# Towards Robust Designs Via Multiple-Objective Optimization Methods

Man Mohan Rai*
NASA Ames Research Center, Moffett Field, CA-94035, USA

## INTRODUCTION

Fabricating and operating complex systems involves dealing with uncertainty in the relevant variables. In the case of aircraft, flow conditions are subject to change during operation. Efficiency and engine noise may be different from the expected values because of manufacturing tolerances and normal wear and tear. Engine components may have a shorter life than expected because of manufacturing tolerances. In spite of the important effect of operating- and manufacturing-uncertainty on the performance and expected life of the component or system, traditional aerodynamic shape optimization has focused on obtaining the best design given a set of deterministic flow conditions. Clearly it is important to both maintain near-optimal performance levels at off-design operating conditions, and, ensure that performance does not degrade appreciably when the component shape differs from the optimal shape because of manufacturing tolerances and normal wear and tear. These requirements naturally lead to the idea of robust optimal design wherein the concept of robustness to various perturbations is built into the design optimization procedure.

Recognition of the importance of incorporating the probabilistic nature of the variables involved in designing and operating complex systems has led to several investigations in the recent past. Some of the basic principles of robust optimal design are discussed by Egorov et al.[1]. Several commonly used approaches such as maximizing the mean value of the performance metric, minimizing the deviation of this metric and, maximizing the probability that the efficiency value is no less than a prescribed value are discussed in their paper. Egorov et al.[1] make the observations that a) robust design optimization is in essence multi-objective design optimization because of the presence of the additional objective (robustness) and, b) the addition of the robustness criterion may result in an optimal solution that is substantially different from that obtained without this criterion. Various approaches to robust optimal design are also mentioned in this article.

While the discussion above focused on the effect of uncertainty in the variables on performance, their effect on constraint satisfaction is equally important from a reliability perspective. Here the focus is on maximizing the probability of constraint satisfaction. Koch et al.[2], provide a discussion of this and related concepts. Some of the basic steps involved in both robust optimal design as well as reliability-based optimization such as a) identifying random variables and their associated probability density functions, b) reducing this set of variables to a smaller subset of key random variables, to reduce optimization costs and, c) the effective utilization of Monte Carlo techniques to obtain estimates of performance variability or reliability, are discussed by the authors.

Simulation based design optimization can be computationally expensive in cases where the underlying physics is complicated. Some of the contributing factors are three-dimensionality, a large disparity in the largest and smallest scales that are required for an accurate analysis etc. The addition of the robustness criterion can greatly increase computational requirements because of the need to estimate the variance in performance or reliability. Koch et al.[2], reduce computational cost by first obtaining the optimal solution via a deterministic approach and subsequently adding the reliability requirement. In a separate article Koch et al.[3]use Kriging models to compute performance variability and reliability.

The imposition of the additional requirement of robustness results in a multiple-objective optimization problem requiring appropriate solution procedures. Typically the costs associated with

*Senior Scientist, Exploration Technology Directorate multiple-objective optimization are substantial. Therefore efficient multiple-objective optimization procedures are crucial to the rapid deployment of the principles of robust design in industry. Hence the companion set of lecture notes (Single- and Multiple-Objective Optimization with Differential Evolution and Neural Networks [4]) deals with methodology for solving multiple-objective optimization problems efficiently, reliably and with little user intervention.

Genetic and evolutionary algorithms have been applied to solve numerous problems in engineering design where they have been used primarily as optimization procedures. These methods have an advantage over conventional gradient-based search procedures because they are capable of finding global optima of multi-modal functions (not guaranteed) and searching design spaces with disjoint feasible regions. They are also robust in the presence of noisy data. Another desirable feature of these methods is that they can efficiently use distributed and parallel computing resources since multiple function evaluations (flow simulations in aerodynamics design) can be performed simultaneously and independently on multiple processors. For these reasons genetic and evolutionary algorithms are being used more frequently in design optimization. Deb[5] reviews numerous genetic and evolutionary algorithms for use in multiple-objective optimization. More recent developments such as 1) using hierarchical population topologies, 2) surrogate models to compute the objective function, 3) clustering of data into multiple classes for improved algorithm performance and constructing multiple response surfaces and 4) using non-dominated solutions from previous generations, can be found in Refs.6 - 8.

Here we focus on applications of an evolutionary algorithm for multiple-objective optimization developed by Rai.[9] This method is based on the method of Differential Evolution (DE) developed by Price and Storn[10] for single-objective optimization. One goal of this developmental effort was a method that required a small population of parameter vectors to solve complex multiple-objective problems involving several Pareto fronts (global and local) and nonlinear constraints. Applications of this evolutionary method to some difficult model problems involving the complexities mentioned above are also presented in Ref.9. The computed Pareto-optimal solutions closely approximate the global Pareto-front and exhibit good solution diversity. Many of these solutions were obtained with relatively small population sizes. Rai[9] also explores the possibility of using neural networks to obtain estimates of the Pareto optimal front. Achieving solution diversity and accurate convergence to the exact Pareto front usually requires a significant computational effort with the evolutionary algorithm. The use of neural network estimators has the potential advantage of reducing or eliminating this effort thus reducing cost to design. The estimating curve or surface can be used to generate any desired distribution of Pareto optimal solutions. This method is discussed in detail in the companion set of lecture notes[4].

Applications of this new method[9] to robust design are presented here. The evolutionary method is first used to solve a relatively difficult problem in extended surface heat transfer wherein optimal fin geometries are obtained for different safe operating base temperatures. The objective of maximizing the safe operating base temperature range is in direct conflict with the objective of maximizing fin heat transfer. This problem is a good example of achieving robustness in the context of changing operating conditions. The evolutionary method is then used to design a turbine airfoil; the two objectives being reduced sensitivity of the pressure distribution to small changes in the airfoil shape and the maximization of the trailing edge wedge angle with the consequent increase in airfoil thickness and strength. This is a relevant example of achieving robustness to manufacturing tolerances and wear and tear in the presence of other objectives.