15th EAWE PhD Seminar on Wind Energy
29–31 October 2019
Centrale Nantes, France

# Three-dimensional aerodynamic shape optimization of wind turbine rotors

A project outline

A Dicholkar[a], F Zahle[a], N N Sørensen[a], and M McWilliam[a]

[a]Department of Wind Energy, Technical University of Denmark, Building 118, Frederiksborgvej 399, Roskilde 4000.

E-mail: acdi@dtu.dk

*Keywords*: Computational Fluid Dynamics, Aerodynamics, Multi-fidelity optimization, Wind turbine

## 1 Introduction

Wind power installations have grown steadily in the last decade, with the growth being driven by reduction in the levelized cost of energy (LCOE) enabling it to compete with conventional power generation sources such as coal and natural gas. These improvements stem from a trend towards larger rotors. In order to enable the structure to withstand the high loads, the larger blades are designed to be flexible and have slender profiles. Additional measures, such as prebending and sweeping of the blades also aid in the design process. However, the current engineering models used to model the blade aerodynamics are limited by their inadequacy in accurately capturing the complex flow effects produced as a result of these out-of-plane geometries.

Instead, high-fidelity models involving 3D computational fluid dynamics (CFD) that solve the Navier-Stokes equations can be used to accurately capture the flow around wind turbine blades with out-of-plane geometries. Performing design optimizations using high-fidelity flow models that accurately represent the real-world turbine performance would result in realistic optimum designs. But high computational costs and a myriad of numerical issues preclude performing high-fidelity CFD-based design optimizations.

Despite the recent progress in the application of CFD-based shape optimization to 3D rotating wind turbine blades considerable enhancements are required to make it a mainstay in the industry. Some of the areas of improvement include incorporating realistic structural constraints, deep and stable convergence of flow and adjoint variables, turbulence models for realistic load prediction and their adjoint sensitivities, and a complete set of shape and planform design variables covering the whole rotor [1]. The main objective of this project is to make CFD-based aerodynamic shape optimization of wind turbine rotors practically relevant by enhancing the existing optimization methodologies and solving the specific numerical issues related to using CFD for such a purpose.

The robustness of the aerodynamic optimization framework would be tackled by improving a steady RANS-CFD solver to find well-converged solutions for any geometry and flow conditions. Improved robustness would result in efficient optimizations and faster turnarounds by being able to converge to the optimal solution from multiple starting designs in various flow conditions. The optimization efficiency would be further improved by implementing a multi-fidelity optimization framework.

## 2 Project outline

### 2.1 A robust CFD solver

The flow through a rotating wind turbine is by its very nature unsteady with flow separation occurring for thicker airfoil profiles of the blades near-root and for cylindrical cross-sections at the root. In this region, the CFD solution is found to either partially converge with the residuals displaying limit cycle oscillations or not converge at all due to violation of the equilibrium-flow assumption of the Reynolds-averaged Navier-Stokes (RANS) equations. Partially converged solutions cause numerical noise and have a negative effect on the accuracy of the gradients computed using the adjoint method, trapping the optimization in local minima [2]. Time-stepping codes are almost never able to find an unstable steady state, but can be adapted to perform this task.

A class of Newton's methods have been traditionally used to find roots of nonlinear equations. They work really well with a good initial guess and offer quadratic convergence rates in obtaining the steady-state solution. However, they demand heavy computational resources for flow computations involving a large system of equations or when dealing in a large number of unstable eigenmodes [3]. Improvements to the Newton method such as the Jacobian-free Newton-Krylov (JFNK) method [4] and the Approximate Newton-Krylov [5] method seeks to address these issues. The Recursive Projection Method (RPM) [6], the BoostConv method [7] and the Selective Frequency Damping (SFD) method [8] are alternative to Newton's methods. Unlike Newton's methods, they do not require a good approximation of the final solution to converge towards a steady state solution and are relatively computationally inexpensive.

The methods mentioned above would be evaluated and integrated with DTU Wind Energy's in-house time-stepping CFD code EllipSys.

### 2.2 Multi-fidelity optimization framework

The shape optimization would be aided by the implementation of an adjoint solver for the 2D version of DTU Wind Energy's in-house CFD code EllipSys, which would then be used as one of the low fidelity models in the variable-fidelity optimization, with the adjoint-enabled 3D version of EllipSys acting as the high-fidelity model. Applicability of existing multi-fidelity optimization frameworks such as the Approximation Model Management Optimization (AMMO) framework [9] and the Surrogate Management Framework (SMF) [10] would be explored.

The benefit would be a reduction in the computational cost associated with performing multiple evaluations of the objective function for a large number of shape and planform variables with a high-fidelity model. This would in-turn allow for the inclusion of a larger design space. When supplemented by relevant structural constraints, the shape optimization would result in realistic designs.

## References

[1] Madsen M H A, Zahle F, Sørensen N N and Martins J R 2019 *Wind Energy Science* **4** 163–192

[2] Giunta A A, Dudley J M, Narducci R, Grossman B, Haftka R T, Mason W H and Watson L T 1994 *Proc. 5-th AIAA/USAF/NASA/ISSMO Symp. on Multidisciplinary and Structural Optimization* pp 1117–1128

[3] Cunha G, Passaggia P Y and Lazareff M 2015 *Physics of Fluids* **27** ISSN 10897666 URL `http://dx.doi.org/10.1063/1.4930925`

[4] Knoll D A and Keyes D E 2004 *Journal of Computational Physics* **193** 357–397

[5] Yildirim A, Kenway G K, Mader C A and Martins J R 2019 *Journal of Computational Physics* ISSN 00219991

[6] Shroff G M and Keller H B 1993 *SIAM Journal on numerical analysis* **30** 1099–1120

[7] Citro V, Luchini P, Giannetti F and Auteri F 2017 *Journal of Computational Physics* **344** 234–246 ISSN 10902716 URL `http://dx.doi.org/10.1016/j.jcp.2017.04.081`

[8] Åkervik E, Brandt L, Henningson D S, Hœpffner J, Marxen O and Schlatter P 2006 *Physics of Fluids* **18** 6–9 ISSN 10706631

[9] Alexandrov N, Nielsen E, Lewis R and Anderson W 2000 *8th Symposium on Multidisciplinary Analysis and Optimization* p 4886

[10] Marsden A L, Wang M, Dennis J E and Moin P 2004 *Optimization and Engineering* **5** 235–262