The 9th European Congress on Computational Methods in Applied Sciences and Engineering
ECCOMAS Congress 2024
3-–7 June 2024, Lisbon, Portugal

THE CONTINUOUS ADJOINT METHOD WITH CONSISTENT DISCRETIZATION SCHEMES FOR TRANSITIONAL FLOWS AND THE USE OF DEEP NEURAL NETWORKS IN SHAPE OPTIMIZATION IN FLUID MECHANICS

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In this PhD Thesis, methods and tools for shape optimization in fluid dynamics are developed, assessed and applied. Emphasis is laid on (a) the mathematical formulation, programming and assessment of the continuous adjoint method for shape optimization in transitional flows of compressible fluids, (b) the development of consistent discretization schemes for the adjoint PDEs and boundary conditions involved in continuous adjoint and (c) the use of Deep Neural Networks (DNNs) in flow predictions and demonstration of the gain in optimization. The two first subjects are related to gradient-based optimization, whereas the last one is associated with the more efficient use of evolutionary algorithms. Herein, the continuous adjoint method is developed for the $\gamma - \tilde{Re}_{\theta t}$ transition model coupled with the Spalart-Allmaras turbulence model, for the first time in the literature. The "frozen transition" adjoint is evaluated as a possible cheaper alternative and is shown to damage the accuracy of Sensitivity Derivatives (SDs). The main advantages of the continuous adjoint is the clear physical insight into the adjoint PDEs and the low memory footprint of the adjoint code. The discretization schemes used for the adjoint equations can affect the accuracy of SDs since are not always consistent with the discretized flow problem. In discrete adjoint, consistency is not an issue; the main weaknesses are the excessive memory footprint of the adjoint code. This Thesis bridges the gap between the two adjoint variants by proposing consistent discretization schemes (inspired by discrete adjoint) for the continuous adjoint PDEs, with a clear physical meaning. The new *Think-Discrete Do-Continuous* (*TDDC*) adjoint computes SDs as accurate as discrete adjoint, ensuring low memory footprint and physical insight. The continuous adjoint method for transitional flows, that makes use of the *TDDC* discretization schemes, is used to carry out two industrial optimizations, that of a wing and that of a high aspect-ratio wing business jet configuration. In its last part, this Thesis develops and uses DNNs for flow prediction and shape optimization. DNNs are used to replace the numerical solution of the turbulence and/or transition model PDEs and as surrogates in multi-disciplinary and multi-row turbomachinery shape optimization problems. The resulting cost-effective solver is used as an evaluation tool during the shape optimization of aero/hydrodynamics problems.

Keywords: *Aerodynamic Shape Optimization, Continuous Adjoint, Discretization Schemes for the Adjoint Equations, Transition Modeling, Deep Neural Networks, Surrogates for Turbulence Closure, Evolutionary Algorithms*