Mechanical & Industrial Engineering
UNIVERSITY OF TORONTO

MIE498H1: Research Thesis 2025-2026

Supervisor	Pierre Sullivan
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Number of Positions	1
Open to	Mechanical and Industrial Engineering Students
Term Offered	Full-year
Research Area	Thermofluids
Research Topic	Deep Learning with Physical Constraints: Reconstructing and Analyzing 3D Unsteady Wakes Behind Inclined Cubes

Project Description

The wake flow behind bluff bodies such as cubes is a canonical problem in fluid dynamics, characterized by complex three-dimensional and unsteady structures that are highly sensitive to the body's orientation relative to the oncoming flow, making it essential for applications in civil engineering, vehicle aerodynamics, and environmental modeling; while traditional experimental techniques like Volumetric 3-Component Velocimetry (V3V) provide high-fidelity velocity data, they are often limited by spatial resolution, noise, and the inability to directly measure pressure fields—limitations that can be addressed through recent advances in Physics-Informed Neural Networks (PINNs), which embed governing equations such as the Navier–Stokes system into the learning process to reconstruct physically consistent velocity and pressure fields from sparse or noisy data. This thesis proposes to use PINNs to enhance and analyze the 3D wake dynamics behind a cube at varying angles of incidence using high-resolution V3V datasets, with objectives including flow characterization across different orientations, development of a PINN framework to reconstruct full 3D velocity and pressure fields, comparative evaluation against traditional interpolation methods, and extraction of physical insights into how cube orientation affects wake symmetry, vortex shedding, and pressure recovery. The methodology involves training a neural network using spatial coordinates (and potentially time) as inputs and velocity and pressure as outputs, minimizing a composite loss function combining data fidelity, physics residuals, and boundary conditions, followed by visualization and quantitative analysis using metrics such as divergence error and energy spectra. This work bridges experimental fluid mechanics and machine learning, contributing methodologically by demonstrating how PINNs can improve data quality and infer latent quantities like pressure, scientifically by revealing the impact of bluff body orientation on 3D wake behavior, and practically by informing design strategies for flow control and drag reduction. The proposed timeline spans eight months, covering literature review, model development, training, analysis, and thesis writing. Supporting references highlight the potential of PINNs in reconstructing PIV/PTV data with reduced data requirements, super-resolution capabilities, and integration of physical laws, while also noting limitations related to domain size, multi-scale resolution, and enforcement of boundary conditions. Additional technical details and supporting information can be provided upon request.

Application Instructions	Please submit CV and unofficial transcript to pierre.sullivan@utoronto.ca