Precision Engineering 38 (2014) 628–638

Contents lists available at ScienceDirect

Precision Engineering

journal homepage: www.elsevier.com/locate/precision

A normal boundary intersection approach to multiresponse robust optimization of the surface roughness in end milling process with combined arrays

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ARTICLE INFO

Article history:
Received 15 April 2013
Received in revised form 11 January 2014
Accepted 22 February 2014
Available online 6 March 2014

Keywords:
Multiple objective programming
Robust parameter design (RPD)
Normal boundary intersection (NBI)
End milling process
Surface roughness

ABSTRACT

Robust parameter design (RPD) has recently been applied in modern industries in a large deal of processes. This technique is occasionally employed as a multiobjective optimization approach using weighted sums as a trade-off strategy; in such cases, however, a considerable number of gaps have arisen. In this paper, the use of normal boundary intersection (NBI) method coupled with mean-squared error (MSE) functions is proposed. This approach is capable of generating equispaced Pareto frontiers for a bi-objective robust design model, independent of the relative scales of the objective functions. To verify the adequacy of this proposal, a central composite design (CCD) is developed with combined arrays for the AISI 1045 steel end milling process. In this case study, a CCD with three noise factors and four control factors are used to create the mean and variance equations for MSE of two quality characteristics. The numerical results indicate the NBI-MSE approach is capable of generating a convex and equispaced Pareto frontier to MSE functions of surface roughness, thus nullifying the drawbacks of weighted sums. Moreover, the results show that the achieved optimum lessens the sensitivity of the end milling process to the variability transmitted by the noise factors.

1. Introduction

To make a process less sensitive to the action of noise variables, researchers have developed a design of experiments (DOE) approach that promotes the best levels of control factors. The approach, known as robust parameter design (RPD), improves the variability control and minimizes the bias. The ways of utilizing RPD can vary. For example, in their estimating of cutting conditions of surface roughness in end milling machining processes [1], used kernel-based regression and genetic algorithms (GA). Employing a hybrid Taguchi-genetic learning algorithm [2], relied on an adaptive network-based fuzzy inference system to predict surface roughness in end milling processes. To minimize surface roughness in end milling machining processes [3], studied an application of GA so as to optimize cutting conditions.

This work presents an RPD that will facilitate the adaptive control application in end milling processes as well as contribute to computer-integrated manufacturing scenarios [4–7]. Originally developed following a crossed-array, the RPD methodology remains controversial due primarily to its various mathematical flaws and statistical inconsistencies, such as the crossed-array's inability to assess the interaction between control and noise variables [4,7,8]. To resolve such issues [9,10], proposed using response surface methodology (RSM) with combined arrays. This experimental strategy allows the computation of noise-control interactions using a central composite design (CCD) with embedded noise factors, generating the mean and variance equation as from the propagation of error principle.

The general scheme of an RPD-RSM problem consists of performing an experimental design while considering the noise factors to be control variables and eliminating from the design any axial points related to the noise factors [11]. Then a polynomial surface for $f(\mathbf{x}, \mathbf{z})$ is estimated using the OLS or WLS algorithm, obtaining $f(\mathbf{x}, \mathbf{z})$ partial derivatives. This procedure leads to a response surface for the mean $\hat{y}(\mathbf{x})$ and another for the variance $\hat{\sigma}^2(\mathbf{x})$, considering the noise-control factors interactions. This approach is called dual response surface (DRS).

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http://dx.doi.org/10.1016/j.precisioneng.2014.02.013
0141-6359/

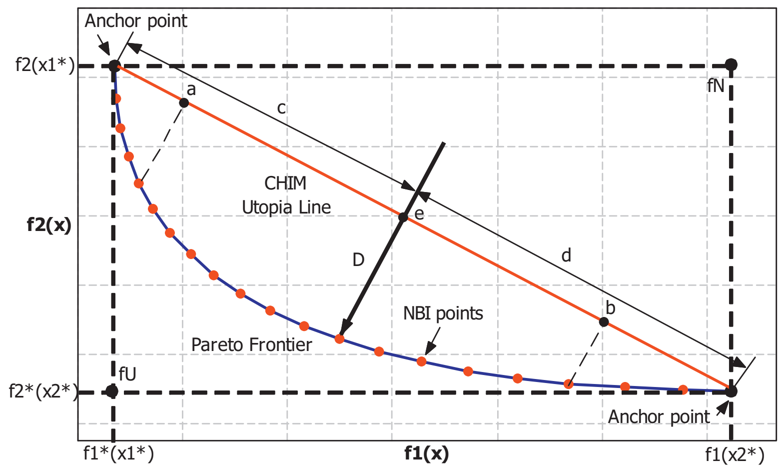

Fig. 1. Graphical description of NBI method.

Applied widely by modern industries, RPD approaches for multiresponse optimization problems have been only sparsely developed [7,12,13]. Even in those works involving multiresponse approaches, researchers appear to have generally neglected the noise-control interactions, computing the mean and variance equations from crossed arrays or design replicates [4,13–19].

In the DRS method, the mean $\hat{y}(\mathbf{x})$ and variance $\hat{\sigma}^2(\mathbf{x})$ may be optimized simultaneously considering different schemes [9,12,20], for example, established an optimization scheme considering $\underset{x \in \Omega}{Min}\, \hat{\sigma}^2(\mathbf{x})$, subject to the constraint of $\hat{y}(\mathbf{x}) = T$, where T is the target for $\hat{y}(\mathbf{x})$, and that, using a Lagrangean multiplier approach, evaluates only one quality characteristic. [21] presented a bias-specified robust design method formulating a nonlinear optimization program that minimizes process variability subject to customer-specified constraints on the process bias, such as $|\hat{y}(\mathbf{x}) - T| \leq \epsilon$. The mean, variance, and target can also be combined in a mean-squared error (MSE) function which must be minimized and subjected to a set of constraints, as, for example, the experimental region. This figure can be stated as $\underset{x \in \Omega}{Min} [\hat{y}(\mathbf{x}) - T]^2 + \sigma^2$ [4,12–14,17,22–24].

Supposing that mean and variance may assume different degrees of importance, the MSE objective function can also be weighted, as $MSE_w = w_1 \cdot (\hat{y}(\mathbf{x}) - T)^2 + w_2 \dot{c} \hat{\sigma}^2(x)$, where the weights w_1 and w_2 are pre-specified positive constants [10,12,19,24]. Still, these weights can be experimented with through different convex combinations, i.e., $w_1 + w_2 = 1$, with $w_1 > 0$ and $w_2 > 0$, generating a set of non-inferior solutions for multiple objective optimization [19].

Extending the MSE criterion to multiobjective problems, an operator like a weighted sum may be used [25,26] leading to an objective function as $MSE_T = \sum_{i=1}^{p} [(\hat{y}_i - T_i)^2 + \hat{\sigma}_i^2]$. If different degrees of importance are attributed to each MSE_i, the global objective function can be written as proposed by [27]

$$MSE_T = \sum_{i=1}^{p} w_i \cdot MSE_i = \sum_{i=1}^{p} w_i \cdot [(\hat{y}_i - T_i)^2 + \hat{\sigma}_i^2] \quad (1)$$

A common concern with multiobjective *MSE* optimization is related to the convexity of Pareto frontiers generated using weighted sums. According to [4], in most RPD applications, a second-order polynomial model is adequate to accommodate the curvature of process mean and variance functions. Thus, mean-squared robust design models would contain fourth-order terms. Consequently, the associated Pareto frontier might be non-convex and non-supported efficient solutions could be generated. It is important to state that a decision vector $\mathbf{x}^* \in S$ is Pareto optimal if there does not exist another $\mathbf{x} \in S$ such that $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^*)$ for all $i = 1, 2, \ldots, k$. According to [4], for the bi-objective case, the weighted sum can be written as a convex combination of two MSE functions, such as:

$$Min \quad MSE_T = wMSE_1 + (1 - w)MSE_2 \quad S.t.: \quad \mathbf{x} \in \Omega \quad (2)$$

The weighted sum method, as described in Eq. (2), is widely employed to generate the trade-off solutions for nonlinear multiobjective optimization problems. According to [4], the bi-objective problem of Eq. (2) is convex if the feasible set X is convex and the MSE functions are also convex. When at least one objective function is not convex, the bi-objective problem becomes non-convex, generating a non-convex and even unconnected Pareto frontier. The principal consequence of a non-convex Pareto frontier is that points on the concave parts of the trade-off surface will not be estimated. This instability is due to the fact that the weighted sum is not a Lipshitzian function of the weight w [28]. Another drawback to the weighted sums is related to the uniform spread of Pareto-optimal solutions. Even if a uniform spread of weight vectors are used, the Pareto frontier will not be equispaced or evenly distributed [28,29].

To overcome these disadvantages [30], proposed the normal boundary intersection method (NBI), showing that the Pareto surface will be evenly distributed independent of the relative scales of the objective functions. So, following the aforementioned discussion, this article will present a two-folded approach to coupling the NBI method with MSE objective functions.

This paper is organized as follows: Section 2 presents the main characteristics of normal boundary intersection method, discussing the concepts of utopia line, payoff matrix and anchorage points. Section 3 presents the NBI-MSE method; Section 4 presents a numerical application to illustrate the adequacy of the work's proposal; and also the confirmation runs that were carried out, demonstrating the mathematical results can be confirmed in practice. Section 5 presents the results and discussion.

2. Normal boundary intersection (NBI)

The NBI method shown in Fig. 1 is an optimization routine developed to find a uniformly spread Pareto-optimal solutions for a general non-linear multiobjective problem [29,30].

The first step in the NBI method establishes the payoff matrix Φ, based on the calculation of the individual minima of each objective function. The solution that minimizes the i-th objective function $f_i(x)$ can be represented as $f_i^*(x_i^*)$. When the individual optima x_i^* is replaced in the remaining objective functions, $f_i(x_i^*)$ is obtained. In