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Optimizing reliability-based robust design model using multi-objective genetic algorithm

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ABSTRACT

Reliability-based robust design optimization (RBRDO) is one of the most important tools developed in recent years to improve both quality and reliability of the products at an early design stage. This paper presents a comparative study of different formulation approaches of RBRDO models and their performances. The paper also proposes an evolutionary multi-objective genetic algorithm (MOGA) to one of the promising hybrid quality loss functions (HQLF)-based RBRDO model. The enhanced effectiveness of the HQLF-based RBRDO model is demonstrated by optimizing suitable examples.

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1. Introduction

The globally competitive market has forced manufacturers to design and manufacture highly reliable products at competitive prices to fulfill the customers' expectations. Design engineers are constantly making strenuous efforts to establish new and effective tools and techniques to design reliable and durable products. Reliability-based robust design optimization (RBRDO) is one of the most useful tools developed in recent years to improve both quality and reliability of the products simultaneously. It optimizes the design for reliability and robustness in the presence of variability and uncertainty. Essentially, the RBRDO is an integration of reliability-based design optimization (RBDO) (Kapur & Lamberson, 1977; Melchers, 1999; Rao, 1992) and robust design (RD) (Phadke, 1989; Taguchi, 1987) in multi-objective optimization domain (Lee, Choi, Du, & Gorsich, 2008; Mourelatos & Liang, 2006; Yadav, Bhamare, & Rathore, 2010; Youn, Choi, & Yi, 2005; Zhuang & Pan, 2010). The RBDO approach optimizes the design for higher reliability by characterizing uncertainty in all the design variables and failure modes. On the other hand, the RD improves product quality and robustness by minimizing the variation in the product performance. To achieve the desired robustness, the RD approach exploits the nonlinearity in the performance functions and finds a blend of the design variables (parameters) that gives the smallest performance variations (Phadke et al., 1989). However, the separate implementation of the RBDO can only provide a reliable design, but it rarely accounts for performance variation. Similarly, the RD optimization alone can minimize the performance variation but may not guarantee the desired reliability (Yadav et al., 2010; Yang, 2007). Therefore, it is quite natural that the integration of these two techniques can complement each other to provide optimal design with high quality and reliability. This has inspired researchers to formulate an integrated RBRDO model and capture the merits of both RBDO and RD methods to ensure the quality and reliability of the products (Du, Sudjianto, & Chen, 2004; Koch, 2002; Lee et al., 2008; Mourelatos & Liang, 2006; Ueno, 1997; Wang & Wu, 1994; Yadav et al., 2010; Youn et al., 2005; Zhuang & Pan, 2010).

In order to achieve the desired robustness in the product design, Taguchi's quality loss concept based objective functions are being used widely, treating performance characteristics as smaller-the-better type (S-Type), larger-the-better type (L-Type), and nominal-the-best type (N-Type) (Chandra, 2001; Yadav et al., 2010; Youn et al., 2005). The required reliability targets are enforced by modeling them as probabilistic constraints in the optimization model. These probabilistic constraints are characterized using first and second statistical moments of a performance function: mean and variance (Chandra, 2001). However, these statistical moments are analytically expressed using multi-dimensional integrals and therefore, practically impossible to calculate. Consequently, various approximation methods are proposed in the literature to estimate these moments more precisely and efficiently. Experimental design (Taguchi, 1987; Cox & Reid, 2000), response surface methodology (Montgomery, 2009), first order Taylor series expansion (Buranathiti, Cao, & Chen, 2004; Kalsi, Hacker, & Lewis, 2001; Su & Renaud, 1997), Monte Carlo simulation, and very recently, a univariate dimension reduction method (Lee et al., 2008; Xu &

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Rahman, 2004) and performance moment integration method (Youn et al., 2005) are reported in the literature. Experimental design and response surface methodologies are exclusively used when the mathematical models are not readily available for the given quality or performance functions. These methods require a large amount of computation when large number of design variables are involved (Lee et al., 2008). The first order Taylor series expansion method is widely used to estimate the moments due to its simplicity, despite its well-known drawbacks (especially when the random variables have large variations). Monte Carlo simulation may provide precise accuracy but it can be very costly from a computational perspective. However, the recently developed univariate dimension reduction and performance moment integration methods have shown some potential to estimate the statistical moments precisely and accurately. A comparative study of these recently developed methods can be found in Lee et al. (2008).

Usually in the RBRDO approaches the performance measures (i.e. expected performance value and performance variation) are traded-off, while maintaining the feasibility imposed by the probabilistic constraints. The literature shows that the weighted sum (WS) method is widely used to form a composite objective function for achieving the trade-off among the performance measures. The simplicity of the WS method makes it a favorite, in spite of its inability to generate points in a non-convex trade-off region (Das & Dennis, 1997; Messac, 1996). To overcome the limitations of WS method, Mourelatos and Liang (2006) have advocated a preference aggregation method to choose the best solution of a multi-objective optimization problem considering the designer's preferences. However, both the methods depend on the user's preferences and hence are subjective in nature.

Further, the probabilistic constraints involved in the RBRDO models require a *double loop* optimization approach; wherein the outer design optimization loop constantly calls inner reliability assessment loops. The outer loop optimizes the design like any normal optimization approach and the inner reliability analysis loop uses performance measure or reliability index approach to locate the *most probable point* for achieving the desired reliability level (Du & Chen, 2002; Liang, Mourelatos, & Tu, 2008). The double loop optimization methods have proven to be computationally expensive. To minimize the computational burden researchers have proposed *single loop* and *decoupled loop* methods. The basic idea behind the single loop approach is to convert probabilistic constraints into deterministic constraints or combine both design optimization and reliability analysis tasks (Liang et al., 2008; Shan & Wang, 2008). Recently, a computationally efficient decoupled method called sequential optimization and reliability assessment (SORA) is proposed by Du and Chen (2002). The SORA uses a conventional gradient based optimization method and performance measure approach to determine the most probable point. Additionally, Youn et al. (2005) have suggested physical programming for optimization of the RBRDO model, which was intended to obtain a Pareto front. Yadav et al. (2010) have used sequential quadratic programming and Zhuang and Pan (2010) have recommended a Memetic algorithm for optimization of the RBRDO models. The Memetic algorithm is a hybrid search method that combines a global optimization technique like genetic algorithms (GA) for global search and a gradient based technique for local search. These methods use gradient based techniques in one or other forms that are local in scope and highly dependent of the initial conditions and user's preferences. In addition to this, they also demand continuity in objective functions and design space, and therefore, face difficulties in exploring the entire Pareto region.

The objective of this paper is to perform a comparative study of different formulations of RBRDO models to find a promising RBRDO model(s). The paper further explores a solution approach that can give multiple solutions covering the entire Pareto region without user intervention, as this has been our prime motivational aspect behind this study. Finally, an evolutionary, multi-objective genetic algorithm (MOGA)-based solution approach is proposed to enhance the effectiveness of the HQLF-based RBRDO model. The suitability of the proposed solution approach is demonstrated by considering two different examples.

The rest of the paper is organized as follows: Section 2 provides discussion on different RBRDO model formulation approaches and performs a comparative study. The MOGA-based solution approach is presented in Sections 3 and 4 concludes the paper with future research direction.

2. RBRDO models formulation approaches

Engineering product designs are plagued with uncertainties such as variability in manufacturing processes, material properties, and uncertainties in users' behavior and operating conditions (Du & Chen, 2000). Therefore, while designing the product for the desired quality and reliability, it is important to combine robustness and reliability considerations. This requires that the product's expected functional performance and performance variability are *simultaneously* optimized to deal with these uncertainties. This requirement led to the formulation of several RBRDO models using different concepts and approaches. The existing work on RBRDO can be grouped under three different formulation approaches as given below:

i. Moment-based RBRDO model reported in Youn et al. (2005),
ii. Percentile difference-based RBRDO model reported in Du et al. (2004), Mourelatos and Liang (2006), Lee et al. (2008), Zhuang and Pan (2010), and
iii. Hybrid quality loss functions (HQLF)-based RBRDO model reported in Yadav et al. (2010)

2.1. Moment-based RBRDO model

The moment-based RBRDO model (Youn et al., 2005) uses three different types of the robustness objectives treating performance characteristics as N-Type, S-Type, and L-Type. The formulations of robustness objectives are derived using Taguchi's quality loss function to capture the robustness requirements. Taguchi, Elsayed, and Hsiang (1989) have defined a quality loss in terms of deviation from the target value that can be approximated as:

$$C_{ql}(H) = k'(H - h_t)^2 \tag{1}$$

where k' is a constant called quality loss coefficient and h_t is a target value of the response or performance characteristic H.

Using Taguchi's quality loss concept, Youn et al. (2005) have derived three different robustness objectives. For N-Type of the performance characteristic (H) with the target value h_t, the expected quality loss function can be expressed as:

$$C_{ql}(H) = k'[(\mu_H - h_t)^2 + \sigma_H^2] \tag{2}$$

where μ_H and σ_H are the mean and the standard deviation of the performance characteristic H.

The quality loss function for S-Type of the performance characteristic can be defined as:

$$C_{ql}(H) = k'[\mu_H^2 + \sigma_H^2] \tag{3}$$

Similarly, the quality loss function for L-Type of the performance characteristic is defined by taking reciprocal of (H) as:

$$C_{ql}(H) = k'[(1/\mu_H^2) + \sigma_H^2] \tag{4}$$