



A NEW FORMULATION FOR BI-OBJECTIVE OPTIMIZATION THROUGH A COMBINED APPROACH

By

Mohamed Shahat Abdel-Azim Badawi

A Thesis submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

MECHANICAL DESIGN AND PRODUCTION ENGINEERING

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Key Words: Bi-objective Optimization, Feasibility Robustness, Objective Robustness, Pareto Solutions, Perturbation Analysis, Robustness Index.

Summary:

In this work, we present a new robust optimization approach based on the combined conventional and minimum sensitivity optimization approaches. For the new approach, we provide a new formulation in which the conventional objective function and the minimum sensitivity function are solved in a bi-objective optimization problem. A perturbation analysis is carried using Monte Carlo (MC) simulation approach. A comparison among the three optimization approaches is provided. The validity of the new approach is ascertained through test bed problems. Five case studies involving the optimization of real engineering systems are presented using the developed approach. An optimization code is developed using Matlab environment.



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DEDICATION

To my father.....

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NOMENCLATURE

f	Response of a system
f_1	Main objective function
f_2	1st derivative of the main objective w.r.t. to the design variables
F_1	Minimum sensitivity formulation 1
F_2	Minimum sensitivity formulation 2
F_3	Minimum sensitivity formulation 3
b	Vector of design variables
b^*	Values of design variables at minimum sensitivity
pdf's	Probability density functions
X	Uncertain variable
χ^{e}	Estimated value of x
x_{i}	Design variable number i
$x_i \pm 1 \%$	Perturbation interval of 1 %
$x_i \pm 5 \%$	Perturbation interval of 5 %
$x_{\rm i} \pm 10 \%$	Perturbation interval of 10 %
β	Robustness index
# of V	Number of variables
# of C	Number of constraints
N.O.C.	Nature of constraints
# of O.F _s .	Number of objective functions
Eq.	Equality
Ineq.	Inequality
CBFS	Correlation Based Feature Selection
CCD	Central Composite Design
CLT	Central Limit Theorem
DOE	Design of Experiments
DRDT	Deterministic Robust Design Techniques
DRSA	Dual Response Surface Approach
DVHS	Design Variation Hyper Sphere
FOSM	First Order Second Moment

GA Genetic Algorithm

L Linear

MC Monte Carlo simulation

MPNN Mathematical Programming Neural Network

MPP Most Probable Point

MS Minimum Sensitivity Approach

NL Nonlinear

OA Orthogonal Arrays

POSA Post Optimality Sensitivity Analysis

PP Physical Programming

RBDM Robust Bayesian Data Mining

RCEM Robust Concept Exploration Method

RDO Robust Design Optimization

RMOGA Robust Multi Objective Genetic Algorithm

RPD Robust Parameter Design

RS Response Surfaces

RSM Response Surface Methodology

SI Sensitivity Index

SPSA Simultaneous Perturbation Stochastic Approximation

SQP Sequential Quadratic Programming

SRDT Stochastic Robust Design Techniques

TRF Tunable Robust Function

ABSTRACT

Developing robust design solutions with respect to performance, as well as feasibility, is one of the most important concerns in engineering optimization. In this work, a new robust optimization approach is presented. It incorporates the two main concepts of robust optimization: objective robustness and feasibility robustness. The majority of robust optimization techniques consider one of the two concepts of robustness. The new approach is based on the combined conventional and minimum sensitivity optimization approaches. The conventional optimization approach provides a solution which has the highest performance, where the minimum sensitivity approach develops a solution with the least sensitivity to variations. For the new approach, a new formulation is provided, in which the conventional objective function and the minimum sensitivity function are solved in a bi-objective optimization problem. A perturbation analysis is carried using Monte Carlo (MC) simulation approach. A comparison among the three optimization approaches (conventional, minimum sensitivity, and combined) is provided. The validity of the new approach is ascertained through test bed problems. Five case studies involving the optimization of real engineering systems are presented using the developed approach. An optimization code is developed using Matlab environment.

CHAPTER 1

INTRODUCTION

1.1. MOTIVATION AND OBJECTIVE

Uncontrollable variations and noises are unavoidable in engineering design. Temperature variations, deviations of material properties from specifications, and dimensional tolerances of a design are just few examples of uncontrollable parameter variations. When designing a system, these variations cannot be ignored because they can seriously affect the performance of a design. One way to counter the effects of these variations is to try to reduce or eliminate the parameter variations themselves. However, this approach is usually very difficult to undertake and/or expensive to implement. Furthermore, it is quite possible that such variations will re-appear. A better approach is to try to reduce the sensitivity of the design to variations so that deteriorations caused by these variations are kept within an acceptable level.

Genichi Taguchi (Taguchi, 1993) introduced the idea of reducing the sensitivity of a design, through parameter design. Since then, this "least-sensitive design" idea is developed and the "robust design" is coined. Later, "objective robustness" and "feasibility robustness" are introduced to refer to the robustness with respect to the objective and constraint functions in an optimization problem.

The first robust optimization approach is advocated by Belegundu and Zhang (1989). This method is called the minimum sensitivity approach. It assumes the existence of analytical model and attempts to minimize the sensitivity with respect to decision variables through minimization of the first derivatives with respect to design parameters. This approach is straightforward and problem-independent manner. No assumptions are made on the probability distributions of uncertain variables. Compared to the conventional deterministic optimization, the minimum sensitivity approach provides a robust design that is least sensitive to variations. However, the existence of the solution close to one or more constraint results in infeasible solution.

It is important to achieve robust design objectives, but also to maintain the robustness of design feasibility under the effect of variations. The evaluation of feasibility robustness is often a computationally extensive process. Simplified