MULTIOBJECTIVE EVOLUTIONARY COMPUTATION FOR SUPERSONIC WING DESIGN

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Abstract

This lecture demonstrates design optimization of a wing for supersonic transport (SST) using Multiobjective Evolutionary Algorithms (MOEAs). Three objective functions are used to minimize the drag for supersonic cruise, the drag for transonic cruise, and the bending moment at the wing root for supersonic cruise. The wing shape is defined by 66 design variables. An Euler flow code is used to evaluate supersonic performance, and a potential flow code is used to evaluate transonic performance. To reduce the total computational time, flow calculations are parallelized on an NEC SX-4 computer using 32 processing elements. The detailed analysis of the resulting Pareto front suggests a renewed interest in the arrow wing planform for the supersonic wing.

1 Introduction

The development of next-generation supersonic transport has been considered worldwide to respond to the increasing demand on air traffic. Aerodynamic design of such aircraft must account for drag reduction as well as sonic boom minimization. However, drag reduction is in conflict with sonic boom minimization. Since the acceptability of supersonic transport is very sensitive to sonic booms over populated areas, one of the design choices is to only allow supersonic flight over sea and to have transonic flight over land. Although such a decision excludes the sonic boom from the design consideration, the design is now faced with transonic performance of the aircraft.

This lecture demonstrates multipoint aerodynamic optimization of a wing shape for supersonic aircraft both at a supersonic cruise condition and at a transonic cruise condition. Aerodynamic drag will be minimized at both cruise conditions under lift constraints. Aerodynamic optimization of the wing planform, however, drives the wing to have an impracticably large aspect ratio. In reality, the aspect ratio of the wing is constrained by other disciplines, such as structure and equipment.

In standard aircraft design procedure, the wing planform shape has to be determined at an early stage because the planform shape is closely related to aircraft sizing. In this stage, designers should account for tradeoffs between aerodynamic performance, structural strength and weight, fuel storage, and so on. Therefore, an automated design of the wing planform shape requires multidisciplinary design optimization (MDO) based on a system composed of aerodynamics, structural dynamics, etc. [1]. Because cross-disciplinary tradeoffs are built into the MDO model implicitly, a highly sophisticated MDO model is needed to obtain realistic wing planform shapes.

For the simplicity of the present wing model, however, the MDO model of a wing is not considered. Instead, aerodynamic load is minimized by assuming that less aerodynamic load will lead to a lighter, sustaining wing structure. Therefore, minimization of the wing root bending moment is added as a third design objective. On the other hand, the present wing model does not have any built-in cross-disciplinary tradeoffs originally because no wing structure is specified. This means that each design objective may be treated independently.

The present optimization problem can be regarded as multiobjective (MO) optimization. MO optimization seeks to optimize the components of a vector-valued objective function. Unlike single objective optimization, the solution to this problem is not a single point, but a family of points known as the Pareto-optimal set. Thus, it is more natural to find a set of compromise solutions known as Pareto solutions, than to find a single optimal solution corresponding to a particular tradeoff.

By maintaining a population of solutions, Evolutionary Algorithms (EAs) can search for many Pareto-optimal solutions in parallel. This characteristic makes EAs very attractive for solving MO problems. As a solver for MO problems, the following two features are desired: 1) the solutions obtained are Pareto-optimal and 2) they are uniformly sampled from the Pareto-optimal set. To achieve these, MOEAs have been introduced successfully in [2-5].

The next section outlines the standard genetic operators used in EAs and their extensions to MOEAs. Then, the computed solutions are demonstrated. The role of MOEAs in the design environment will unfold by analyzing the Pareto solutions,

2 Approach

2.1 Evolutionary Algorithms

Evolution is a phenomenon of adapting to the environment and passing genes to next generations. In *On the Origin of Species by Means of Natural Selection* [6], Charles Darwin did not know about the underlying genetics, but he identified three basic principles driving natural evolution; reproduction, natural selection, and diversity of individuals, maintained by variations from one to the next generation. These features of natural evolution have found entrance to a broad class of evolutionary algorithms that mimic biological evolution and natural selection. It was 1960s that American and European researchers gave birth to stochastic search methods inspired by Darwinian evolution theory, all independently of each other: they are Evolutionary Programming (EP)[7-9], Evolutionary Strategies (ESs) [10-13], and Genetic Algorithms