{i0}, can be ignored in what follows as it has no influence in our calculations. The total cost function (TC) of the component i can now be defined by

$$TC_i = E(L(X_i)) + MC_i = k_i\sigma_i^2 + \frac{b_i e^{-c_i\Delta_i}}{\Delta_i^{a_i}} = k_i\left(\frac{\Delta_i}{3C_{pi}}\right)^2 + \frac{b_i e^{-c_i\Delta_i}}{\Delta_i^{a_i}},$$
$$b_i, k_i, \Delta_i, C_{pi} > 0, a_i, c_i \geqslant 0 \text{ and } \Delta_i \in \left[\Delta_i^l, \Delta_i^u\right]. \tag{4}$$

The result of minimizing Eq. (4) will be the optimum point for the semi-tolerance, e.g. Δ_i', that can be easily achieved through any common search methods. Moradinaftchali et al. (2015) have shown that this value cannot always be the best value if other sources of variability get involved into the model. This is because only a few sources of variability for which manufacturing cost is calculated are taken into account and hence the manufacturing cost function only reflects the cost incurred by controlling these few sources. Therefore, applying improvement operations by controlling the other sources of variability may lead to a better choice of the tolerance with maximum productivity. In their work, the fixed relationship between standard deviation and tolerance of the component is relaxed as taking improvement operations will affect such a relationship. For this reason, where improvement operations are applied, the process capability index is treated as a variable. Moreover, It is further assumed that for the component i, there are p_i mutually independent and normally distributed sources of variability with the mean zero and variance $\sigma_{ik}^2, k = 1, 2, \ldots, p_i$, each in r_k levels of control. Since in most real-life applications the sources of variability can be controlled only in some few levels, there will be no functional relationship between the cost and the level of control. Therefore, the total variance of the process i can be written as: $\sigma_i^2 = \sum_{k=1}^{p_i}\sigma_{ik}^2 + \sigma_{ie}^2$, where σ_{ie}^2 is the variance of intangible sources and those sources for which manufacturing cost is calculated. Table 2 shows the different tangible sources with their levels of control and corresponding costs. The first level of these sources shows the current situation of the process which means the situation before applying improvement operations. The other rows represent the amounts of reduction in variability (σ_{ikj}^2) and their corresponding costs C_{ikj}, for $k = 1, 2, \ldots, p_i$ and $j = 1, 2, \ldots, r_k$, which is incurred to the producer for a unit of component i after taking the relative improvement operations.

To enter the new sources into the model defined in Eq. (4) and to control the amount of improvement, Moradinaftchali et al. (2015) first constructed a new process capability index, which