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TURBOMACHINERY AIRFOIL DESIGN OPTIMIZATION USING DIFFERENTIAL EVOLUTION

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ABSTRACT

An aerodynamic design optimization procedure that is based on a evolutionary algorithm known at Differential Evolution is described. Differential Evolution is a simple, fast, and robust evolutionary strategy that has been proven effective in determining the global optimum for several difficult optimization problems, including highly nonlinear systems with discontinuities and multiple local optima. The method is combined with a Navier-Stokes solver that evaluates the various intermediate designs and provides inputs to the optimization procedure. An efficient constraint handling mechanism is also incorporated. Results are presented for the inverse design of a turbine airfoil from a modern jet engine and compared to earlier methods. The capability of the method to search large design spaces and obtain the optimal airfoils in an automatic fashion is demonstrated. Substantial reductions in the overall computing time requirements are achieved by using the algorithm in conjunction with neural networks.

INTRODUCTION

Remarkable progress has been made in recent years in the ability to design turbomachinery airfoil shapes that are optimal with regard to certain desired characteristics. This progress has been achieved by combining improved methods for predicting the complicated flow fields in turbomachinery with efficient numerical optimization techniques and by harnessing the powerful capabilities of modern computers. Both steady and unsteady Navier-Stokes and Euler solvers have been combined with various optimization techniques (gradient-based methods,[1,2] response surfaces, etc.) to optimize the design of turbomachinery airfoils.

More recently, there has been considerable interest in the development of turbomachinery airfoil design optimization techniques that are based on nontraditional approaches such as evolutionary algorithms and neural networks. Various approaches based on neural networks (see, for example Sanz,[3] Rai,[4] Pierret and Braembussche[5]), neural networks in conjunction with response surfaces (Rai and Madavan,[6] Papila et al.[7]), genetic algorithms (Obayashi and Takahashi,[8] Dennis et al.[9]), genetic algorithms in conjunction with neural networks (Quagliarella and Cioppa,[10] Uelschen and Lawerenz,[11] Poloni et al.[12]) have been reported in the literature. These techniques offer several advantages over traditional optimization methods.

This paper deals with the development of an turbomachinery airfoil design optimization procedure that is based on a relatively new evolutionary algorithm known as Differential Evolution[13] (DE) developed for single-objective optimization in continuous search spaces. It is conceptually simple and possesses good convergence properties that have been demonstrated in a variety of applications. DE is best characterized as an evolutionary strategy (ES) rather than as a genetic algorithm (GA), although the distinction between GAs and ESs have blurred in recent years. Perhaps the main ideological difference lies in the relative importance given to the two main evolutionary operators, recombination (crossover) and mutation, with GA-based approaches relying heavily on the former and ES-based approaches on the latter. DE has proven to be an effective approach in determining the global optimum for several difficult optimization problems in a variety of applications. Its application in aeronautics, however, has been rather limited. Nho and Agarwal[14] used it in predictive control of aircraft dynamics. Rogalsky et al.[15] used DE in conjunction with a potential flow solver in the inverse design of turbomachinery airfoils; Rogalsky et al.[16] also presented a hybridized version of DE by using it in conjunction with a local search method to minimize the number of objective function evaluations using the potential flow solver.

In this paper the DE algorithm is combined with a Navier-Stokes solver that provides inputs to the optimization procedure. An efficient constraint handling mechanism is also incorporated in the algorithm. An airfoil geometry parametrization that uses a minimal number of variables is also used to minimize the number of objective function evaluations. The procedure is also combined with neural networks that are incrementally trained on the Navier-Stokes simulation data and can then be used in the objective function evaluation. This results in substantial reductions in the overall computing time. Additionally, the procedure has been implemented on a distributed parallel computer in a straightforward manner that relies on the simultaneous computation of multiple, independent aerodynamic simulations on separate processors. The procedure is primarily script-based and allows for a variable number of processors to be used depending on the size of the population used in the DE algorithm. Details of the method and its implementation are described in the final paper along with results for the inverse design of a turbine airfoil to demonstrate its capabilities.

DESIGN OPTIMIZATION METHOD

The DE approach uses a population of n-dimensional, real-valued parameter vectors. The population is usually initialized in a random fashion and the population size is maintained constant throughout the optimization process. As with all ES-based approaches, mutation is the key ingredient of DE. The basic idea is to generate new parameter vectors for the subsequent generation by using weighted differences between two (or more) parameter vectors selected randomly from the current population to provide appropriately scaled perturbations that modify another parameter vector (or, comparison vector) selected from the same population.

Geometry parameterization and prudent selection of design variables are among the most critical aspects of any shape optimization procedure. Here, the airfoil geometry parameterization method described in Rai and Madavan[6] that uses a total of 13 parameters to define the turbine airfoil geometry is used.

A two-dimensional Navier-Stokes solver is used to perform the flow simulations (direct function evaluations) that serve as inputs to the optimization process. Multiple grids are used to discretize the flow domain. The flow parameters that are specified are the turbine pressure ratio, inlet temperature and flow angle, flow coefficient, and unit Reynolds number based on inlet conditions.

RESULTS

The design method was used in the inverse design of a turbine airfoil with a specified pressure distribution. The target pressure distribution was obtained at the midspan of a turbine vane from a modern jet engine and was supplied by Pratt and Whitney (Private Communication, F. Huber, 1997). Several flow and geometry parameters were also supplied and used in the design process. The design objective function was formulated as the equally-weighted sum-of-squares error between the target and actual pressure obtained during the optimization process at 45 locations on the airfoil.

Figure 1 shows the pressure distribution for the optimal airfoil obtained using the DE optimization method. The results compare well with the target distribution. The method allows for the number of design variables to be gradually increased during the design process. Figure 1 also shows the pressure distribution from intermediate results obtained using six design variables.

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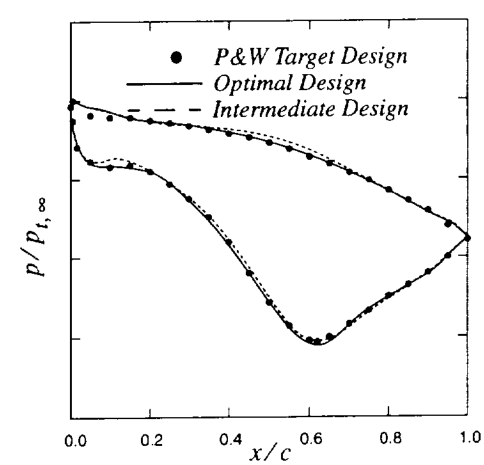

Figure 1. Airfoil surface pressure distributions obtained from CFD simulations for the final optimal design and an intermediate design (using 6 design variables).