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Fuzzy nonlinear programming approach to the evaluation of manufacturing processes

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ABSTRACT

The quality of a product produced by a manufacturing process should be able to lie within an acceptable variability around its target value. The signal-to-noise (S/N) ratio, served as the objective function for optimization in Taguchi methods, is a useful tool for the evaluation of manufacturing processes. Most studies and applications focus on the calculation of S/N ratios with deterministic observations, and the literature receives little attention to the consideration of S/N ratio with fuzzy observations. This paper develops a fuzzy nonlinear programming model to calculate the fuzzy S/N ratio for the assessment of the manufacturing processes with fuzzy observations. A pair of nonlinear fractional programs is formulated to calculate the lower and upper bounds of the fuzzy S/N ratio. By model reduction and variable substitutions, this pair of nonlinear fractional programs is transformed into quadratic programs. Solving the transformed quadratic programs, we obtain the optimum solutions of the lower bound and upper bound fuzzy S/N ratio. By deriving the ranking indices of the fuzzy S/N ratios of manufacturing process alternatives, the evaluation result of the alternatives is obtained.

1. Introduction

Under the conditions of a constantly changing environment, together with the increasing trend in global competition, companies must produce a variety of products and deliver a high-quality service to strive for the competitiveness and flexibility to remain in business. Manufacturing is a complicated system that involves sets of tasks, materials, resources (including human resources, facilities and software), products, and information. Askin and Standridge (1993) divided the manufacturing system into five interrelated functions: product design; process planning; production operations; material flow/facilities layout; and production planning and control. Process planning is a stage in the product life cycle that connects product design and manufacturing. A well-designed manufacturing process provides more benefits over manufacturing techniques, including reduced material waste, lower energy intensity, just-in-time production, and so on. Additionally, to meet or exceed the customers' expectations, any product should be produced by a manufacturing process that is repeatedly stable. In real world applications, there are cases that observations might be inexact and have to be estimated. For example, real observations of continuous quantities are not accurate numbers and the output measurements are judged with humans' partial knowledge. One way to deal quantitatively with uncertainty in observations is to represent uncertain observations by fuzzy numbers.

In the literature there are some studies discussing fuzzy product development and process performance evaluation. Vasant and Barsoum (2006) employed the modified S-curve membership function methodology to a real life industrial problem of mix product selection. The fuzzy outcome showed that higher units of products need not lead to higher degree of satisfaction. Chen and Chang (2008) developed the economic design of the variable parameters $\overline{X}$ control chart, where the process was subject to a disturbance cause that can result in a fuzzy mean shift. A fuzzy-simulation-based genetic algorithm was employed to search for the optimal values of the design parameters. Wu (2009) presented a set of confidence intervals of sample mean and variance that produced triangular fuzzy numbers for the estimation of C_{pk} index. Additionally, a step-by-step procedure was developed to assess process performance based on fuzzy critical values and fuzzy p-values. Chen and Ko (2010) considered the close link between the four phases, namely, design requirements (phase 1), critical parts characteristics (phase 2), critical processes parameters (phase 3), and product requirements (phase 4), in a typical quality function deployment (QFD) to build up a family of fuzzy linear programming models to determine the contribution levels of each "how" for customer satisfaction. Khodaygan and Movahhedy (2012)

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presented a method, based on fuzzy concepts, for process capability analysis of assembly dimensions in mechanical assembly. Their method is able to estimate the ability of the manufacturing process in satisfying the assembly quality. Shu and Wu (2012) proposed a methodology for obtaining the fuzzy estimate of C_{pm} using fuzzy data, which is based on "resolution identity" in fuzzy set theory. They propose decision rules to judge the process condition and present a sequence of testing steps for assessing manufacturing process performance using the critical value for C_{pm} with fuzzy data. Chen et al. (2013) developed fuzzy approaches for constructing the house of quality in QFD and described its application from a group decision-making perspective. A modified fuzzy clustering approach was proposed for finding the consensus of the QFD team. Wang and Zheng (2013) proposed a fuzzy linear programming model to find a maximal profit production strategy with degree of satisfaction. The results showed that the developed model can provide useful information for developing profit-effective oil refinery strategies in an uncertain environment. Chen and Ko (2014) established a fuzzy linear programming model to determine the optimal fulfillment levels of design requirements to maximally satisfy customer requirements. Wu and Liao (2014) formulated fuzzy numbers to represent the quality characteristic measurements, and a nonlinear programming approach was applied to solve the fuzzy estimator S_{pk}. Mousavi et al. (2015) introduced a distance-based decision model for multi-attributes analysis by considering intuitionistic fuzzy sets and grey relations with an application to the inspection planning in manufacturing firms. Hsu et al. (2016) presented an agent-based fuzzy constraint-directed negotiation mechanism to solve distributed job shop scheduling problems, and the experimental results revealed that their model can provide cost-effective job shop scheduling.

The signal-to-noise (S/N) ratio, designed for optimizing the robustness of a product or process in Taguchi methods, is useful to compare manufacturing processes and measure the performance of process design (Tsai, 2002; Chang and Kuo, 2007; Ali and Wadhwa, 2010; Pinarbasi et al., 2013; Fountas et al., 2015; Kong et al., 2017). Since the S/N ratio is simple and effective, it has long been widely used as a powerful tool so that high quality products can be produced quickly with low cost. Conventionally, one calculates the S/N ratio with deterministic observations. However, there are cases that observations in manufacturing processes are difficult to measure precisely, or observations need to be estimated, and these observations can be expressed by fuzzy numbers. Nevertheless, the literature receives little attention to the consideration of S/N ratio with fuzzy observations. The purpose of this paper is to develop a fuzzy nonlinear programming model to calculate the fuzzy S/N ratio for the assessment of manufacturing processes with fuzzy observations. A pair of nonlinear fractional programs is formulated to calculate the lower bound and upper bound of the fuzzy S/N ratio. By model reduction and variable substitutions, the original nonlinear fractional programs, which there is no guarantee to have stationary points, are transformed into quadratic programs. Solving the transformed quadratic programs, we obtain the optimum solutions of the lower bound and upper bound of the fuzzy S/N ratio. Since the derived S/N ratio is a fuzzy number, the associated fuzzy number ranking method is applied to obtain the assessment result of manufacturing processes.

In the sections that follow, we first introduce the concept of S/N ratio, and a pair of nonlinear fractional programs is formulated to find the lower bound and upper bound of the fuzzy S/N ratio with fuzzy observations. Next, we utilize the model reduction and variable substitutions to transform the pair of nonlinear fractional programs into a pair of quadratic programs to solve. We then employ the developed methodology to evaluate the manufacturing processes for a company in Taiwan. Finally, some conclusions of this work are presented.

2. Fuzzy S/N ratio

Taguchi method is an important tool for robust design to produce high quality products efficiently, and has been adopted by successful manufacturers around the world because of their results in creating superior production processes at much lower costs. In Taguchi method, log functions of desired outputs, known as the signal-to-noise (S/N) ratio, serve as the objective functions for optimization. There are three forms of S/N ratio, namely, the smaller-the-better-type, the larger-the-better-type, and the nominal-the-best-type that are of common interest for optimization of static problems. A nominal-the-best-type problem is the one where the minimization of the mean square error around a specific target value is desired. There are two important features of the nominal-the-best-type problem. One is that when the mean is zero, the standard deviation is also zero, and the other is that an adjustment factor can be found to move the mean on the target (Su, 2013). For the nominal-the-best-type problem, we need to consider both the effect of the mean and variance. That is, the nominal-the-best-type S/N ratio is designed to minimize variability around the mean. Therefore, it is suitable to adopt the nominal-the-best-type S/N ratio for the evaluation of manufacturing processes. The nominal- the-best-type S/N ratio can be conceptually described as:

$$r = 10 \times \log_{10}\left(\frac{\text{effect of mean}}{\text{variability around mean}}\right) \tag{1}$$

Denote y_i be the ith observation of an experiment, Taguchi proposed the following S/N ratio for the nominal-the-best-type problems (Su, 2013):

$$r = 10 \times \log_{10}\left(\frac{\bar{y}^2}{s^2}\right), \tag{2}$$

where $\bar{y} = \sum_{i=1}^{n} y_i/n$ and $s^2 = \sum_{i=1}^{n}(y_i - \bar{y})^2/(n-1)$.

2.1. Analytical solution

We first give a simple example to introduce how to use the tool of α-level sets to find the membership function of the fuzzy S/N ratio. This example also shows that the analytical derivation of the membership function of the fuzzy S/N ratio from those of the fuzzy observations is very complicated, even for a simple problem with only one fuzzy observation.

Consider a simple case of four observations. Among them, three observations have crisp values, and the remaining one is approximately known and has to be estimated. That is, we have $y_1 = 3, y_2 = 4, \widetilde{Y}_3 = (5, 6, 7)$, and $y_4 = 8$, where $\widetilde{Y}_3$ is the estimated observation that is a triangular fuzzy number with a membership function of:

$$\mu_{\widetilde{Y}_3}(y_3) = \begin{cases} L(y_3) = y_3 - 5, & 5 \le y_3 \le 6, \\ R(y_3) = 7 - y_3, & 6 \le y_3 \le 7. \end{cases} \tag{3}$$

Its α-cut is $[(Y_3)_\alpha^L, (Y_3)_\alpha^U] = [5+\alpha, 7-\alpha]$.

Since one observation in the sample data is fuzzy, intuitively, the calculated S/N ratio is fuzzy as well. In this example, we let $\widetilde{R}$ and $\mu_{\widetilde{R}}$ denote the fuzzy S/N ratio and the membership functions of $\widetilde{R}$, respectively, and we need to find $\mu_{\widetilde{R}}$ with these four observations. At $\alpha = 0$, the value of $(Y_3)_{\alpha=0}$ lies between 5 and 7, which is the widest range of $\widetilde{Y}_3$. Based on (2), the associated nominal-the-best-type S/N ratio, r, is calculated as:

$$\begin{aligned} r &= 10 \times \log_{10}\left(\frac{\left(\frac{1}{4}\left(15 + y_3\right)\right)^2}{\frac{1}{3}\sum_{i=1}^{4}\left(y_i - \frac{1}{4}(15+y_3)\right)^2}\right), \\ &= 10 \times \log_{10}\left(\frac{16}{3}\left[\frac{89}{(15+y_3)^2} + \left(\frac{y_3}{(15+y_3)}\right)^2\right] - \frac{4}{3}\right)^{-1}, \\ &= -10 \times \log_{10}\left(\frac{16(89+y_3^2)}{3(15+y_3)^2} - \frac{4}{3}\right), \end{aligned} \tag{4}$$

where $5 \le y_3 \le 7$.