Machine Learning–Assisted Airfoil Optimization and Perspectives for Morphing Wing Applications

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Abstract. The design of high-performance airfoils is central to aerodynamic efficiency in aircraft and aerospace systems. Conventional optimization methods often depend on iterative computational fluid dynamics (CFD) simulations or wind-tunnel experiments, both of which are accurate but costly in time and resources. This paper introduces a machine learning (ML)–assisted framework for airfoil optimization that accelerates design while maintaining predictive reliability. A dataset of NACA airfoil profiles is used to train surrogate models capable of estimating aerodynamic coefficients. Bayesian optimization then explores the design space to identify profiles with enhanced lift-to-drag ratios. Preliminary results demonstrate that the framework generates improved geometries compared to standard baselines. Beyond static optimization, the paper outlines a conceptual extension of the methodology toward morphing wing applications, where adaptive aerostructures can dynamically transition between configurations to maximize performance. The study is presented as ongoing work, with detailed validation and implementation results reserved for forthcoming publications.

1 Introduction

The aerodynamic properties of wings and airfoils play a decisive role in aircraft performance. Improvements in airfoil design directly reduce drag, increase lift, and improve fuel efficiency. For both civil and military aviation, as well as emerging applications such as unmanned aerial vehicles (UAVs), achieving optimal performance remains a central challenge. Traditional workflows rely on CFD or wind tunnel testing, which provide high fidelity but are too costly for large design spaces. This limitation has motivated the use of surrogate models, which approximate aerodynamic behavior at a fraction of the cost.

Advances in machine learning (ML) have reinforced this trend. Classical surrogates such as kriging and Gaussian processes have long supported engineering optimization [1]. More recently, regression-based ML methods—gradient boosting, random forests, and neural networks—have proven effective in capturing nonlinear aerodynamics while remaining efficient. Zhang et al [2] showed that surrogate models can replicate aerodynamic polars for

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preliminary design with over 90% cost reduction. Li et al. [3] extended this to deep learning for unconventional shapes, while Sekar et al. [4] demonstrated neural surrogates generalizing across Reynolds and Mach numbers.

Optimization strategies have evolved alongside these models. Bayesian optimization, in particular, efficiently balances exploration and exploitation in expensive black-box problems [5]. In aerospace, it has accelerated shape optimization, supported multi-objective trade-offs, and enabled uncertainty-aware design. Together, surrogate modeling and Bayesian optimization provide a robust framework for rapid airfoil optimization in early development stages.In parallel, morphing wings have emerged as a promising technology. Unlike fixed geometries, morphing wings continuously adapt to flight conditions, improving performance in takeoff, cruise, and landing [6-7]. Sofla et al. [8] noted, however, that structural and actuation challenges remain. A gap persists between computational optimization frameworks and morphing design: most morphing studies focus on mechanisms, while optimization remains tied to static profiles.

This work addresses that gap by linking ML-driven optimization with morphing. Once an improved profile is identified by surrogate-assisted Bayesian methods, morphing systems provide the mechanism to transition smoothly between baseline and optimized geometries. In this way, morphing becomes the physical realization of computational optimization, enabling sustained efficiency across conditions.

The contribution of this paper is twofold: first, it presents a regression-based surrogate framework trained on NACA airfoils and coupled with Bayesian optimization to improve lift-to-drag ratio; second, it interprets these results in the context of morphing, framing adaptability as the natural extension of ML-based aerodynamic design. The paper is organized as follows: Section 2 details the methodology, Section 3 presents results, Section 4 discusses implications for efficiency and morphing, and Section 5 concludes with future directions.

2 Methodology

The proposed framework integrates dataset preparation, surrogate modeling, Bayesian optimization, and CFD validation, with a conceptual extension toward morphing applications. Figure 1 summarizes the overall workflow. The computational branch illustrates the steps leading from parametrization to optimized profiles, while the mechanical branch highlights the potential for translating optimized designs into morphing structures. Airfoil geometries were parameterized using four descriptors: maximum camber, position of maximum camber, thickness, and angle of attack as in Figure 2. These descriptors are widely used within the NACA four-digit family and provide a compact yet physically meaningful representation of aerodynamic shape. By limiting the design space to these variables, the framework balances tractability and flexibility, allowing meaningful variations while avoiding excessive dimensionality.

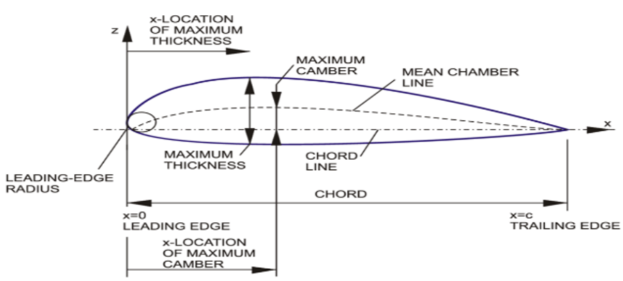

Fig. 2. NACA 4-digit airfoil parametrization

For each candidate geometry, lift (CL) and drag (CD) coefficients were generated using XFOIL. These values formed the basis for training regression-based surrogate models, which can approximate aerodynamic responses without resorting to high-fidelity CFD at every step. Surrogates were chosen for their computational efficiency and ability to capture nonlinear relationships in tabular datasets. Once trained, they enable rapid evaluation of aerodynamic performance across a wide range of geometries.

Bayesian optimization was applied to guide the search for improved airfoils. This method constructs a probabilistic model of the objective function and selects new candidates by balancing exploration of untested regions and exploitation of promising areas. The optimization objective was defined as maximizing the lift-to-drag ratio, subject to constraints on lift and drag values to exclude unphysical solutions. This ensures that improvements are both numerically favorable and aerodynamically credible. Candidate designs identified through the surrogate–Bayesian loop were validated using high-fidelity CFD simulations in Ansys Fluent. This step closes the loop between rapid surrogate-based exploration and physically accurate flow-field verification, ensuring that improvements predicted by the surrogate correspond to real aerodynamic gains.

The methodology is finally extended conceptually to morphing wing applications. Instead of treating optimized profiles as fixed replacements for the baseline, they are interpreted as reachable targets within a continuum of feasible shapes. This perspective makes them suitable reference states for morphing mechanisms, where compliant structures or smart materials could interpolate between baseline and optimized geometries to sustain efficiency under changing flight conditions.

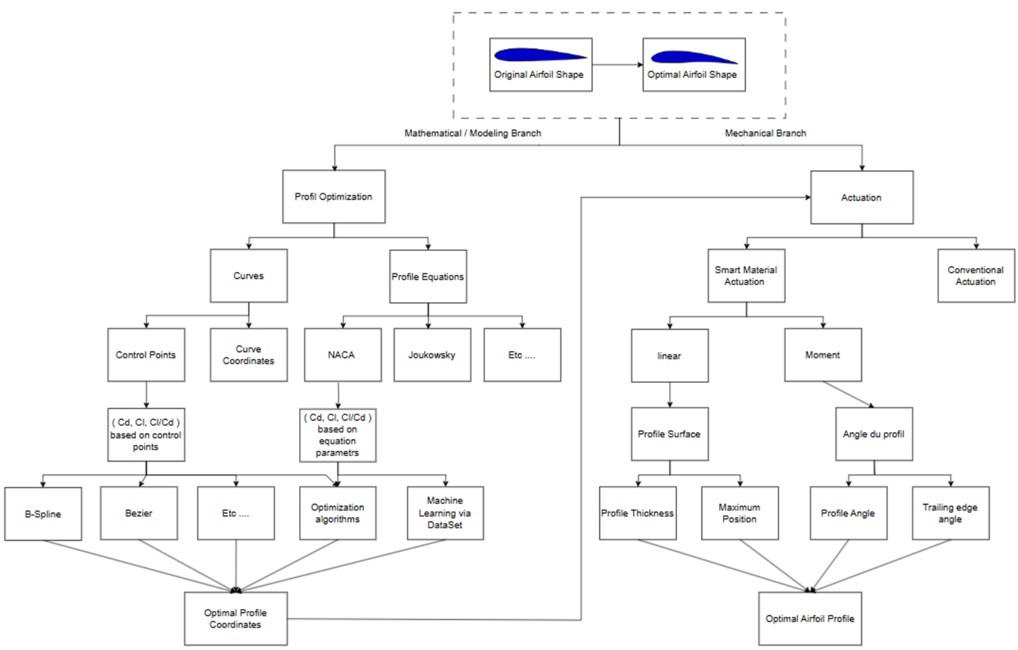

Fig. 1. Workflow of the surrogate–Bayesian optimization framework

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3 Results

The surrogate–optimization framework was applied to a representative case from the NACA four-digit family. For this demonstration, the NACA 2412 airfoil was selected, as it has been widely studied and serves as a benchmark for comparing optimization strategies. The first outcome of the optimization is shown in Figure 3, which compares the baseline NACA 2412 geometry with the optimized profile obtained from the surrogate–Bayesian pipeline. Although the overall shape of the airfoil is preserved, the optimized profile exhibits subtle modifications to the camber distribution and trailing-edge region. These refinements, while visually modest, are sufficient to produce measurable aerodynamic benefits, and their proximity to the baseline highlights the potential for practical morphing implementation.

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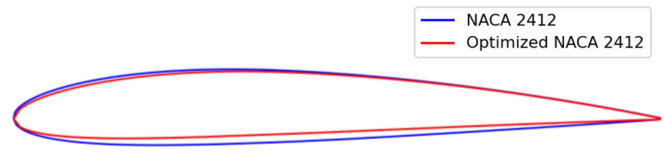

Fig. 3. NACA 2412 vs optimized NACA 2412.

Figure 4 illustrates the aerodynamic consequences of these geometric changes, which presents the pressure distribution at zero degrees angle of attack. The optimized profile shows a smoother suction peak over the upper surface and a more favorable pressure recovery toward the trailing edge. These characteristics are associated with drag reduction and an improved lift-to-drag ratio, confirming that the surrogate–optimization process identifies modifications consistent with aerodynamic theory.

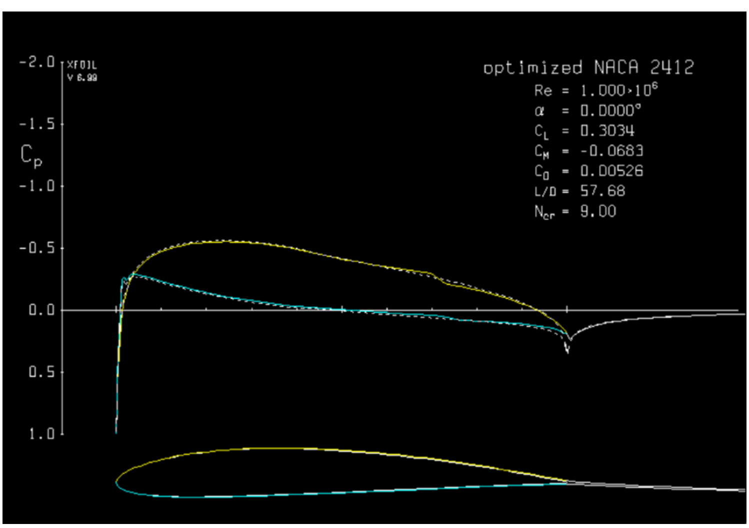

Fig. 4. Pressure distribution of optimized profile at AoA=0

To situate the present work within the context of existing optimization efforts, Table 1 compares the baseline NACA 2412, profiles optimized with genetic algorithms (GA) and particle swarm optimization (PSO) as reported in prior studies [9], and the profile optimized with the present method. At zero degrees angle of attack, the lift-to-drag ratio obtained with the proposed surrogate–Bayesian optimization framework reaches 58.69, exceeding both the baseline and earlier optimization methods. This represents a substantial relative gain, while maintaining a geometry that remains close to the original profile.

Table 1: NACA 2412 optimization results comparison

Parameter	NACA 2412	GA optimized	PSO optimized	Present Work
CL	0.235	0.247	0.278	0.3
CD	0.006	0.005	0.006	0.005
CL/CD	39.17	49.4	46.33	57.68
CD/CL	0.025	0.02	0.021	0.016

The results demonstrate that the surrogate–Bayesian framework not only reproduces the performance improvements obtained by earlier optimization strategies but also surpasses them, highlighting the efficiency of the proposed methodology. At the same time, the similarity between the baseline and optimized geometries reinforces the relevance of these results for morphing applications, where small but aerodynamically significant shape changes can be achieved through practical actuation mechanisms.

4. Discussion

The results obtained in this study confirm that machine learning–assisted surrogate modeling combined with Bayesian optimization provides a powerful tool for aerodynamic refinement. Applied to the NACA 2412 airfoil, the framework achieved performance gains that exceeded those of traditional optimization approaches such as genetic algorithms and particle swarm optimization. Importantly, these improvements were achieved with only subtle modifications to the original geometry.

The computational efficiency of the surrogate–optimization framework also merits attention. Conventional optimization workflows relying solely on CFD are computationally expensive, limiting the scope of design exploration. By introducing machine learning surrogates, the present approach enables rapid evaluation of candidate geometries, thus allowing a broader search of the design space. This makes it particularly well suited for preliminary design phases, where engineers must evaluate many alternatives quickly before committing to high-fidelity simulations or experimental testing.

The agreement between surrogate predictions and high-fidelity CFD validation further underscores the reliability of the framework. Concerns are often raised that surrogate-based optimization might identify “false” improvements that fail under detailed simulation. The present results show that this risk can be mitigated when surrogate models are carefully trained and combined with Bayesian search strategies. The optimized profiles demonstrated credible improvements under CFD validation, strengthening confidence in the method’s robustness

Beyond static optimization, the broader implications of these results lie in their connection to morphing wing applications. Because the optimized profiles remain geometrically close to their baselines, they can be interpreted as reachable states within a continuum of shapes. This opens the possibility of achieving the transition through morphing mechanisms, such as compliant structures or smart materials, rather than through radical redesign. From this perspective, the optimization framework does not simply generate a "better airfoil"; it defines target configurations that can serve as reference points for adaptive aerostructures.

Nonetheless, realizing this potential presents challenges. The structural and actuation requirements for morphing systems are complex, involving trade-offs between responsiveness, reliability, and weight penalties [10-13]. Moreover, optimization must eventually evolve from single-condition improvements toward multi-condition objectives, balancing performance across varying Reynolds numbers, Mach numbers, and angles of attack. These challenges suggest that the integration of aerodynamic optimization with structural and actuation modeling will be an important direction for future work.

Taken together, the discussion highlights the dual contribution of the present work. On one hand, it demonstrates a computationally efficient and physically credible optimization framework capable of surpassing existing methods. On the other, it points toward a longer-term vision in which these optimized shapes are not endpoints but milestones in the development of adaptive morphing wings, capable of sustaining efficiency across a wide range of flight conditions.

5. Conclusion and Future Work

This study presented a surrogate–optimization framework for aerodynamic design, combining data-driven modeling with Bayesian search and high-fidelity validation. Applied to classical NACA profiles, the method demonstrated its capacity to deliver aerodynamic improvements through modest yet effective geometric refinements. The use of machine learning surrogates reduced computational cost while maintaining predictive accuracy, and the subsequent validation with CFD confirmed the physical credibility of the results.

The framework's most promising contribution lies in its adaptability. By ensuring that optimized geometries remain close to their baselines, the approach bridges the gap between theoretical optimization and practical implementation. This characteristic also makes it highly relevant for morphing wing applications, where the transition between original and optimized profiles can be achieved through feasible structural deformation rather than radical redesign.

Future work will extend the present study in several directions. A first priority is the systematic validation of optimized profiles across a wider range of operating conditions, including variations in Reynolds number, Mach number, and angle of attack. Another avenue concerns the integration of uncertainty quantification, which will provide confidence bounds on surrogate predictions and strengthen their robustness. Further, multi-objective optimization will be explored to balance aerodynamic efficiency with structural load constraints and actuation energy requirements. Finally, coupling the aerodynamic framework with morphing actuation models will open the door to comprehensive design studies for adaptive aerostructures.

In this way, the current work establishes both a practical tool for efficient aerodynamic optimization and a conceptual pathway toward the design of next-generation morphing wings.

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