Optimum aerodynamic design for dynamic stall risk mitigation

by

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

I would like to dedicate this thesis to my parents Vinod Raul and Shubhangi Raul, my sister Ashwini Parab, my Aaji Sulochana and my wife Supriya without whose continuous support and encouragement I would not have been able to complete this work.

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ABSTRACT

Mitigating the adverse effects of dynamic stall is critical for many aerodynamic systems as they can be the primary reason for limiting the system performance, fatal structural loads, and reduced fatigue life. Aerodynamic shape optimization (ASO) is a practical approach for mitigating the adverse dynamic stall characteristics without adding any auxiliary systems. The key challenges in ASO for dynamic stall mitigation are (1) computationally intensive and time-consuming computational fluid dynamics (CFD) simulations, (2) multiple and repetitive design evaluations required by conventional optimization algorithms, and (3) high-dimensional parameter space associated with the shape of the aerodynamic surface. The objective of this research is to create efficient ASO algorithms and gain a fundamental understanding of aerodynamic design for dynamic stall risk mitigation.

In this work, an optimization problem formulation is created to mitigate the adverse effects of dynamic stall through ASO. Two global optimal design algorithms are created and implemented using high-fidelity Kriging Regression (HF-KR) and multifidelity Cokriging regression (CKR) surrogate modeling methods. These surrogate models are constructed efficiently using error-based and expected improvement infill criteria. The developed models are utilized for optimization and global sensitivity analysis (GSA). GSA quantifies the sensitivities and the importance of the shape parameters to dynamic stall mitigation. Further, manifold mapping (MM), a multifidelity modeling method, is proposed to determine the local optimal design. Initially, the multifidelity modeling similarity condition is investigated to guide the selection of a low-fidelity (LF) model and a trust-region radius, which are vital for the successful implementation of MM. Later, the MM method is efficiently implemented for ASO-based dynamic stall mitigation using KR to create a fast LF model (LF-KR).

The proposed methods are demonstrated on an airfoil in sinusoidal oscillating motion in uniform flow undergoing deep dynamic stall. The HF-KR and CKR implementation provide optimal designs that delay and mitigate adverse dynamic stall characteristics. Both the acquired optimal designs show similar shape features. However, the CKR model produces a better optimal design than the HF-KR implementation while saving computational cost by almost 41%. The GSA investigation with HF-KR and CKR revealed that the upper airfoil surface thickness, location of thickness, leading-edge radius, and the curvature of the upper surface have a significant effect on the dynamic stall characteristics, whereas the trailing-edge angles has a minimal effect. Further, multifidelity modeling similarity condition investigation with the MM model provided a general approach for LF model selection. The results indicated that the LF model developed from coarser spatial and time discretization can be efficiently used within a small trust-region radius. Lastly, the MM model is implemented with a trust-region-based optimization algorithm and showed significant cost savings in locating an optimal design compared to HF-KR and CKR. Specifically, the MM model demonstrated the capability to determine optimal designs using a LF-KR model with computational cost savings of approximately 84% and 74% compared to the aforementioned HF-KR and CKR implementations.

CHAPTER 1. INTRODUCTION

1.1 Motivation and Challenges

An aerodynamic surface experiencing unsteady motion often shows a complex series of events that involves a dynamic delay of stall beyond static stall limits, followed by formation, convection, and shedding of an energetic leading-edge vortex, typically described as dynamic stall [Carr (1988)]. These characteristics of dynamic stall distort the chord-wise pressure distribution and produce transient forces and moments much larger than their static counterpart [McCroskey et al. (1976)].

The dynamic stall phenomenon was first observed on retreating blades of helicopter rotor [Harris and Pruyn (1968)]. The dynamic stall occurrence on the retreating blades gives rise to large aerodynamic loads and excessive stresses that restrict the helicopter flight envelope [Beddoes and Leishman (1986)]. The dynamic stall adversely affects aeroelastics of the rotor blades, rotor hub loads, and fatigue life [Mani et al. (2012); Carr (1988); Lee and Gerontakos (2004)].

Horizontal and vertical axis wind turbines are also prone to dynamic stall [Butterfield (1988); Butterfield et al. (1991); Butterfield (1989)]. Horizontal axis wind turbines are subjected to dynamic loading from multiple sources such as wind shear, turbulence, yaw angles, upwind turbine wake, and tower shadow that causes unsteady inflow to turbine rotor, which results in dynamic loading and dynamic stall. In vertical axis wind turbines, dynamic stall arises from rapid changes in the angle of attack perceived by each blade in every rotational cycle [Buchner et al. (2015); Wang et al. (2010)]. The dynamic loading on wind turbines increases structural stress on the blade, hub, and tower, which will reduce the turbine life. There are research efforts by the wind turbine industry to model dynamic stall and dynamic loading to improve turbine life [Larsen et al. (2007); Björck (2000)].

Dynamic stall characteristics are studied to understand insect flight and its applications to micro-air vehicles (MAV) [Ellington (1999); Hu et al. (2018)]. Researchers found that most insects rely on strong leading-edge vortex generated by dynamic stall for lift production during flapping motion [Ellington (1999); Ellington et al. (1996); Van Den Berg and Ellington (1997); Andro and Jacquin (2009)]. Recent research in cycloidal rotors shows the effects of dynamic stall and dynamic stall vortex interaction with the blade during its operation [Hu et al. (2018)]. Consideration of dynamic stall effects in the design of MAVs could be crucial for their performance and longevity.

In summary, dynamic stall and its effects have been observed on helicopter rotors, wind turbines, maneuvering aircraft, insect flight, and MAVs. Evidently, accurate understanding and consideration of dynamic stall is a major priority in the design process of such complex systems to improve their performance, structural strength, and fatigue life.

Considerable research has been done experimentally and computationally to quantify the dynamic stall effects and its behaviour [Carr (1988); Carr et al. (1977); McCroskey et al. (1981); McAlister et al. (1982); McCroskey et al. (1982); Sharma and Visbal (2019); Visbal and Garmann (2017); Benton and Visbal (2019)]. Furthermore, significant research has been conducted to mitigate or control dynamic stall via active control techniques involving variable droop leading-edge [Zhao and Zhao (2015)], trailing-edge flap [Lee and Gerontakos (2006)], vortex generators, elevated wire, and cavity [Choudhry et al. (2016)], adaptive blowing [Müller-Vahl et al. (2016)], and plasma actuators [Post and Corke (2006)]. The application of these approaches can increase the system mass and may require an auxiliary control system, which could increase the complexity and cost of the aerodynamic system. Therefore, these approaches may not always be economically viable.

Aerodynamic shape optimization (ASO) [Jameson (2003); Lyu and Martins (2015)] is a passive technique where aerodynamic surface is controlled to improve its performance and fulfill any constraints. The use of ASO for dynamic stall mitigation could provide a cost-effective approach for dynamic stall mitigation. However, the application of ASO in a dynamic stall setting could get computationally intensive, or even impractical, due to the following reasons:

1. Time-consuming physics-based unsteady flow simulations using computational fluid dynamics (CFD),
2. Multiple and repetitive design evaluations required by the optimization process, and
3. High-dimensional parameter space associated with the shape of the aerodynamic surface.

With rising computational capabilities, CFD can be used directly in ASO. Currently, large eddy simulation (LES), hybrid RANS-LES, and unsteady Reynolds-averaged Navier-Stokes (URANS) methods are available for dynamic stall simulations (ordered in decreasing computational accuracy and time requirement). In the past, a majority of dynamic stall studies were done with the URANS equations and turbulence models [Wang et al. (2010, 2012); Buchner et al. (2015); Yu et al. (2010)] due to manageable computational expenses. The URANS investigations of dynamic stall have shown mixed success in capturing complex viscous, turbulent, and temporal effects of dynamic stall accurately due to deficiencies associated with turbulence models [Mani et al. (2012)]. More recently, sophisticated methods, such as LES and hybrid RANS-LES, have been used to investigate dynamic stall and have shown success in capturing detailed flow physics of the transitional dynamic stall vortex evolution and the onset of the dynamic stall vortex [Sharma and Visbal (2019); Visbal and Garmann (2017); Benton and Visbal (2019); Kim and Xie (2016); Guillaud et al. (2018); Wang et al. (2012)]. Although, LES or hybrid LES-RANS provide an accurate representation of the dynamic stall phenomenon, the computational cost associated with a single evaluation is substantially higher than URANS, rendering these methods currently impractical for optimization studies. As computational capabilities continue to grow, the drive towards including high-fidelity analysis for design and optimization will lead to increased computational expense making it prohibitively expensive for many systems of interest [Robinson et al. (2008)]. Thus, the selection of an appropriate optimization approach is critical to the cost-effective implementation of ASO for dynamic stall mitigation.

Surrogate-based optimization (SBO) [(Leifsson and Koziel, 2016; Koziel and Yang, 2011; Giselle Fernández-Godino et al., 2019)] has been suggested to alleviate the computational cost of ASO by shifting the computational burden from the time-consuming physics-based simulations to a fast surrogate model. The surrogate model is typically utilized for optimization using either gradient-based or gradient-free methods. In general, surrogate methods are categorized as data-fit modeling and multifidelity modeling. Data-fit surrogate models are approximations involving interpolation or regression of sampled data from a single-fidelity model (generally, a high-fidelity model) generated through design of experiments. Kriging [Simpson et al. (2001)], polynomial regression [(Zhou et al., 2005)], radial basis functions [Forrester et al. (2008)], neural networks [Papila et al. (2001)], and support vector regression [Forrester et al. (2008)] are examples of data-fit surrogate modeling methods. Multifidelity surrogate models [Peherstorfer et al. (2018)] are developed by utilizing information from multiple fidelities of physics-based models with varying degrees of evaluation speed and accuracy. Cokriging [Forrester et al. (2007)], space mapping [Koziel et al. (2008)], manifold mapping [Echeverría et al. (2007)] and shape-preserving response prediction are examples of multifidelity modeling techniques. Typically, multifidelity surrogate models are more efficient than data-fit surrogate models as they reduce the amount of high-fidelity information needed by encoding knowledge of the system physics within the multifidelity model using a hierarchy of low- and high-fidelity models [Du and Leifsson (2019)]. SBO has been utilized in various research areas, including ASO investigations; however, it has not been used for ASO-based dynamic stall risk mitigation where the cost of optimization is a major obstacle.

1.2 Research Objectives

The objective of this research work is to gain a fundamental understanding of how an aerodynamic surface can be designed for dynamic stall risk mitigation efficiently. The current study will achieve this goal by accomplishing the following research objectives:

1. Model the dynamic stall physics in an accurate and practical way in the context of design,
2. Develop a problem formulation to effectively mitigate dynamic stall,
3. Create efficient local and global optimal design algorithms for dynamic stall risk mitigation, and
4. Understand and quantify the effects of aerodynamic shape features on the dynamic stall flow physics and its mitigation.

1.3 Thesis Outline

Chapter 2 introduces the application of surrogate-based optimization for delaying airfoil dynamic stall through aerodynamic shape optimization [Raul and Leifsson (2021b)]. In this chapter, single-fidelity Kriging regression, along with an infill strategy, is used for determining global optimum design of an airfoil in unsteady subsonic flow. Additionally, a global sensitivity analysis is conducted to provide the effects of the aerodynamic shape features on the dynamic stall mitigation. Chapter 3 presents the application of Cokriging regression to the problem of dynamic stall risk mitigation of an airfoil. In this chapter, Cokriging regression is constructed efficiently using Latin hypercube sampling and infill strategies (expected improvement and error-based infill) to determine the global optimum design. Results of global sensitivity analysis are also presented in this chapter. Chapter 4 investigates the similarity requirements for the application of manifold mapping, a local multifidelity modeling technique for the prediction of airfoil dynamic stall using CFD simulations [Raul and Leifsson (2021a)]. Chapter 5 presents the application of manifold mapping for dynamic stall mitigation through ASO. In this chapter, manifold mapping is implemented efficiently with a low-fidelity Kriging regression model to iteratively locate the local optimum design that mitigates dynamic stall adverse effects. Chapter 6 summarizes the contribution of this thesis and provides suggestions for future work.

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