

DEEP GAUSSIAN PROCESSES FOR PROBABILISTIC PREDICTION OF UAV PROPELLER AERODYNAMICS

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Abstract

Accurate prediction of propeller aerodynamic performance is essential for the design and optimisation of small Unmanned Aerial Vehicles (UAVs), where propellers directly influence thrust generation, energy efficiency, and overall flight capability. Traditional prediction approaches range from analytical models such as Blade Element Momentum Theory (BEMT) to high-fidelity Computational Fluid Dynamics (CFD) simulations and experimental wind tunnel testing. While these techniques provide reliable performance estimates, they often require detailed geometric information or involve significant computational and experimental costs, making them less suitable for rapid design exploration.

Recent work has demonstrated that machine learning models can serve as efficient surrogate models for propeller performance prediction. In particular, neural networks have shown promising results when trained on datasets combining numerical simulations and experimental measurements. However, these approaches typically provide deterministic predictions and hence limited uncertainty quantification, which can be problematic in engineering design contexts.

This work investigates the use of Deep Gaussian Processes (DGPs) as a probabilistic machine learning framework for predicting thrust and torque of small UAV propellers. The proposed model is trained using a dataset previously developed from a combination of adapted BEMT simulations and wind tunnel experiments conducted on 19 APC propellers with diameters ranging from 7 to 20 inches, covering a wide range of operating conditions including rotational speed and free-stream velocity.

DGPs extend conventional Gaussian Process regression by stacking multiple latent layers, enabling the modelling of highly nonlinear relationships while preserving the ability to quantify predictive uncertainty. The performance of the DGP model is evaluated against previously implemented regression approaches, including Multi-Layer Perceptrons and standard Gaussian Processes. Results show that the proposed approach achieves similar or improved predictive capability across the operating envelope while maintaining robust uncertainty estimates.

The results highlight the potential of Deep Gaussian Processes as reliable surrogate models for aerodynamic performance prediction, enabling faster and more informed decision-making during early-stage UAV propeller design and optimization.