

DATA-DRIVEN SHAPE PARAMETERIZATION FOR EFFECTIVE AERODYNAMIC DESIGN OPTIMIZATION OF PROPELLERS

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Abstract

The growing demand for low-altitude aircraft and urban air mobility has driven higher requirements for improved propeller efficiency and reduced design cycle times. Data-driven aerodynamic design optimization of propeller shapes, whether using the blade element momentum theory or high-fidelity numerical simulations, is significantly hindered by the curse of dimensionality, wherein the computational cost scales exponentially with the number of geometric design variables. To address this challenge, we propose a data-driven propeller shape parameterization method that leverages lightweight aerodynamic models to construct a compact, aerodynamically regularized geometric design space. Specifically, candidate propeller shapes are first screened using lightweight aerodynamic evaluations, and a generative model is subsequently trained on the resulting high-quality designs to learn a compact latent representation. This process concentrates the geometric design space on aerodynamically favorable shapes, substantially reducing the dimensionality of the optimization problem. Comparative optimization studies conducted in the proposed compact space and two conventional geometric spaces demonstrate that the compact representation yields superior optimization effectiveness. This work establishes an aerodynamics-regularized paradigm for propeller design that effectively balances computational economy with predictive accuracy, offering broad applicability to urban air mobility platforms.

Keywords: Propeller design, Data-driven shape parameterization, Aerodynamic shape optimization, Urban air mobility

1. Introduction

The rapid expansion of the low-altitude economy [1, 2], encompassing electric vertical take-off and landing (eVTOL) aircraft, unmanned aerial vehicles, and urban air mobility platforms, has created unprecedented demand for high-performance propulsion systems. Propellers are central to determining the aerodynamic efficiency, acoustic signature, and overall mission capability of these platforms [3], and intense commercial pressure continues to drive manufacturers toward designs that are simultaneously efficient and rapidly deployable.

Meeting these demands places critical requirements on the underlying design methodology, where both cycle time and aerodynamic performance have become key differentiators. Conventional design approaches, whether gradient-based or surrogate-based, rely on real-time calls to aerodynamic analysis solvers and are therefore ill-suited to fast delivery timelines. Data-driven methods have emerged as a promising alternative [4], with models based on Gaussian process models and neural networks having been widely applied to accelerate design exploration for airfoils and wings [5, 6, 7, 8, 9, 10, 11]. More recently, multi-fidelity neural network frameworks have extended this paradigm to propeller design in electric aircraft, coupling low- and high-fidelity aerodynamic models to reduce surrogate training costs [12, 13, 14]. Despite these advances, the *curse of dimensionality* [15] remains a fundamental bottleneck. As the number of geometric design variables grows, the training data required for an

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accurate data-driven model increases exponentially, rendering high-dimensional parameterizations impractical in data-limited settings.

Aerodynamic shape parameterization is therefore not merely a preprocessing step but a fundamental determinant of the tractability and effectiveness of any data-driven aerodynamic optimization. Conventional parameterizations such as free-form deformation (FFD), B-spline surfaces, and class-shape transformation are agnostic to aerodynamic quality, meaning the resulting design space is populated with large fractions of geometrically valid but aerodynamically inferior shapes [16]. Data-driven parameterization approaches address this limitation by learning compact latent representations from databases of realistic designs, thereby concentrating the design space on high-quality geometries [16, 17, 18, 19, 20, 21, 22]. However, applying such approaches to propeller blades presents a specific challenge. Unlike the well-established UIUC or NACA airfoil databases, publicly available repositories of diverse, high-quality propeller blade geometries are severely limited, making it difficult to construct a training set that adequately covers the relevant design space.

To bridge this gap, this paper introduces a hybrid framework that combines aerodynamic regularization with data-driven generative modeling to construct a compact, aerodynamically informed geometric design space for propeller blades. The key contribution is an *aerodynamically regularized compact geometric parameterization method*. First, we generate candidate blade shapes and pre-screen them using a fast BEM-based aerodynamic analysis solver [23], ensuring that the generative model is trained exclusively on aerodynamically promising geometries. A generative model is subsequently employed to learn a low-dimensional latent space that captures the essential geometric variation of high-quality designs while implicitly encoding aerodynamic and geometric constraints. The compact parameterization is then coupled with a data-driven optimization framework. Comparative optimization studies conducted across the proposed compact space and two conventional high-dimensional parameterization spaces demonstrate that the compact representation consistently yields superior aerodynamic performance.

The remainder of this paper is organized as follows. We introduce the aerodynamically regularized compact shape parameterization of propellers in Section 2.. In Section 3., we present comparative data-driven optimization results with other parameterization methods. We summarize the conclusions in Section 4..

2. Data-driven Propeller Shape Parameterization

2.1 Propeller Shape Definition

Propeller blades are complex three-dimensional geometries that can be fully described by a set of spanwise cross-sectional airfoil profiles and their spatial arrangement along the blade radius. Following standard aeronautical conventions, we define the blade shape using two categories of geometric parameters: (1) *blade planform parameters* that govern the overall layout in the radial direction, and (2) *sectional parameters* that describe the local airfoil shape at spanwise stations.

As shown in Figure 1, the propeller blade planform is characterized by chord and twist distribution functions defined along the non-dimensionalized radial coordinate r/R, where r and R are the station radius and the tip radius, respectively. Each of these spanwise distributions is parameterized using four control points placed at discrete radial stations, and smooth cubic-spline interpolation is used to recover continuous distributions. The sectional airfoil geometry at each spanwise station is described by 14 airfoil modes [24, 19], and the final sectional shape are scaled according to the spanwise chord distribution. In our implementation, a propeller blade is represented by a parameter vector $\mathbf{x} \in \mathbb{R}^d$, where $d = 22$, yielding a moderately high-dimensional design space.

2.2 Aerodynamic Pre-selection using CCBlade

A naive approach to building a training database would be to uniformly sample the 22-dimensional design space using methods such as Latin Hypercube Sampling (LHS). However, a large fraction of the resulting shapes are geometrically infeasible or aerodynamically poor. Including such shapes in the training database wastes computational resources and pollutes the latent space learned by subsequent generative models. Therefore, we introduce an *aerodynamic pre-selection* step that acts as a physics-informed filter. First, $N_{\text{LHS}} = 50{,}000$ candidate blade shapes are sampled from the

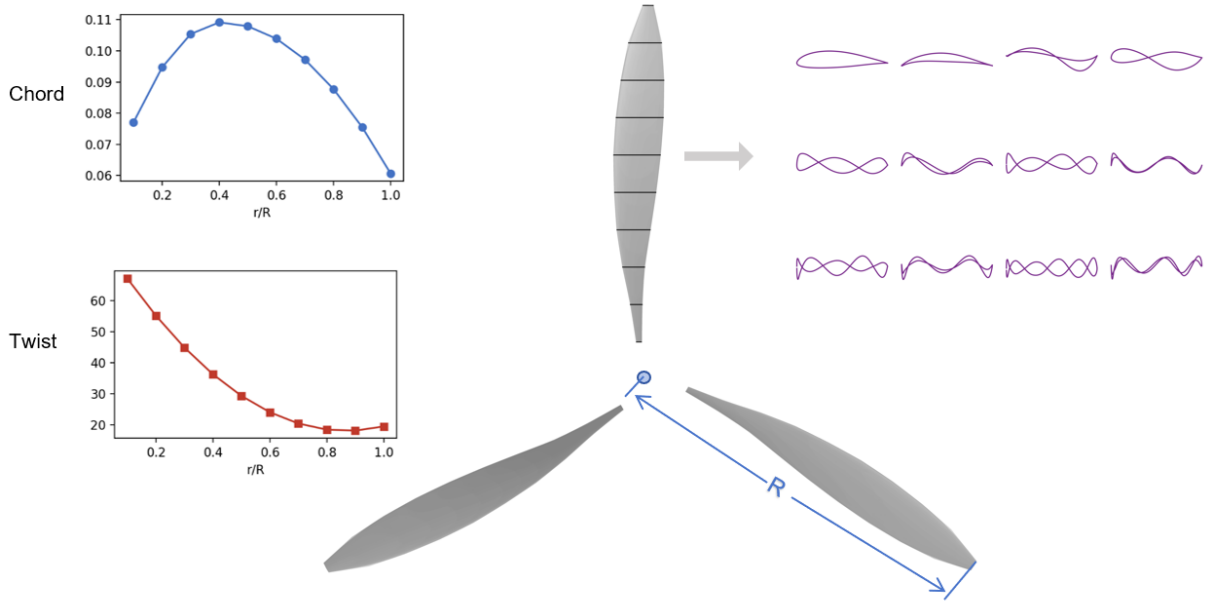


Figure 1 – Propeller blade shape definition.

full 22-dimensional parameter space using LHS, which ensures broad, space-filling coverage without replication. Each candidate is then evaluated using CCBlade [23], a computationally efficient open-source BEM solver. The aerodynamic evaluation is performed at a representative cruise operating condition relevant to urban air mobility, where the propeller rotational speed $n = 2000$ rpm and freestream velocity $V_\infty = 50 m/s$.

The selection merits are the propulsive efficiency η and the thrust T. Only blades with $\eta \geq 0.87$ at the design point and $T \geq 900N$ are retained, yielding a pre-selected database of $N_{\text{sel}} \approx 2{,}000$ shapes. This selection criterion ensures that the training database is dominated by aerodynamically competitive designs, effectively concentrating probability mass in the high-performing region of the design space. Figure 2 shows a comparison of the LHS-sampled shapes and the aerodynamically pre-selected subset, illustrating that the selection step substantially narrows the distribution of chord, pitch, and airfoil shape parameters to a physically meaningful subspace.

2.3 Generative Compact Representation of Propellers

Given the pre-selected database of high-quality blade shapes, a *generative adversarial network* (GAN) [**?**] is trained to learn a compact, continuous latent representation of the design space. GAN consists of a generator G and a discriminator D. The generator maps a low-dimensional standard Gaussian noise vector $\mathbf{z}$ to a blade parameter vector $\hat{\mathbf{x}}$, while the discriminator learns to distinguish generated samples from real shapes in the database. Both networks are trained via the standard minimax objective

$$\min_G \max_D \; \mathbb{E}_{\mathbf{x}}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]. \tag{1}$$

We use the Wasserstein GAN with gradient penalty [25] variant to improve training stability, and we set the latent dimension to $k = 10$, yielding a compression ratio of approximately $2.2\times$ relative to the original 22-dimensional space. After training, the generator G implicitly defines a smooth 10-dimensional manifold embedded in the 22-dimensional parameter space, constrained to the region populated by aerodynamically promising blade shapes.

For shape optimization, the latent vector $\mathbf{z} \in \mathbb{R}^{10}$ becomes the new design variable, and any point in this compact space maps via $G(\mathbf{z})$ to a full, feasible blade geometry. This approach reduces the geometric dimensionality and enforces implicit aerodynamic constraints inherited from the pre-selected training database. It also provides a smooth and differentiable design space that is well-suited for data-driven optimization. Figure 3 shows representative blades decoded from the latent space. Figure 4 shows the parameter distributions of training dataset and generated data of GAN,



Figure 2 – Comparison of propeller shapes before and after aerodynamic pre-selection

which demonstrates that the GAN model captures the full geometric diversity of the pre-selected database while producing smooth interpolations between design modes.

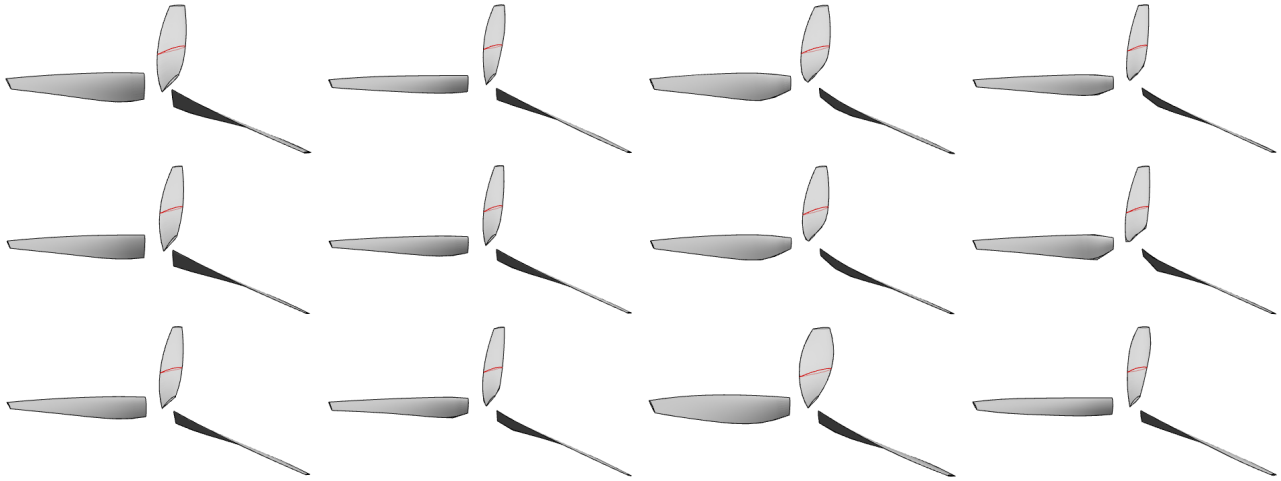


Figure 3 – Results of the compact geometric design space.

3. Propeller Optimization Comparison using Different Parameterization Approaches

To quantitatively assess the benefit of the proposed compact parameterization, we conduct a controlled comparison against two conventional alternatives: *FFD* and *proper orthogonal decomposition (POD)*. The two conventional approaches differ only in how the sectional airfoils are parameterized, that is, the FFD approach uses 14 control points per section, while the POD-based approach uses 14 airfoil modes. Apart from the parameterization, the data-driven aerodynamic optimization workflow is identical across all three methods. For each parameterization, $N_{\text{train}} = 50,000$ blade shapes are

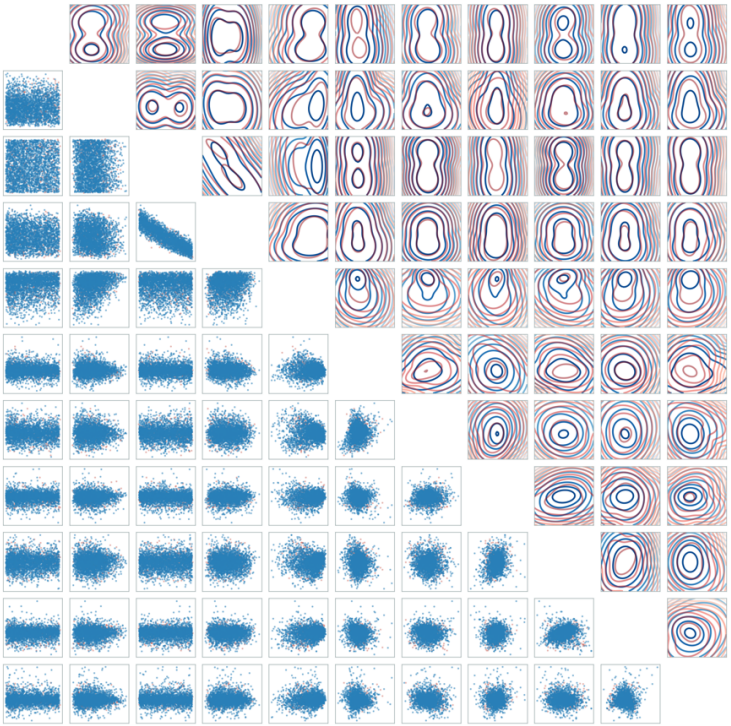


Figure 4 – Geometric parameter distributions of training dataset and generated data of GAN.

sampled from the respective design space, evaluated using CCBlade, and used to train a data-driven model. Optimization is then performed on the data-driven model using a gradient-based optimizer [26] to maximize propulsive efficiency η subject to a minimum thrust constraint $T \geq 1000\ N$.
Figure 5 shows the diversity of training shapes generated by the FFD parameterization method. The FFD approach produces a broad but geometrically heterogeneous shapes that include many infeasible or aerodynamically poor shapes. As shown in Figure 2, the POD-based approach yields smoother geometric variations, yet still admits abnormal shapes because it does not account for the statistical distribution of the underlying airfoil modes. By contrast, the GAN-based compact parameterization (see Figure 3) generates a population that is both geometrically realistic and aerodynamically competitive.

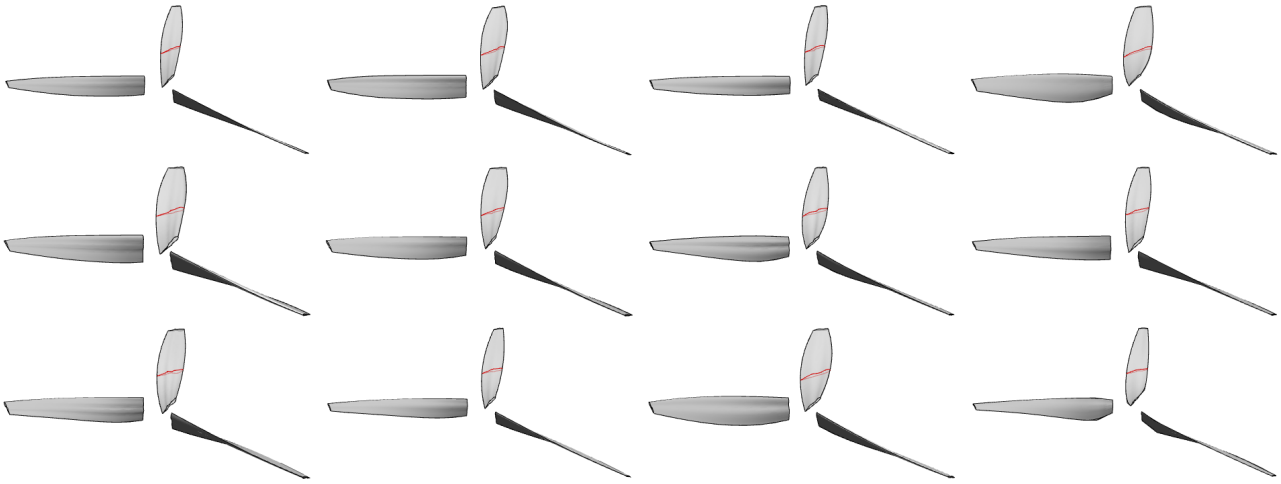


Figure 5 – Training blade shapes generated by FFD.

Data-driven aerodynamic models are trained on the three datasets using the same multilayer perceptron architecture. Figure 6 shows the training and validation loss curves for all three models. The GAN-based compact parameterization yields models with lower error, reflecting the more structured

and learnable nature of its geometric design space.

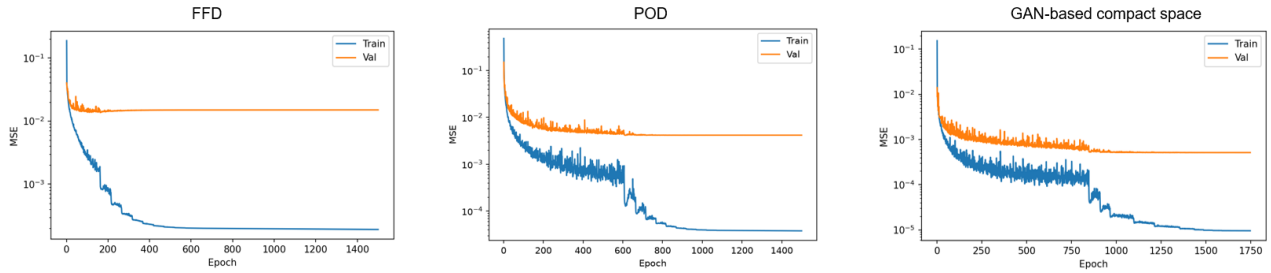


Figure 6 – Data-driven aerodynamic model training loss functions across the three parameterization approaches.

The optimized blade shapes obtained from all three parameterization methods are shown in Figure 7. The GAN-based approach achieves a propulsive efficiency of $\eta = 0.8945$ at the design condition, compared with $\eta = 0.8909$ for the POD-based approach and $\eta = 0.857$ for the FFD approach. These results confirm that the compact GAN-based parameterization outperforms both conventional alternatives in data-driven propeller shape optimization.

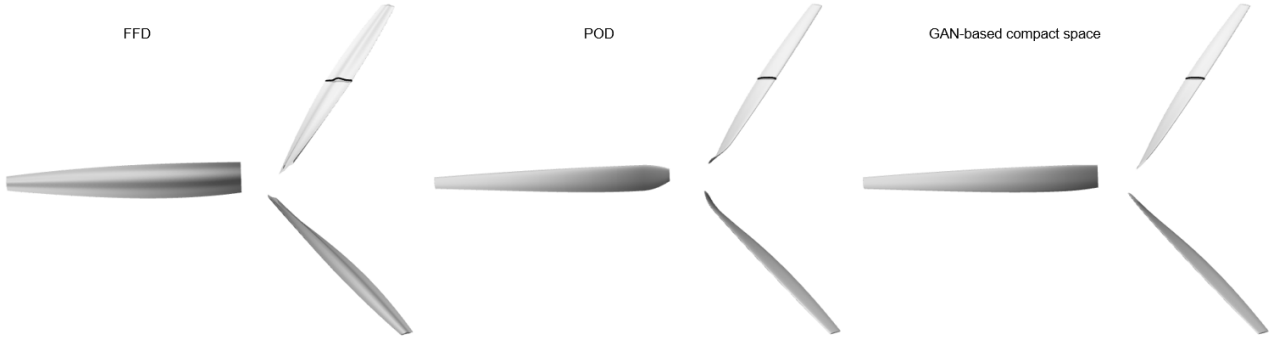


Figure 7 – Optimized blade shapes for data-driven optimization using the three parameterization approaches.

4. Conclusions

This paper presents a data-driven framework for propeller blade shape parameterization and aerodynamic design optimization. The central contribution is a compact, aerodynamically regularized geometric representation that enables fast and effective data-based optimization of propeller blades. Aerodynamic pre-selection using a low-fidelity BEM solver concentrates the training database on physically meaningful, high-performing geometries, eliminating wasted evaluations on infeasible designs. The resulting GAN-based compact parameterization outperforms both the POD-based and FFD alternatives in model accuracy and optimization performance. Future work will explore physics-informed generative models that incorporate RANS flow solutions directly into training, further improving the physical fidelity of the learned design space.

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