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Combining game theory and genetic algorithms with application to DDM-nozzle optimization problems

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Abstract

The goal of this paper is to discuss a new evolutionary strategy for the multiple objective design optimization of internal aerodynamic shape operating with transonic flow. The distributed optimization strategy discussed here and inspired from Lions' new distributed control approach (J.L. Lions, Distributed active control approach for pde systems, Fourth WCCM CD-ROM, Buenos Aires, Argentina, 1998) relies on genetic algorithms (GAs). GAs are different from traditional optimization tools and based on digital imitation of biological evolution. Game theory replaces here a global optimization problem by a non-cooperative game based on Nash equilibrium with several players solving local constrained sub-optimization tasks. The transonic flow simulator uses a full potential solver taking advantage of domain decomposition methods and GAs for the matching of non-linear local solutions. The main idea developed here is to combine domain decomposition methods for the flow solver with the geometrical optimization procedure using local shape parameterization. Numerical results are presented for a simple nozzle inverse problem with subsonic and transonic shocked flows. A comparison of the nozzle reconstruction using domain decomposition method (DDM) or not for the simulation of the flow is then presented through evolutionary computations and convergence of the two surface parts of the throat is discussed. The above results illustrate the robustness and primising inherent parallelism of GAs for mastering the complexity of 3D optimizations. © 2001 Published by Elsevier Science B.V.

1. Genetic algorithms

Classic deterministic optimization methods are powerful and fast tools for solving optimization problems dealing with smooth, unimodal objective functions. They require few objective function

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evaluations compared to stochastic optimization methods but have several drawbacks, in particular, with multi-modal function or non-convex optimization problems. One powerful alternative to these methods are genetic algorithms (GAs), a stochastic approach based on natural selection mechanisms and Darwin's main principle: survival of the fittest. Many realistic optimizations require robust tools able to deal with non-convex optimization problems. GAs have been introduced by Holland who explained the adaptive process of natural systems [1]. More recently, Goldberg brought GAs in non-convex optimization theory for quantitative study of optima and introduced a decisive thrust in the GAs field [2]. The basic principle is a parallel established between an individual and a solution on the one hand, and between an environment and a problem on the other. A good solution to a given problem is an individual who is likely to succeed in a given environment. Each individual (i.e. solution) has a fitness function which measures how fit it is to the environment (i.e. problem), or in other words how good the solution is.

The mechanisms of a simple GA for a minimization problem may be found in [2].

GAs using binary coding are directly used for the problem of domain decomposition method (DDM) whereas for inverse problems discussed in the following sections, we consider the use of floating point coding with non-uniform mutation (see [3] for details).

2. Multi-objective optimization

The simplest way to address the problem of multiple objective optimization is to use a scalar objective, generally obtained through some linear combination of weighted objectives [4]. Such an approach may be of interest in some cases – particularly if the weight of each criterion is known before hand – but besides its ad hoc character, it has several drawbacks since there is a loss of information and a need to define the weights associated to each objective. Moreover, the behaviour of the algorithms is very sensitive and biased by the values of these weights [5] Shaffer was the first to propose a GA approach for multi-objectives through his vector evaluated genetic algorithm (VEGA [6]), but it was biased towards the extreme of each objective. Goldberg proposed a solution to this particular problem with both non-dominance Pareto-ranking and sharing, in order to distribute the solutions over the entire Pareto front [2]. This cooperative approach was further developed in [7], and lead to many applications [8]. All of these approaches are based on Pareto-ranking and use either sharing or mating restrictions to ensure diversity; a good overview can be found in [9]. Another non-cooperative approach with the notion of a player has been introduced by Nash [10] in the early 1950s for multiple objective optimization problems originating from game theory and economics. The following section is devoted to an original non-cooperative multiple objective algorithm, which is based on Nash equilibria.

3. Nash equilibria

3.1. Definition

For an optimization problem with G objectives, a Nash strategy consists of having G players, each optimizing his own criterion. However, each player has to optimize his criterion given that all