NATIONAL TECHNICAL UNIVERSITY OF ATHENS
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PhD Thesis

PARALLEL, MULTILEVEL ALGORITHMS FOR THE AERODYNAMIC OPTIMIZATION IN TURBOMACHINES

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Abstract

This PhD thesis focuses on the development and assessment of design optimization methods, based on evolutionary algorithms, that perfectly suits to aerodynamic shape optimization problems. Based on the proposed methods, a generic optimization software (EASY software, http://velos0.ltt.mech.ntua.gr/EASY) is developed by laying emphasis on the minimization of the total CPU cost using surrogate evaluation models (metamodels) and hierarchically structured multilevel schemes. Moreover, parallel processing using cluster and grid computing middleware contributes to reducing the wall clock time required.

Computational fluid dynamics (CFD) is an important aspect of this work, due to the nature of the applications presented (i.e. shape optimization of turbomachinery components and airfoils in which the evaluation of each candidate solution requires the numerical flow field prediction by means of a time-consuming CFD solver). In this context, in-house grid generation and CFD software are employed. Over and above (a) a software for generation of 3D unstructured hybrid (with tetrahedral, prismatic, pyramidal, and hexahedral elements) grids, suitable for the solution of the Navier-Stokes equations using low Reynolds number turbulence models in turbomachinery cascades and (b) a parallel flow solver for graphics cards (GPUs) have also been developed.

The multilevel algorithm is based on a hierarchical distributed evolutionary algorithm developed during a preceding PhD thesis at the Laboratory of Thermal Turbomachines of NTUA. An efficient and flexible multilevel optimization software is herein proposed. Each level is associated with (a) an evaluation tool, (b) a search technique and (c) a parameterization scheme. In total, three multilevel schemes were investigated. On each of the levels, the multilevel evaluation scheme resorts to different evaluation tools, the multilevel parameterization handles problem variants with different numbers of degrees of freedom (coarse and fine) and the multilevel search employs different optimization methods (gradient-based and heuristics).In these schemes, the search on the low levels is based on low fidelity/ low cost tools, stochastic search methods which do not require the gradient of the objective functions with respect to the design variables, a coarse parameterization and/ or relaxed constraints. The so-computed `optimal' solutions are communicated to the higher levels in order to guide the search. Apart from using the three distinct modes (multilevel evaluation,

search and parameterization) as stand-alone methods, extra gain was reported from their combined use.

Thus far, a hierarchical distributed search scheme was described. The use of different evaluation software may, alternatively, be placed within each deme of a distributed evolutionary algorithm. This yields a distributed hierarchical evolutionary algorithm, in which evaluation models of different fidelity serve to successively screen out the non-promising individuals at each generation. The number of the offspring to undergo exact evaluation decreases as the fidelity (and CPU cost) of the evaluation tool is increased. The lowest pass is based on metamodel (trained on previously evaluated offspring) predictions. All demes of the distributed hierarchical evolutionary algorithm regularly exchange their best-so-far solutions using a migration operator.

Metamodels significantly contribute to reducing the CPU cost. They are employed in the context of the Inexact Pre-Evaluation (IPE) algorithm, to screen out non-promising offspring during the evolution and reduce the number of candidate solutions to undergo exact evaluation. Without loss in generality, radial basis function networks (RBFN) and multilayer perceptrons (MLP) serve as metamodels. Where appropriate, support vectors machines (SVM) are additionally employed. The latter are used to classify the candidate solution in terms of feasibility. Feasible solutions acquire approximate costs using RBFN or MLP which are trained on individuals that exclusively reside on the feasible region of the design space. Moreover, a new class of metamodels able to take into account both response and gradient (computed solving the adjoint equations) of the training set is presented. This new class of gradient-assisted metamodels yields increased generalization abilities, combined with reduced prediction error compared to conventional metamodels, trained on samples acquired at the same CPU cost. Fitness inheritance approximating the fitness of any offspring based on the fitness values of its parents, is also employed. Fitness inheritance is used during the first couple of generations of the evolutionary algorithm, in which the database of previously evaluated candidate solutions is not sufficient to train a metamodel. Once adequate entries are archived, RBFN or MLP are used in place of fitness inheritance.

Multiprocessing is an important aspect of each algorithm presented. Three types of multiprocessing are discussed: (a) the concurrent evolution of each level (and all demes within the levels) using threads, (b) the concurrent evaluation of more than one candidate solutions during the evolution of the multilevel algorithm and (c) the parallel execution of the evaluation software of each candidate solution. Both (b) and (c) aim to reduce the wall clock time required until the final solution is obtained. In the context of the concurrent evaluation of candidate solutions, the optimization software makes use of middleware (Condor & Gridway) that allows the efficient utilization of clusters and grids. The parallel evaluation of candidate solutions is carried out using a parallel version of the flow solver either for CPUs or GPUs (NVIDIA GeForce GTX280). All CFD computations, (including the GPU implementation of the flow solver) were carried out on the three clusters of the Laboratory of Thermal Turbomachines and the Parallel CFD and Optimization Unit of the Fluids Section of the School of Mechanical Engineering of the National Technical University of Athens.

The efficiency of the multilevel optimization algorithm is demonstrated on a number of well known mathematical test cases from the literature, design-optimization problems in the field of aerodynamics (inverse design problems, aiming to increase lift or reduce drag) and turbomachinery (viscous losses reduction, static pressure rise maximization). Apart from 2D

applications, two large scale problems are presented: (a) the design of a supersonic business jet which is a multidisciplinary optimization problem involving structural analysis (NASTRAN), aerodynamic analysis and fluid-structure interaction and (b) the optimization of a 3D peripheral compressor cascade in the presence of tip clearance.

Keywords: Thermal Turbomachines, Optimization, Evolutionary Algorithms, Multilevel Techniques, Computational Fluid Dynamics, Grid Computing.