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Progress in design optimization using evolutionary algorithms for aerodynamic problems

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ABSTRACT

Evolutionary algorithms (EAs) are useful tools in design optimization. Due to their simplicity, ease of use, and suitability for multi-objective design optimization problems, EAs have been applied to design optimization problems from various areas. In this paper we review the recent progress in design optimization using evolutionary algorithms to solve real-world aerodynamic problems. Examples are given in the design of turbo pump, compressor, and micro-air vehicles. The paper covers the following topics that are deemed important to solve a large optimization problem from a practical viewpoint: (1) hybridized approaches to speed up the convergence rate of EAs; (2) the use of surrogate model to reduce the computational cost stemmed from EAs; (3) reliability based design optimization using EAs; and (4) data mining of Pareto-optimal solutions.

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1. Brief introduction of evolutionary algorithms

1.1. Evolutionary algorithms

Evolutionary algorithms (EAs) mimic mechanics of natural selection and natural genetics, in which a biological population evolves over generations to adapt to an environment by selection, crossover, and random mutation. Likewise, EAs start with a random population of candidates (chromosomes), for each of them both the objective and constraint functions are evaluated. Based on the objective function value and constraint violations a metric (fitness) is defined and assigned to each candidate. In general, penalty is put on infeasible candidates so that all infeasible solutions have a worse fitness than feasible solutions. Typically EAs involve three operators, selection, crossover, and mutation. The primary purpose of selection operator is to make duplicates of good candidates and eliminate bad candidates in a population while often keeping population size constant [16]. Tournament selection, proportionate selection, and ranking selection are common methods to achieve the task. For single-objective optimization problems, the ranking is based on the fitness of a candidate. For multi-objective optimization problems, the ranking can be based on Fonseca's non-dominated ranking method in which an individual's rank is equal to the number of individuals in the present generation who are better than the corresponding individual in all the objective functions [23]. After ranking, the N best candidates, same size as the initial population, are chosen from both the current and previous generations and then placed in the mating pool. The elitist strategy [17] is often chosen to ensure a monotonic improvement for the EA, in which some of the best individuals are copied directly into the next generation without applying any evolutionary operators. The ranking selection method assigns selection probability p_s based on an individual's rank instead of its fitness value. The selection probability function is defined as

$$p_s = c(1-c)^{(\text{rank}-1)}, \tag{1}$$

where $c<1$ is a user-defined parameter. That is, the selection probability is reduced by a factor of $(1-c)$ each time when the rank is increase by 1. Then, a pair of parents are selected by using either stochastic universal sampling or roulette-wheel section, with which same candidate can be selected more than once to become a parent. As a consequence, the selection operator ensures that good candidates are preserved at the cost of bad candidates.

A crossover operator is applied next to create offsprings. For example, using the blend crossover (BLX$-\alpha$) operator, two parent candidates, Parent 1 and Parent 2, will have two offspring as follows:

$$\text{Child } 1 = \gamma \text{ Parent } 1 + (1-\gamma) \text{ Parent } 2, \tag{2}$$

$$\text{Child } 2 = (1-\gamma) \text{ Parent } 1 + \gamma \text{ Parent } 2, \tag{3}$$

where

$$\gamma = (1+2\alpha)u - \alpha \tag{4}$$

u is a uniform random number in the range of [0 1]. The value of $\alpha = 0.5$ is usually chosen because it can maintain a good balance between two conflicting goals of a crossover operator: exploiting good solutions and exploring the search space [9].

The mutation operator is used to maintain the population diversity. For real-coded EA a uniform random number is added to each design variable at a probability of p_m. If x_i represents such a design variable, then the corresponding variable of the new offspring after mutation has the following form:

$$x_i^{\text{new}} = x_i[1+(r_i-0.5)\Delta_i], \tag{5}$$

where x_i^{new} is the design variable after mutation, r_i is a random number ranging [0 1], Δ_i is the user-defined maximum perturbation allowed in the i-th decision variable. We set the mutation probability $p_m = 0.1$ and mutation amplitude $\Delta_i = 0.1$ in our computations.

EAs have been successfully applied to aerodynamic design optimization problems because of their ease of use, broad applicability, and global perspective. For example, Oyama et al. applied an EA in their redesign of the NASA Rotor67 transonic compressor blade [64]. Benini implemented an EA to improve the performance of the NASA rotor37 blade [7]. Oyama and Liou [63] and Lian et al. [44,47] utilized EAs to the redesign of rocket turbo pumps. Another thrust behind these broad applications is that EAs are particularly suitable for multi-objective optimization problems, which are often encountered in aerospace designs. For example, in the turbo pump design problems, the objectives are to maximize the total head rise and to minimize the input power [63,44,47]. These two objectives are competing: improving one objective will inevitably deteriorate the other. Unlike a single objective optimization problem, a multi-objective optimization problem does not have such an optimal solution that is better than others in terms of all objectives. Instead, one expects a set of compromised solutions, each of which is better than the others in one objective but is worse in the other objectives. These solutions are largely known as the non-dominated solutions or Pareto-optimal solutions. When dealing with multi-objective optimization problems, classical methods, such as the gradient-based methods, usually convert a multi-objective problem into multiple single-objective problems by introducing parameters such as weight vectors [16]. In this approach, each optimal solution is associated with a particular vector. To find another Pareto-optimal solutions, one has to choose a different weight vector and solve the resulting single-objective optimization problem repeatedly. On the other hand, EA's population approach can be exploited to emphasize all non-dominated solutions in a population equally and to preserve a diverse set of multiple non-dominated solutions using a niche-preserving operator [16]. As a consequence, EAs eliminate the need of choosing different parameters and can find as many Pareto-optimal solutions as possible in one run.

2. Optimization using hybridized EAs

EAs are powerful tools in optimization. However, EAs suffer a slow convergence because they do not use gradient information. The required population size and generation size usually demand tremendous amount of computing resources. For instance, Benini redesigned the NASA rotor37 with an EA, with a population size of