AI-Controlled Deployable Vortex Generators for Adaptive Airflow Optimization on Airfoils

Grant Proposal

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Executive Summary

Parasitic drag from vortex generators (VGs) imposes persistent efficiency penalties during aircraft cruise, particularly for UAVs and small aircraft where fixed flow control devices operate outside their useful envelope for most missions. While VGs effectively delay boundary layer separation, their fixed height and permanent deployment cause unnecessary drag outside critical maneuvers and high-angle-of-attack situations. Current research gaps include non-optimized operational VG heights and deployable systems lacking truly adaptive control. This work designed and evaluated a deployable VG system capable of actively minimizing drag while preserving separation control when needed. A mechanically actuated VG array was developed using servo actuators and a lightweight machine learning algorithm for microcontroller implementation. The controller combines Gaussian Process regression with a neural network to capture uncertainty in separation onset and nonlinear aerodynamic response. Training data were generated through a multi-fidelity approach, pairing medium-fidelity RANS simulations with high-fidelity URANS simulations via Co-Kriging. Without fully integrated wind tunnel testing, system performance was assessed using a highly realistic flight simulation. Results show adaptive height control improved average lift-to-drag ratio (Cl/Cd) by 6.5% and saved 2.55% fuel compared to standard fixed VG airfoils. These findings demonstrate that VG height optimization, beyond simple deployment or retraction, is critical for reducing parasitic drag. The system is directly applicable to UAVs and light aircraft operating at moderate Reynolds numbers, where adaptive flow control can yield measurable efficiency gains without compromising stability.

Keywords: active flow control, vortex generators, Gaussian regression, machine learning, CFD

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Section I: Introduction

This project proposes an alternative to static vortex generators by developing deployable vortex generators with a machine learning-based control system. While static vortex generators effectively delay stall and enhance post-stall behavior by energizing the boundary layer, they introduce parasitic drag during cruise conditions when separation control is unnecessary, reducing overall aircraft efficiency. This project addresses this limitation through an adaptive deployable vortex generator system using machine learning control trained on both computational fluid dynamics (CFD) simulations and wind tunnel data to optimize deployment height in real-time based on instantaneous flow conditions.

Boundary Layer Behavior, Fluid Dynamics, and Stall

Boundary Layer and Adverse Pressure Gradients

The boundary layer is the thin region of fluid adjacent to a solid surface where velocity rises from zero at the wall to the free-stream value (Leishman, 2023). Its behavior is governed by viscous effects, and the Reynolds number determines whether it remains laminar or becomes turbulent. At the Reynolds numbers relevant to this project (approximately 500,000–2,000,000), the boundary layer is mostly turbulent but can still separate under strong adverse pressure gradients. Adverse pressure gradients develop on the suction side at high angles of attack, decelerate the near-wall flow, and may cause separation, reduce lift and increase drag (Leishman, 2023).

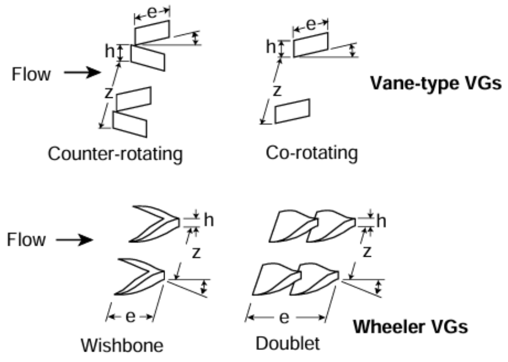
Stall and Its Consequences

Stall occurs when the boundary layer separates extensively from the airfoil surface near or beyond the critical angle of attack, typically producing a loss of lift and a sharp rise in drag (Leishman, 2023). In the stalled state, the separated shear layer (the region of the airflow where there is a significant velocity difference between the high-speed free stream and the low-speed air near the surface or in the wake) rolls up into large-scale vortices, and the downstream wake becomes highly unsteady, significantly degrading aerodynamic performance and compromising vehicle controllability (Leishman, 2023). In moderate-to-high Reynolds number applications such as large UAVs and small aircraft, delaying stalls and achieving smooth post-stall behavior are essential for expanding the safe operating envelope and improving overall efficiency. Literature consistently frames VG deployment as a stall-prevention technology, assuming the primary goal is delaying separation onset rather than shaping the post-stall response, and this is questionable as vortex generators must fulfill both of those duties to be effective.

Vortex Generators

Principles of Vortex Generators

Vortex generators (VGs) are small surface-mounted devices that create streamwise vortices, mixing high-momentum fluid into the near-wall region to increase boundary-layer momentum and resist separation. Their purpose is to delay stalls and produce smoother post-stall behavior (Jayanarasimhan & Balasubramanian, 2025). They can take various shapes, such as rectangular, triangular, wedge-shaped, or airfoil-like vanes, with typical arrangements shown in Figure 1. VG effectiveness depends on Reynolds number and flow conditions: at low Reynolds numbers, they cause an earlier transition to turbulence or reattachment, while at higher Reynolds numbers they help maintain attachment under strong adverse pressure gradients and can control shock-induced separation in transonic and supersonic flows (Lin, 2002; Titchener & Babinsky, 2015). Performance is also strongly influenced by geometry and placement, particularly the ratio of vane height relative to the boundary-layer thickness, which determines the amount of high-momentum fluid into the boundary layer (Lin, 2002). Different heights and configurations produce variable effects depending on flow conditions, and the deployable VG system in this project is designed to adaptively optimize VG height rather than rely on a fixed height.



(b) VG geometry and device parameters.

Figure 1: Image of different configurations of vortex generators (Lin, 2002). This shows the shape of different vane-type vortex generators and defines the geometric parameters that influence the effectiveness of a given shape and configuration.

Limitations of Static Vortex Generators

While static VGs effectively improve stall resistance and post-stall behavior, they introduce parasitic drag even when separation control is not needed (Lin, 2002). Static VGs introduce parasitic drag through their protrusion into the flow and inevitably increase skin friction by disturbing the near-wall boundary layer, and this reduces the efficiency of the aircraft during cruise. Under cruise conditions, where the boundary layer is already attached and separation is not imminent, static VGs generally provide no aerodynamic benefit yet still produce additional drag and reduce fuel efficiency (Jayanarasimhan & Balasubramanian, 2025). Static devices are typically sized and located to be effective near stall, particularly during takeoff and landing, so they typically sacrifice maximum efficiency at cruise for acting as a mechanism to prevent stalls, and an example of this can be observed in Figure 2.

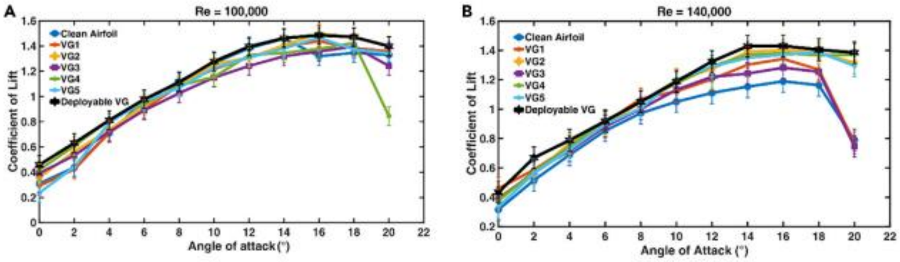


Figure 2: Graphs that show the coefficients of lifts of vortex generators at different heights and configurations over varying angles of attack at Reynolds numbers (Mamman et al., 2023).

Deployable Vortex Generators and Active Flow Control

Deployable Vortex Generators and Actuation Technologies

Active flow control technologies use actuators to modify the boundary layer in response to changing conditions with the aim of using adaptive control to increase efficiency greater than static flow control (Mamman et al., 2023). Deployable vortex generators are a form of active flow control. They can change geometry or orientation between a retracted, low-drag state and one or more deployed states, providing separation control only when needed. This approach retains most of the stall-delay benefits of static VGs while significantly reducing average drag (Mamman et al., 2023). Other methods of active flow control include plasma actuators and hydraulic actuators, but these are limited due to high voltage needs and heavy.

Prior work has demonstrated several actuation concepts for deployable VGs, including shape memory alloys and twisted spiral artificial muscles. Mamman et al. (2023) employ twisted spiral artificial muscle actuators with electro-thermal actuation, which introduces temperature sensitivity, and they use binary actuation schemes, which switch between fully deployed and retracted states, limit precise control over deployment height and timing (Mamman et al., 2023). Le Pape et al. (2012) demonstrated mechanical deployable vortex generators with continuous height control from 0.1 to 3 mm, avoiding some of these limitations.

Knowledge Gap: Control and Adaptivity

Current deployable vortex generator systems have several limitations in terms of control and design. Many rely on binary actuation, switching between fully deployed and fully retracted states without precise control over deployment height, angle, or exact timing (Mamman et al., 2023). In many implementations, actuation schedules are open-loop, based on pre-programmed thresholds (e.g., angle of attack or Mach number) rather than real-time feedback from local flow conditions such as pressure gradient or boundary-layer state (Mamman et al., 2023). Shape memory alloy and twisted spiral artificial muscle-based systems are additionally constrained by thermal actuation and sensitivity to things like temperature, limiting their responsiveness and robustness.

The main research gap is the lack of real time control methods that adaptively optimize the deployment of a vortex generator given conditions in real time. This project focuses on filling this gap by developing a system of deployable vortex generators, implemented with AI control and low-latency actuation that is robust to the environment.

Computational Fluid Dynamics for Vortex Generator Flows

CFD simulations are numerical simulations that calculate versions of the Navier Stokes equations that govern the behavior of fluids on geometries that are broken into tiny parts called mesh. Despite being more computationally expensive than three-dimensional CFD simulations are necessary to capture the vortical structures generated by vortex generators and their effects on boundary-layer behavior, separation, and stall due to the inherent 3D nature of vortices. Detached Eddy Simulation (DES) will be used, as it provides a practical and relatively efficient way to simulate moderate-to-high Reynolds number flows with vortex generators (Titchener & Babinsky, 2015). For this project, 3D DES simulations will generate accurate pressure and flow field data on airfoils with different VG heights at different Reynolds numbers.

Machine Learning for Aerodynamic Flow Prediction and Control

Portal-Porras et al. (2022) demonstrated the use of convolutional neural networks to predict both flow fields and aerodynamic forces for airfoils with flow control devices with lift prediction errors of less than 1% and drag errors of around 6%, while running approximately ten thousand times faster than conventional simulations. Though the largest errors occurred in the wake region, this is precisely where vortex generator effects are most important to capture accurately. Fuchi et al. (2022) introduced a framework that approximates solutions from high fidelity simulations, allowing effective training with minimal high-fidelity data; however, it has only been tested on simple, steady flows on bluff bodies, not the turbulent or separated flows typical of vortex generator applications. Similarly, Zhang et al. (2025) developed a machine-learning-enhanced surrogate model to efficiently predict surface pressures and lift with reduced data requirements, demonstrating approaches that could inform real-time reduced-order models for active VG control. Negoita & Hothazie (2024) trained neural networks on simulation data to predict lift and drag, but the model was never tested on experimental or field data, highlighting a key challenge for applying ML-trained CFD models to practical airflow control scenarios.

This literature reveals a gap between machine learning for airflow and real-world active flow control applications. While computational speedups (from hundreds of hours to real-time) benefit design optimization, it remains uncertain whether reduced order models can achieve both high accuracy and real-time output. Additionally, these studies don't address the three-dimensional, unsteady, turbulent separated flows characteristic of deployable VGs at moderate Reynolds numbers. The wake prediction errors in Portal-Porras et al. (2022) are particularly concerning since accurate capture of VG-induced vortices in the downstream wake is essential for predicting effectiveness. Current ML models lack validation against experimental data, being trained solely on CFD data. This project addresses that gap by training models on both CFD and wind tunnel data.

Section II: Overview of Specific Aims

This proposal's objective is to develop a deployable vortex generator system that adjusts its height in real time to reduce drag and delay flow separation on an airfoil. The rationale is to avoid the constant drag penalty of static vortex generators by creating a device that deploys only when needed and achieves the optimal VG height for a given set of conditions for maximum aerodynamic efficiency. The proposed solution combines a lightweight actuation mechanism, sensor-fused, machine learning-based control, CFD simulations, and wind tunnel testing with reinforcement learning.

Specific Aim 1: Quantify the effects of vortex generators at different heights at different conditions that vary over angle of attack, for subsonic applications.

Specific Aim 2: Develop a lightweight reduced order model that takes in inputs of flow velocity, and static pressure distribution to output the optimal vortex generator; this model should be trained with data from CFD simulations.

Specific Aim 3: Physically design and manufacture a model of an airfoil equipped with a deployable vortex generator system that is controlled by a reduced order model on a microcontroller. This model should include low voltage actuation and control, compact linking of vortex generators, and vortex generators that remain flush with the surface of the airfoil.

The expected outcome of this work is a system of deployable vortex generators that have adaptive machine learning based control and can be altered to be adapted to a variety of aircraft.

Section III: Project Goals and Methodology

Relevance/Significance

This project has applications in both industry and research. The regime of Reynolds numbers that this system is designed for include many different types of aircraft that use airfoils such as large UAVs, small general aviation vehicles, sailplanes, among others. This project is projected to save XXX percent of fuel because it would optimally reduce drag by XXX percent and increase aerodynamic efficiency (Cl/Cd) by XXX which would save millions of dollars across a fleet of XXX aircraft. This project is also significant because vortex generators are generally nonintrusive to the overall performance of an aircraft, and this is a very low risk solution that could be implemented without risk of massive failure if a malfunction occurs. These deployable vortex generators could ultimately make air travel cheaper, safer, and more reliable.

Innovation

AI control has never been implemented in physical active flow control technology, and this is significant because machine learning based control eliminates the extremely complex and ultimately inefficient process of capturing the transient and nonlinear nature of airflow, vortices, the effects of vortex generators on an airfoil. This machine learning based approach also makes it possible and simple to actuate these vortex generators over a range of values rather than fixed values as was previously done, and this would result in optimal aerodynamic efficiency for a given set of conditions.

Methodology

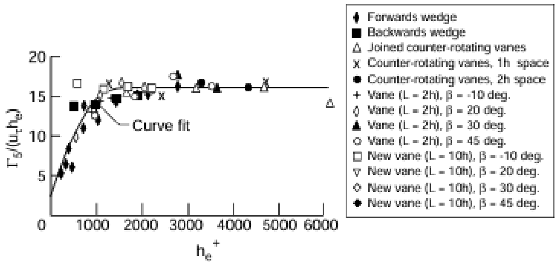
CFD simulations will be run on a NACA 4415 airfoil across a range of Reynolds numbers, angles of attack, and VG heights. Data on pressure, lift, and drag will be recorded. Adequate mesh resolution will be used with a y+ that is less than 1. For preliminary testing, RANS k-omega will be used, but for the machine learning training data, DES (Detached-Eddy Simulation) will be used to increase precision.

A small neural network will be trained with Tensorflow/Keras. The model will take inputs of flow speed and static pressure, and it will output optimal VG height. It will be trained on the full CFD dataset, where each case includes the pressure inputs and flow speeds, and the known VG height that caused those readings.

A physical model of the airfoil equipped with pressure sensors across the span, an actuator to move the vortex generators, rectangular vortex generators linked by a rigid carbon fiber rod, a Raspberry Pi 4 microcontroller, and a battery for a power source.

After loading the trained neural model onto the Raspberry Pi, the complete airfoil system will be tested in the wind tunnel. These tests will then be used to run a reinforcement-learning stage, allowing the controller to adjust its policy and reduce the gap between the pretrained (simulation-based) model and the actual tunnel behavior.

Specific Aim #1 (Quantifying the effects of vortex generators at different heights):



(b) Non-dimensional circulation based on effective height versus non-dimensional effective height.

Fig. 9. Device geometry and correlation of vortex strength against device Reynolds number [20].

Figure 3: Chart from Lin, J.C. (2002) depicting a trend with vortex generator heights and Reynolds number

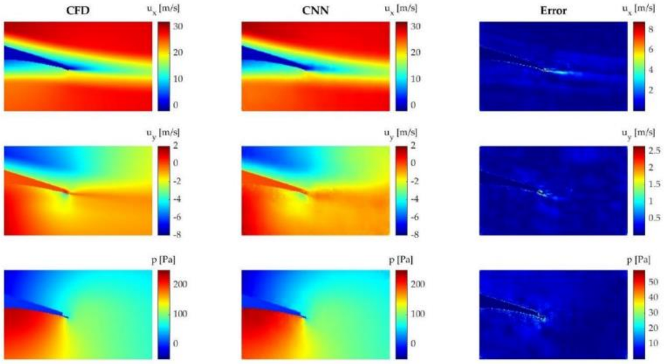
Justification and Feasibility: The rationale for this approach is that CFD simulations allow for the testing of a high volume of configurations and changing of conditions without the need for spending time or materials on wind tunnel tests. CFD simulations can provide insight as to the lift, drag, and pressure on the airfoil under different conditions and with different vortex generators. The graph below from Lin, J.C. (2002) demonstrates that vortex strength (vertical axis, given by non-dimensional circulation) varies with different effective height expressed in wall units h_e+, which acts as a device Reynolds number linking VG size and operating Reynolds number, and the curve shows how for any given device Reynolds number, a different height or configuration of vortex generators can be chosen to achieve the desired vortex strength, hinting at how it is useful to quantify different VG heights in the Reynolds range of this project.

The overall expected outcome of this aim is to gain insight as to how vortex generator height impact lift, drag, and pressure on airfoils at the Reynolds number range of this project (500,000 –

2,000,000). This knowledge will be used for design choices regarding vortex generator geometry and placement.

Specific Aim #2 (Developing a machine learning model for optimal VG height prediction):

Justification and Feasibility: A lightweight reduced order model enables real-time predictions of the forces and flow behavior and therefore vortex generator height without repeatedly solving computationally expensive CFD simulations. Portal-Porras et al. (2022) demonstrated that CNNs trained on CFD data can predict flow control device performance by reducing the computational time in four orders of magnitude, which validates the feasibility of neural networks trained on CFD simulation.



The below figure from Portal-Porras et al. (2022) shows the difference between a flow field predicted by CFD versus a flow field predicted by a CNN, and it is visibly evident that there was a low amount of error between the output of the CNN and the CFD simulation.

The expected outcome of this aim is a reduced-order model that will accurately predict optimal vortex generator heights in real time, closely matching the forces and flow behavior from full CFD simulations, enabling adaptive control of deployable vortex generators.

Specific Aim 3 (Development of a physical model with actuators and onboard control):

Justification and Feasibility: The airfoil model and deployable vortex generators can be manufactured and integrated with sensors and actuators with adequate spacing. Pressure sensors can be embedded along the chord without significantly disturbing the airflow, as demonstrated in prior work on deployable vortex generators (Le Pape et al., 2012), making this setup practical and feasible for wind-tunnel testing. The model will be able to remain small enough for effective wind tunnel testing.

Section III: Resources/Equipment

ANSYS Fluent, ANSYS Design Modeler, ANSYS Mechanical, CFD-Post, Microsoft Office Excel, Python, Sci-Kit Learn, NumPy, Pytorch, Solidworks, Airfoil Tools/UIUC Airfoil Database, Resin 3D Printer, Carbon Fiber Tubing, Aluminum Plates, Servo Actuator, Microcontroller (ESP 32 or Raspberry Pi 5), CNC Router/Laser Cutter, 3D Printer, Wind Tunnel.

Section IV: References

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