AIAA SciTech
5-9 January 2015, Kissimmee, Florida
53rd AIAA Aerospace Sciences Meeting

AIAA 2015-1721

Evolutionary Optimization of Benchmark Aerodynamic Cases using Physics-based Surrogate Models

Emiliano Iuliano* and Domenico Quagliarella*

CIRA, the Italian Aerospace Research Center, Capua (CE), 81043, Italy.

Abstract

The paper proposes the application of evolutionary-based optimization coupled with physics-based and adaptively-trained surrogate model to the solution of two aerodynamic benchmark problems defined within the AIAA Aerodynamic Design Optimization Discussion Group. The benchmark problems are represented respectively by the drag minimization of the RAE 2822 airfoil in transonic viscous flow and of the NACA 0012 airfoil in transonic inviscid flow. The shape parameterization approach consists of the Class-Shape Transformation (CST) method with a sufficient degree of Bernstein polynomials to cover a wide range of shapes. Mesh convergence is demonstrated on single-block C-grid structured meshes. The in-house ZEN flow solver is used for Euler/RANS aerodynamic solution. Results show that, thanks to the combined usage of surrogate models and intelligent training, optimal candidates may be located in the design space even with limited computational resources with respect to brute force optimization approaches.

I. Introduction

The solution of aerodynamic shape optimization problems by high-fidelity Navier-Stokes models requires a huge amount of computational resources even on modern state-of-art computing platforms. Indeed, not only a single evaluation can be time-demanding, but often hundreds or thousands of CFD analyses have to be performed to find an optimal solution. In order to speed up the optimization process while keeping a high level of fidelity, the scientific community is increasingly focusing on surrogate methodologies like meta-models, multi-fidelity models or reduced order models, which can provide a compact, accurate and computationally efficient representation of the aircraft design performance. Nevertheless, the usage of such models is not straightforward as the amount and quality of information the user has to provide in the learning phase is not known a priori; furthermore, the efficient exploitation of learning data may be hampered by the inherent complexity of the design problem, e.g. non-linearities in the physical model, constraints handling, curse of dimensionality, multi-modal fitness landscape, accuracy *vs* computational effort trade-off. Hence, no general rule exists on the optimal choice of the type of surrogate model, the training and validation strategy, the combination of surrogate model and optimization algorithm. Finding the set of parameters which best fit the model to the available data is usually known as the training phase. The training dataset is usually obtained by sampling the design space (Design and Analysis of Computer Experiments, DACE) and performing expensive high-fidelity computations on the selected points. Depending on the adopted surrogate technique, design objectives and constraints or vector/scalar fields of interest are used to feed the surrogate model. The strategy to properly and optimally choose the DACE sampling data set is of paramount importance to achieve a satisfactory accuracy of the surrogate model. Unfortunately, classical sampling methods, like Latin Hypercube sampling, are very sensible to the nature of the problem at hand and they may deceive the surrogate-based optimization by hiding or masking the true optima locations. This is especially true in aerodynamic shape design problems where both model non-linearities and the dimension of the search space combine to emphasize this issue: classical DACE techniques would lead to intensively sample the search space, thus vanishing the actual advantage of surrogate-based optimization.

*PhD, Senior Aerospace Engineer, Fluid Dynamics Lab, Via Maiorise, 81043 Capua