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Aerodynamic Shape Optimization using Reinforcement Learning and Surrogate Models

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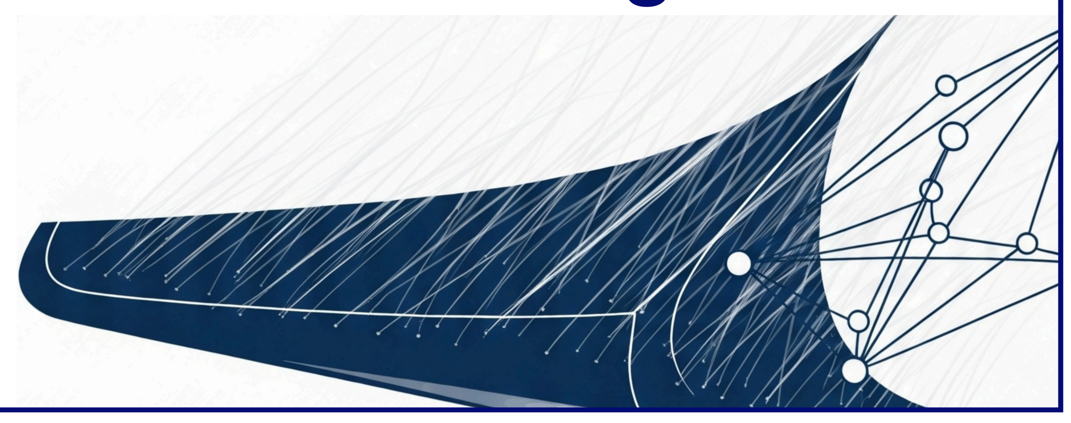


STATE OF THE ART

- **Aerodynamic shape optimization** is essential for enhancing **aircraft performance, efficiency, and safety**.
- **Traditional methods**, such as **wind tunnel tests and CFD simulations**, can be computationally **expensive and time-consuming** [1].
- **Machine learning (ML)**, **Reinforcement Learning (RL)** and **surrogate models** offer promising avenues to address these challenges [1, 2].
- **RL** can **navigate complex design spaces** and **adapt to varying conditions**, potentially **reducing the reliance on costly simulations** [2, 3].
- **Surrogate models**, such as **deep neural networks**, can **approximate** the high computational cost of **CFD evaluations**, thereby **accelerating the optimization process** [1, 4].
- However, **effectively integrating** these advanced techniques and **rigorously validating** their **outcomes** remain significant research **challenges** [5].

MOTIVATION

This research pursues the development of **more efficient and reliable aerodynamic shape optimization frameworks**.

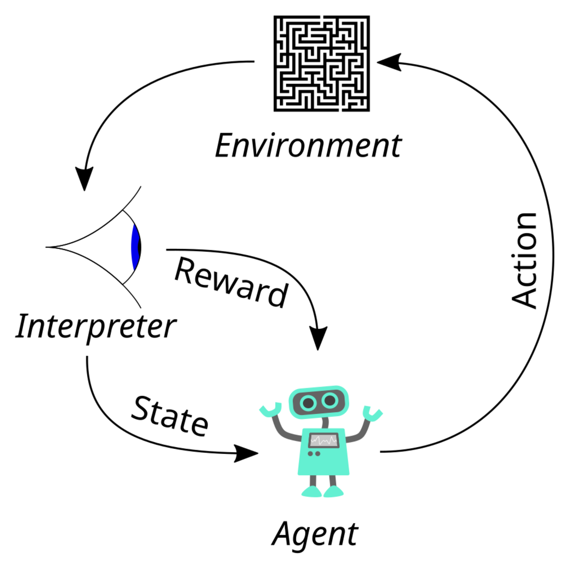
By leveraging the capabilities of **RL and surrogate models**, this work aims to:

- **Development and validation of novel and efficient aerodynamic shape optimization frameworks** that integrate Reinforcement Learning and surrogate modelling techniques.
- **Demonstration of the effectiveness of Reinforcement Learning** in optimizing complex aerodynamic shapes, including airfoils, propeller blades, and potentially wings, under various flow conditions, including unsteady regimes.
- **Faster iterations** in preliminary design phases, **maintaining or enhancing the accuracy** of aerodynamic performance predictions.
- **Significant reduction in the computational cost** associated with aerodynamic optimization processes through the strategic use of surrogate models and multi-fidelity techniques.

ROADMAP

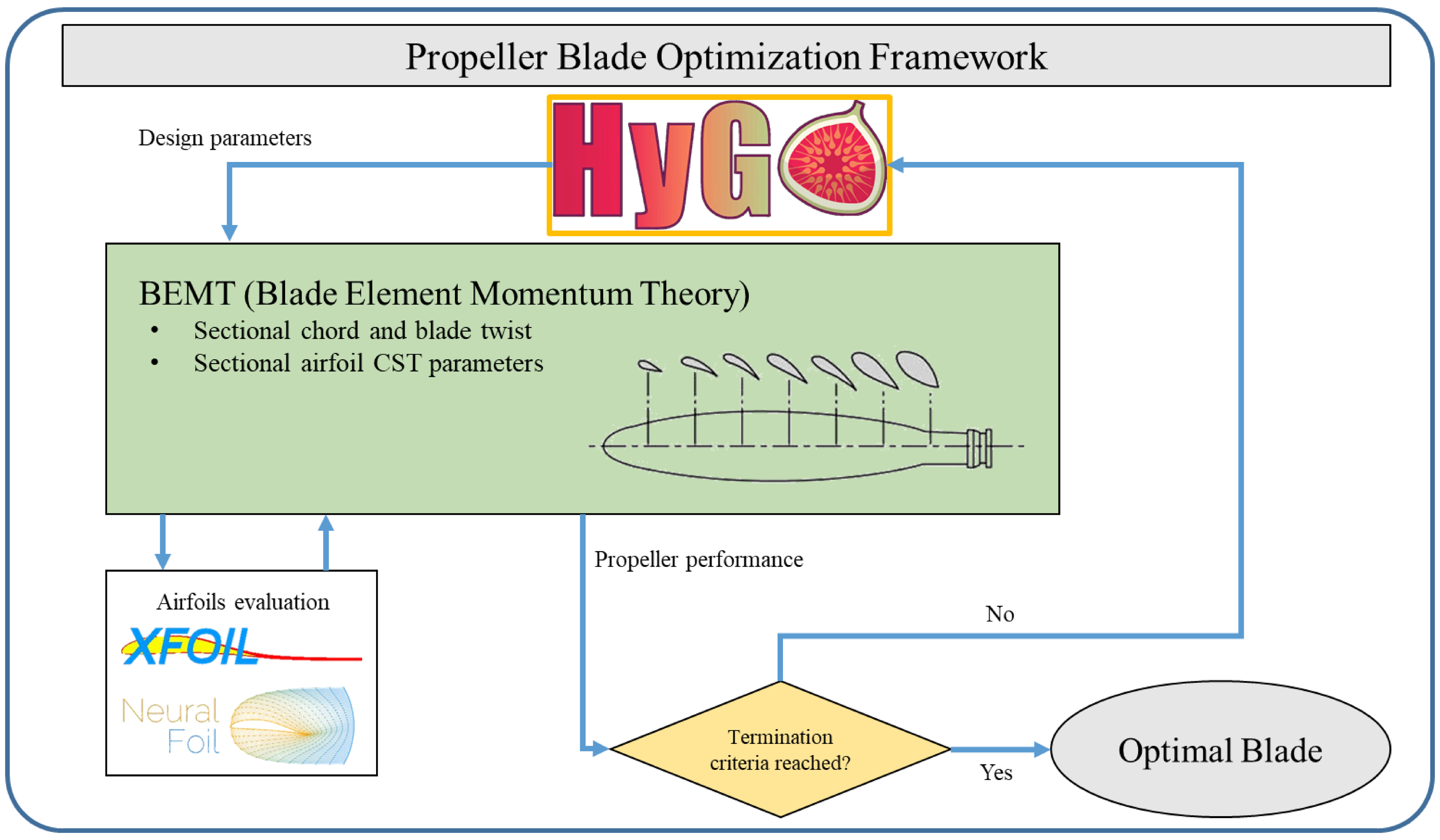
This doctoral research will follow a structured, multi-stage approach to develop a comprehensive aerodynamic shape optimization framework:

- **Initial Propeller Blade Optimization Framework:**
  - A propeller shape optimization framework is developed, combining a **Hybrid Genetic Algorithm (HyGO)** [6] for optimization, **Blade Element Momentum Theory (BEMT)** for aerodynamic performance evaluation, and **NeuralFoil** [7] for rapid airfoil analysis. It constitutes a robust yet fast and efficient framework for rapid exploration of propeller blade design space.
- **Integration of Reinforcement Learning:**
  - **RL** will be incorporated as the main driver of the optimization framework, exploiting its model-free capabilities in different scenarios, including airfoils and wings. This phase involves defining the aerodynamic design problem and training an RL agent. The RL agent will interact with a surrogate of the aerodynamics, which will define the performance of each state. Exploration of constrained RL-based optimization will allow us to limit the design space, which is critical in realistic aeronautical applications.



- **Incorporation of Surrogate Modelling and Multi-Fidelity Techniques:**
  - **Surrogate models** commonly are **data-driven methods** that are trained with low- to mid-fidelity data to minimize cost. Data fusion and multi-fidelity techniques will be explored to **enhance the fidelity of the surrogates** within the optimization framework so that **minimal prediction cost** is guaranteed while high-fidelity estimations can be achieved.
- **Expansion to Complex Aerodynamic Shapes and Conditions:**
  - Shape optimization frameworks commonly focus on a single (or few) flight conditions, which drive the main shape of the specimen under investigation. We will also explore a **dynamic adaptive morphing based on RL**, **following classic control problems**. The RL agent will continuously adapt the shape to maximize performance, leading to an online shape optimization problem.

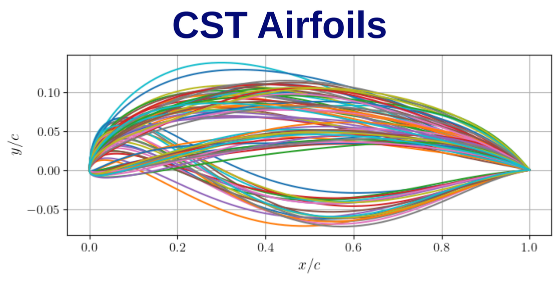
INITIAL WORK



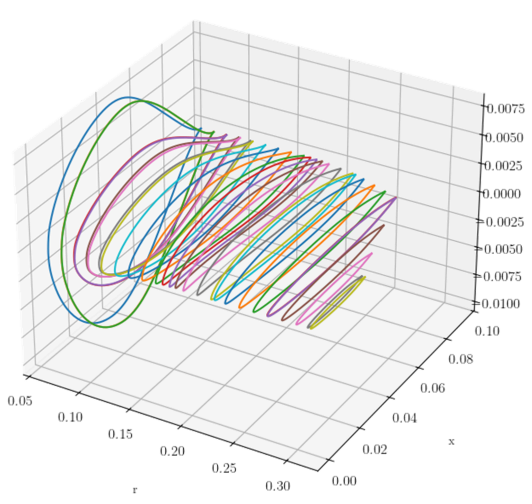
Foundational framework for aerodynamic shape optimization, specifically focusing on **propeller blades for fixed-wing, propeller-driven aircraft during cruise conditions, to enhance propulsive efficiency.** It integrates:

- **HyGO:** A Python toolbox using a hybrid genetic algorithm which combines the gradient-free exploratory nature of genetic algorithms with exploitative characteristics, providing a robust, versatile, and fast optimization capability.
- **BEMT**: For physics-based, cost-effective, and rapid evaluation of propeller performance.
- **NeuralFoil**: An open-source, physics-informed machine learning tool for fast and accurate airfoil analysis.

CST Airfoils



Blade airfoil control sections



The framework optimizes **sectional chord, blade twist, and sectional airfoil shape** defined by **CST (Class Shape Transformation)** parameters by iteratively using **HyGO** to propose designs and **BEMT** (with **NeuralFoil**) to evaluate them until convergence. The methodology combines **low-cost physics-based models**, **neural surrogate methods**, and a **state-of-the-art hybrid genetic** optimization framework.

References

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