Invertible neural networks for aerodynamic design of wind turbine blades

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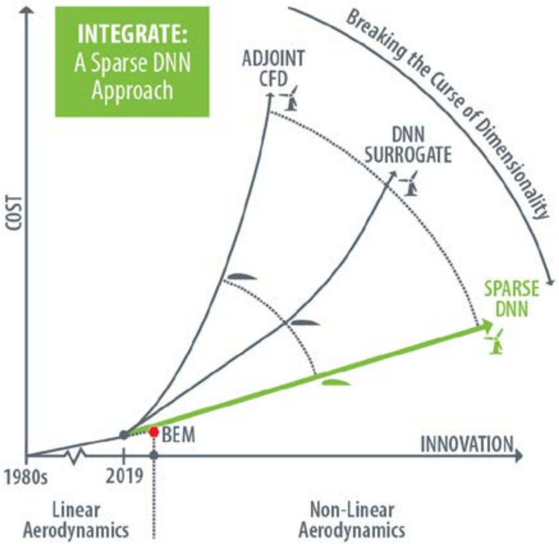
Overview

Goal: enable full 3D inverse design of wind turbine blades using machine learning techniques



- Design workflows generally rely on engineering tools e.g., blade element momentum (BEM) theory
  - For larger offshore rotors, nonlinear aerodynamic effects dominate, and BEM assumptions break down
- Use ML to bring computational fluid dynamics (CFD) fidelity in the design process
  - Grassmann-based shape representations
  - Invertible neural network (INN) framework
  - Trained on high-fidelity CFD data

Inverse problems and INNs

Consider a forward mapping $\boldsymbol{f}: (\mathcal{X} \subset \mathbb{R}^m) \to \left(\mathcal{F} \subset \mathbb{R}^d\right)$ with the input space weighted by ρ: $(\mathcal{X} \subset \mathbb{R}^m) \to \mathbb{R}^+$

We seek to characterize the inverse image

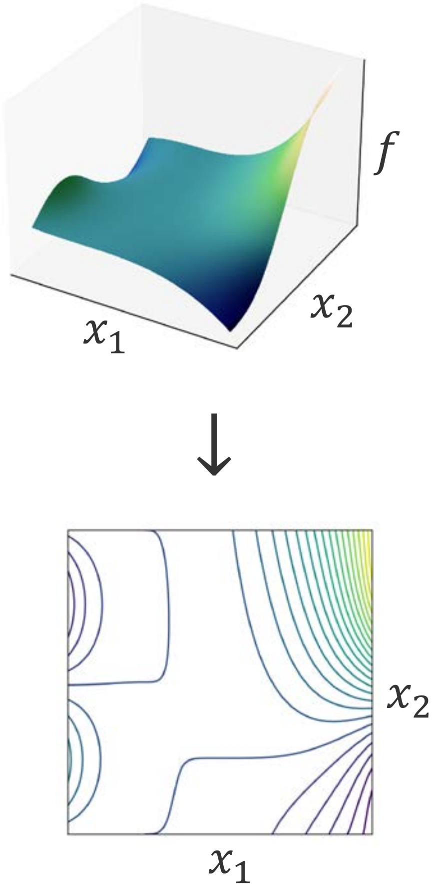
$$\boldsymbol{f}^{-1}(\bar{\mathbf{f}}) = \{\, \mathbf{x} \in \mathcal{X} : \boldsymbol{f}(\mathbf{x}) = \bar{\mathbf{f}} \,\}, \quad \rho\left(\mathbf{x} \middle| \bar{\mathbf{f}}\right)$$

for some conditional value $\bar{\mathbf{f}} \in \mathcal{F}$

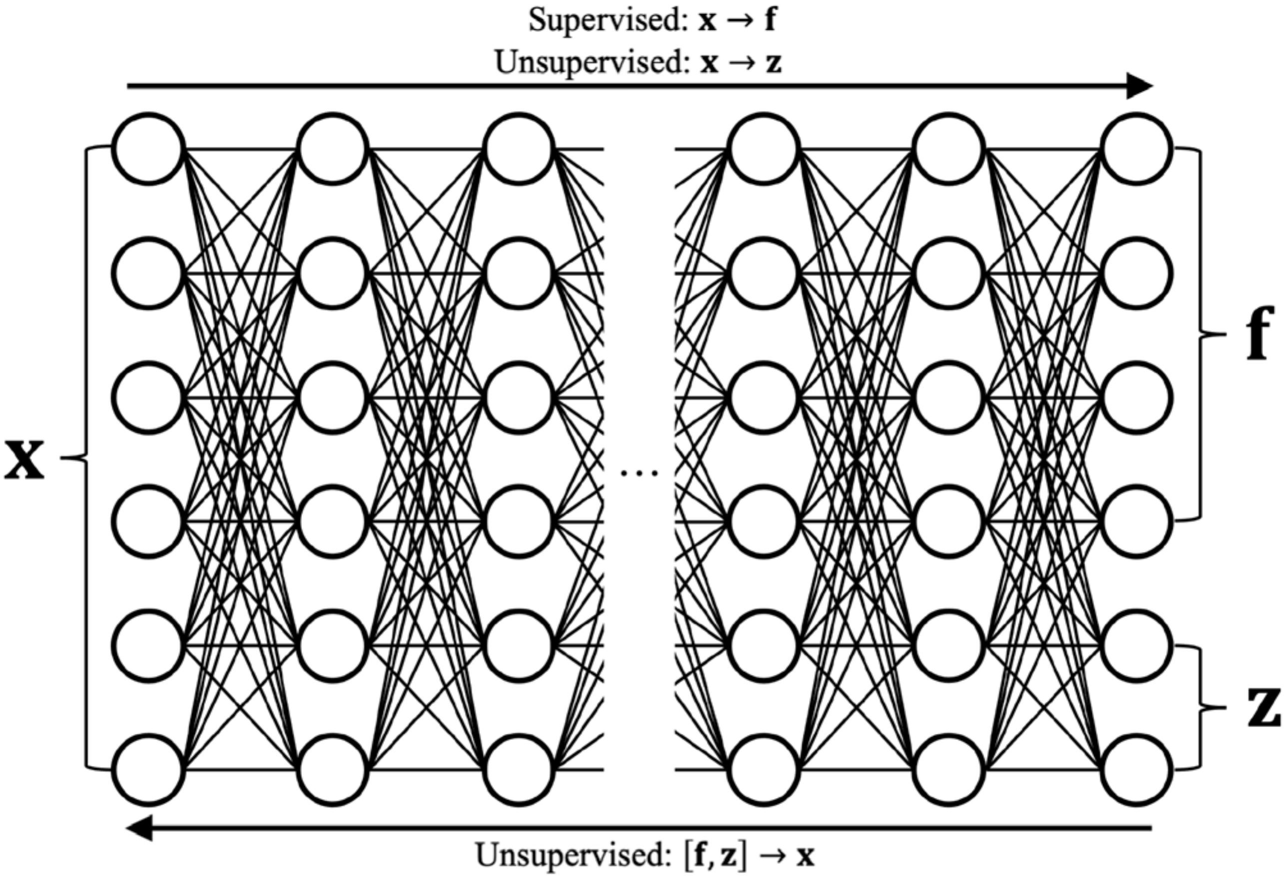
Use an invertible neural network that learns a bijection

$$\boldsymbol{f}_{INN}(\mathbf{x}; \boldsymbol{\Theta}) = \begin{bmatrix} \mathbf{f} \\ \mathbf{z} \end{bmatrix}$$

where the latent variables $\mathbf{z} \to \mathbb{R}^{m-d}$ parameterize the set $\boldsymbol{f}^{-1}$



INN architecture



Invertible blocks

Partition the incoming vector into two equal pieces and apply

$$\phi_i(\mathbf{x}_i) = \phi_i\left(\begin{bmatrix}\mathbf{u}_i \\ \mathbf{v}_i\end{bmatrix}\right) = \begin{bmatrix}\mathbf{u}_i \odot e^{s_1(\mathbf{v}_i)} + t_1(\mathbf{v}_i) \\ \mathbf{v}_i \odot e^{s_2(\mathbf{u}_i)} + t_2(\mathbf{u}_i)\end{bmatrix} = \begin{bmatrix}\mathbf{u}_{i+1} \\ \mathbf{v}_{i+1}\end{bmatrix} = \mathbf{x}_{i+1}$$

which has the closed–form invertible mapping

$$\phi_i^{-1}(\mathbf{x}_{i+1}) = \phi_i^{-1}\left(\begin{bmatrix}\mathbf{u}_{i+1} \\ \mathbf{v}_{i+1}\end{bmatrix}\right) = \begin{bmatrix}\left(\mathbf{v}_{i+1} - t_2(\mathbf{u}_{i+1})\right) \odot e^{-s_2(\mathbf{u}_{i+1})} \\ \left(\mathbf{u}_{i+1} - t_1(\mathbf{v}_{i+1})\right) \odot e^{-s_1(\mathbf{v}_{i+1})}\end{bmatrix} = \begin{bmatrix}\mathbf{u}_i \\ \mathbf{v}_i\end{bmatrix} = \mathbf{x}_i$$

regardless of the form of $s_1, t_1, s_2, t_2\colon \mathbb{R}^{m/2} \to \mathbb{R}^{m/2}$

[Ardizzone, et al., 2019]

Training losses

- Supervised quantities are trained using MSE losses

$$\mathcal{L}_{\mathbf{f}} = \left\| \mathbf{f} - \mathbf{f}_{\mathrm{INN}}(\mathbf{x}; \boldsymbol{\Theta})_{[1:d]} \right\|_2^2$$

- Unsupervised quantities are trained using the maximum mean discrepancy (MMD)

[Gretton, et al. *2012*]

Two probability distributions are identical if and only if

$$MMD(p,q) \coloneqq \sup_{\phi \in \mathcal{H}} \left| \mathbb{E}_{x\sim p}[\phi(x)] - \mathbb{E}_{y\sim q}[\phi(y)] \right| = 0$$

In practice, we compute

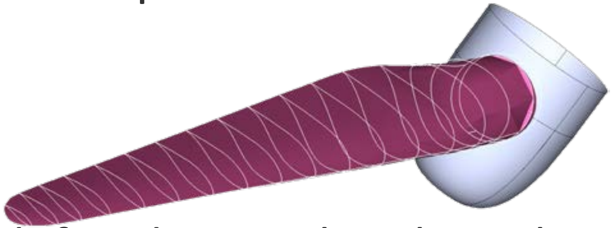
$$MMD^2(p,q) = \mathbb{E}_{x,x'\sim p}[k(x,x')] - 2\mathbb{E}_{x\sim p, y\sim q}[k(x,y)] + \mathbb{E}_{y,y'\sim q}[k(y,y')]$$

where $k(\cdot,\cdot)$ is some kernel function

→ for this work, we use $k(x,y) = \frac{1}{1+\|x-y\|_2^2}$

Blade Shape Representation

- We need a framework for blade shape representations that to enable design with the INN model
  - Blade is comprised of a sequence of landmark airfoils

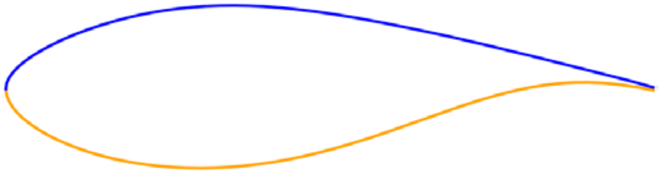


  - Each airfoil shape is defined using the Class-Shape Transformation (CST)

$$\zeta(\psi) = C_{N2}^{N1}(\psi)S(\psi) + \psi\zeta_T$$

$$C_{N2}^{N1} = \psi^{N1}(1-\psi)^{N2}$$

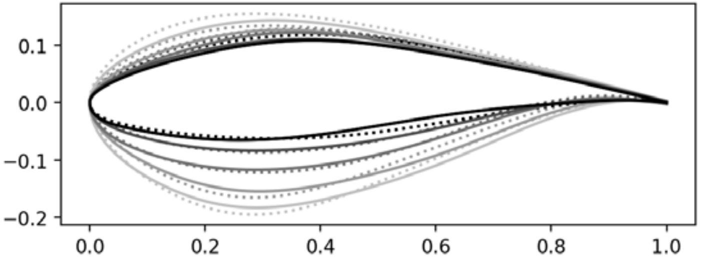
$$S(\psi) = \sum_{i=0}^{n} a_i S_i$$

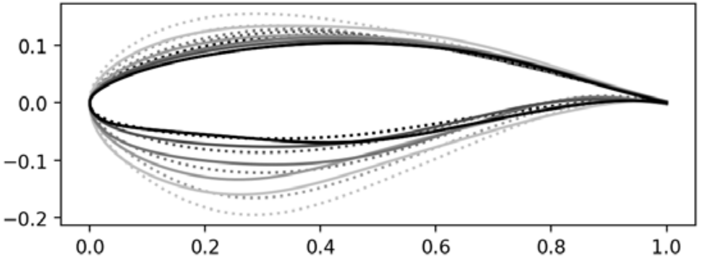


- 5 landmark shapes $\times$ 20 shape parameters $=$ 100 dimensions
  - Doesn’t account for chord or twist

Blade Shape Representation

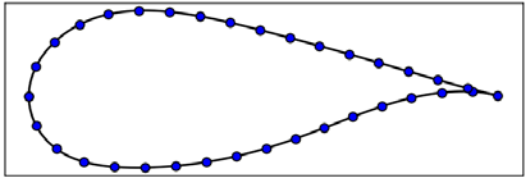
- Treating airfoil shape perturbations independently can result in bad blade shapes with undesirable features (e.g., kinks or dimples)
  - Define cohesive perturbations applied to each airfoil
  - Pathway for dimension reduction
- Consistent perturbations applied to CST coefficients does not map to consistent shape deformations



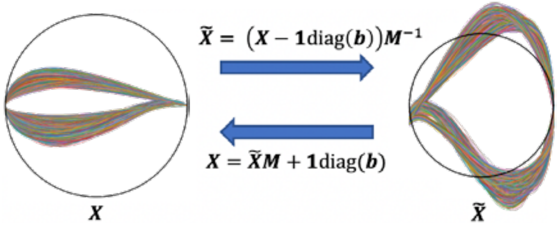


Grassmannian Shape Representations

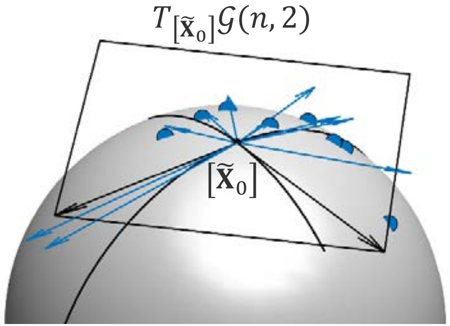
- Represent shapes as n (x, y)-landmarks along the curve



- Perform landmark-affine (LA) standardization to shapes
  - Treats each airfoil shape as an element of the Grassmann manifold $\mathcal{G}(n, 2)$
  - Remaining differences in shapes are driven by higher order variations



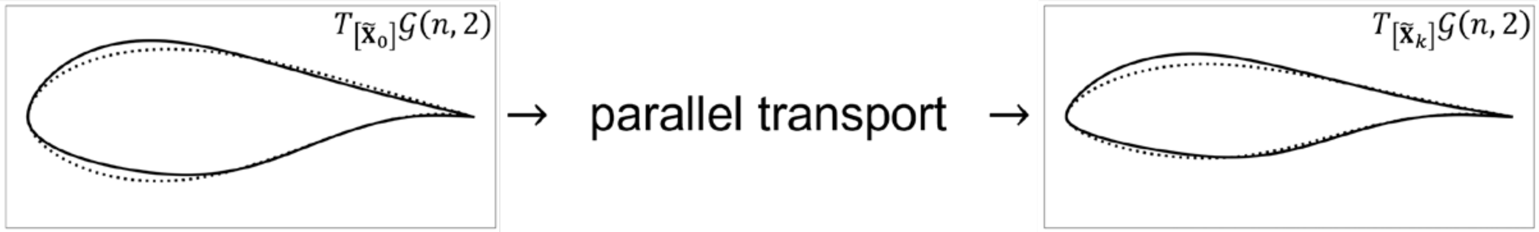
- Perform principal geodesic analysis on Grassmann shapes
  - A generalization of principal component analysis (PCA) to Riemannian manifolds
  - Defines principal components within the central tangent space $T_{[\tilde{\mathbf{X}}_0]}\mathcal{G}(n, 2)$ at some point $[\tilde{\mathbf{X}}_0]$



PGA-based Blade Design

Goal: Seek to apply cohesive perturbations to the landmark airfoils in the blade blade

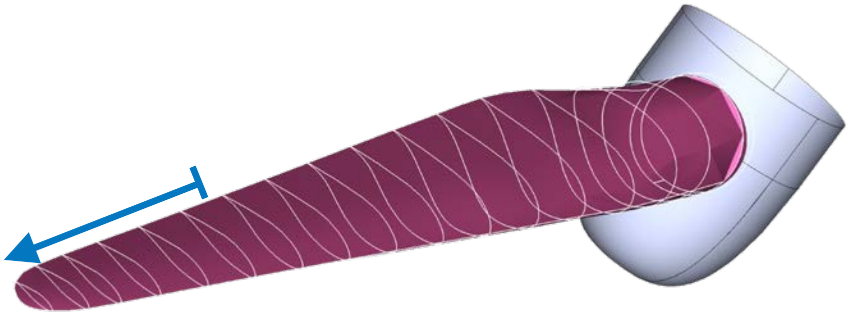
- PGA coordinates are defined relative to a central tangent space of the Grassmannian defined at a specific point $T_{[\tilde{\mathbf{X}}_0]}\mathcal{G}(n,2)$
- Parallel transport is a process by which we can smoothly translate the PGA coordinates to a new tangent space $T_{[\tilde{\mathbf{X}}_k]}\mathcal{G}(n,2)$



- Blade shape is defined by four PGA coordinates and a thickness value

Outer blade section design

Building towards full blade design, we two perform INN-based designs on the outboard section of the blade



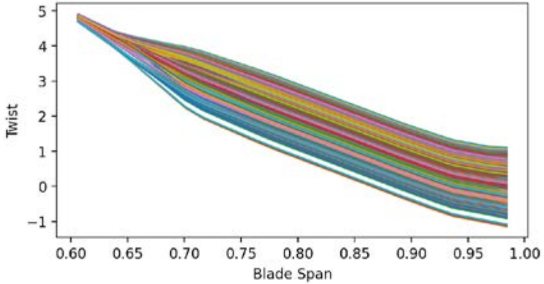
Goal: Trade-off some power to mitigate loads

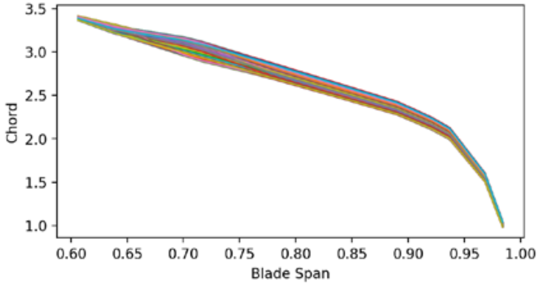
Consider two design problems:

1. Design of chord & twist profiles based on 3D CFD
2. Design of blade tip shape and chord & twist profiles based on BEM

Blade Twist & Chord

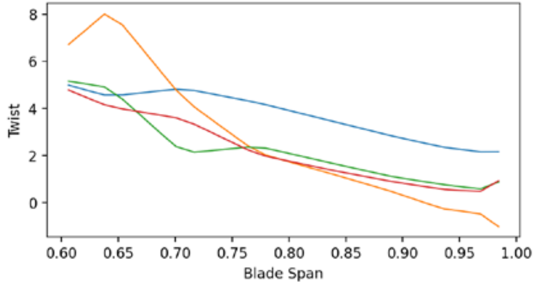
- Need to encode twist and chord profiles along the blade span in a manner that is compatible with our INN framework

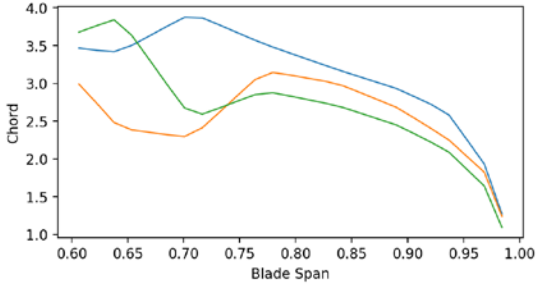




- Parameterize profiles using a Karhunen–Loève basis expansion

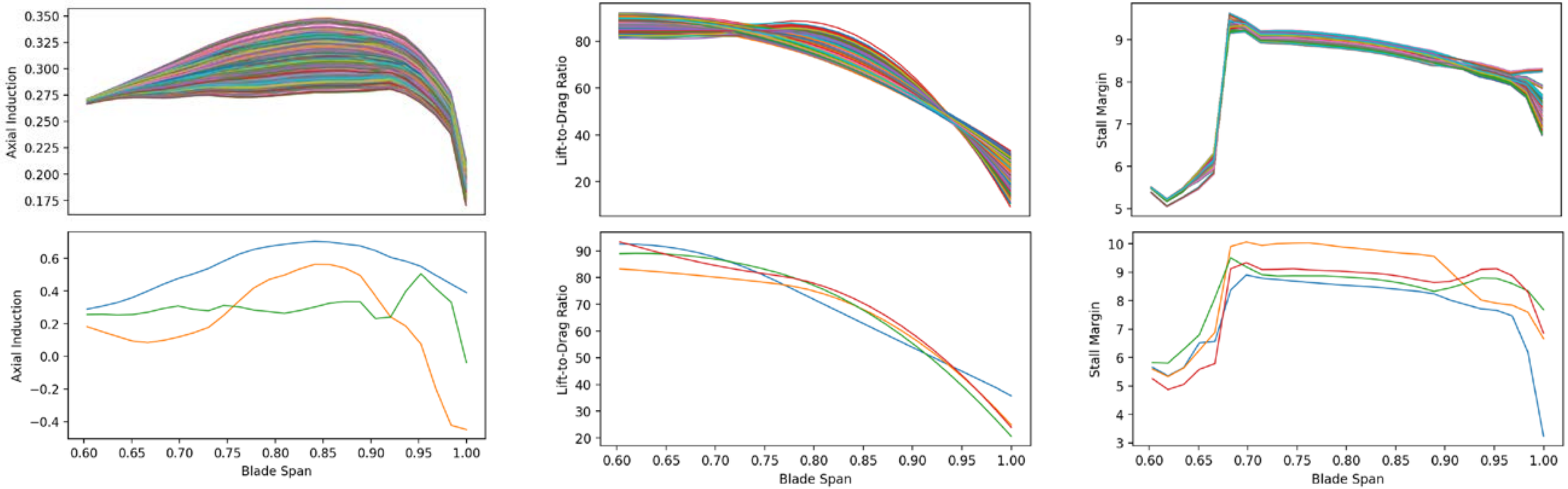
$$\int k\big(f(\tilde{r}), f(r)\big)\, \phi(\tilde{r})\, \mathrm{d}\tilde{r} = \lambda\, \phi(r) \quad \rightarrow \quad f(\alpha) \approx \sum_{i=0}^{N} c_i\, \phi_i(r)$$





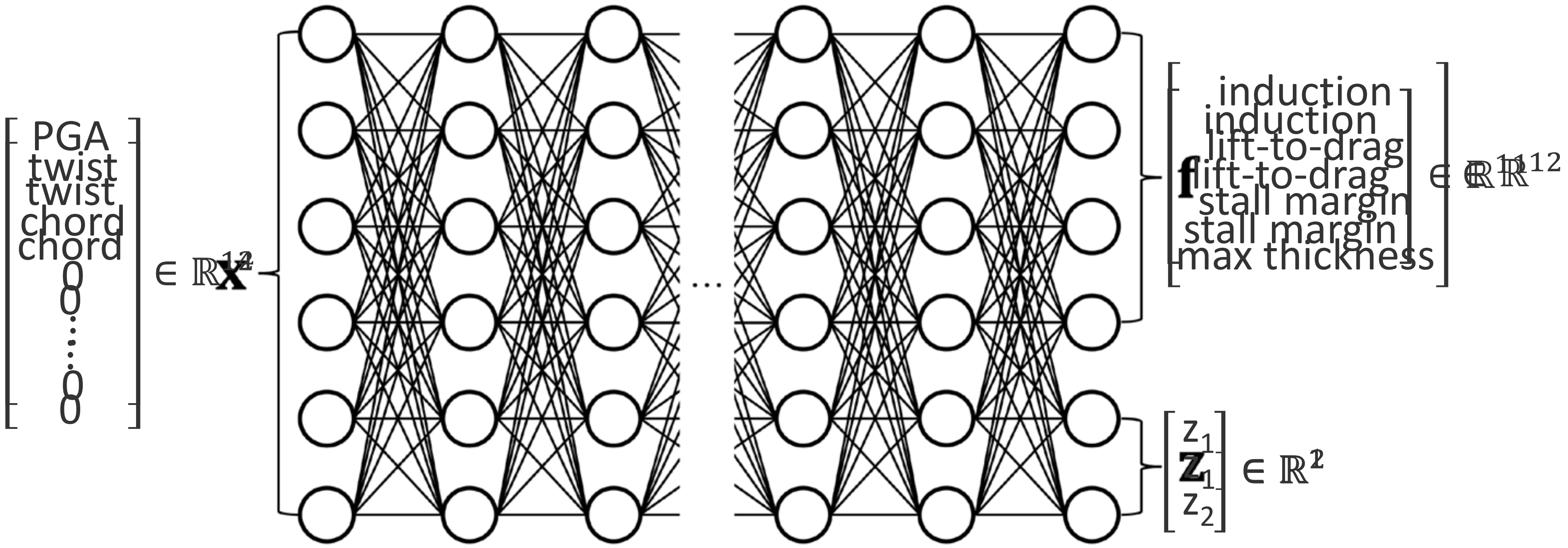
Design Metrics

- Aerodynamic design metrics are (i) axial induction factor, (ii) lift-to-drag ratio, and (iii) stall margin



- Max thickness-to-chord ratio is included as a structural design for the BEM design problem

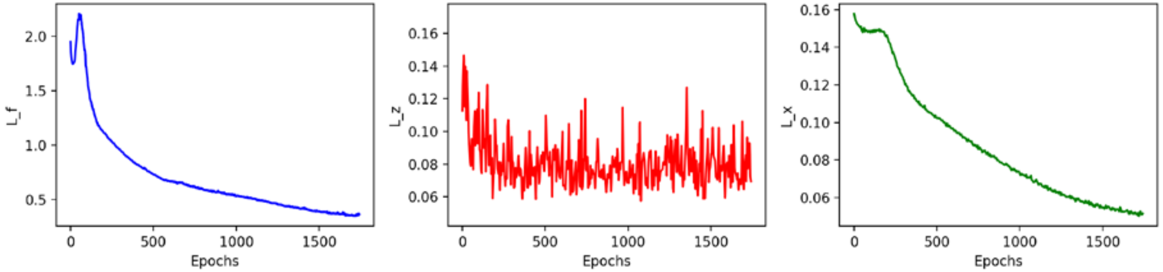
INN architecture – Scenario 2 – BEM



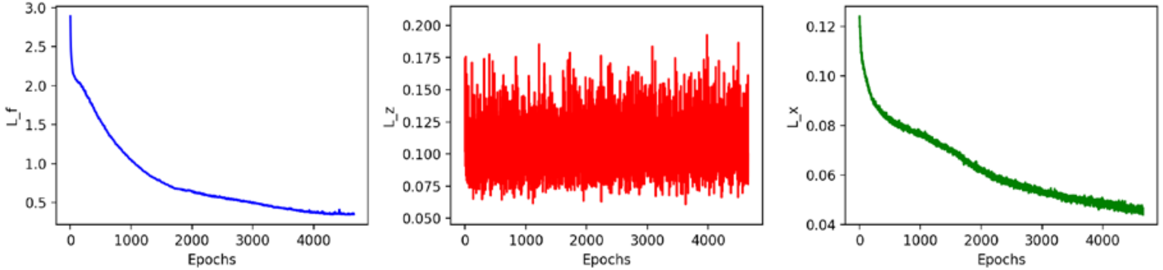
Training

- MSE losses of aerodynamic quantities improve by an order of magnitude before leveling off
- Unsupervised losses
  - Gaussian distribution over latent variables is nearly recovered at initialization
  - Target input distribution converges relatively quickly

Scenario 1 – CFD

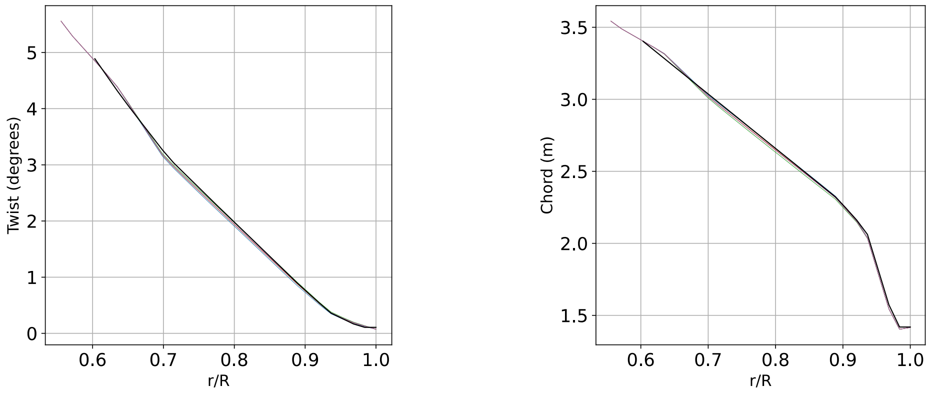


Scenario 2 – BEM

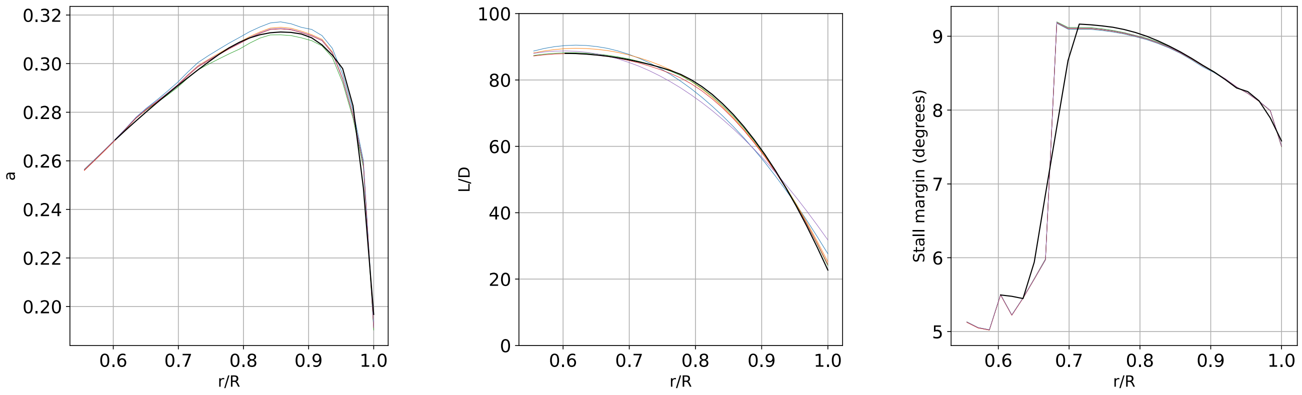


Results – Scenario 1 – CFD

Five generated twist/chord profiles →

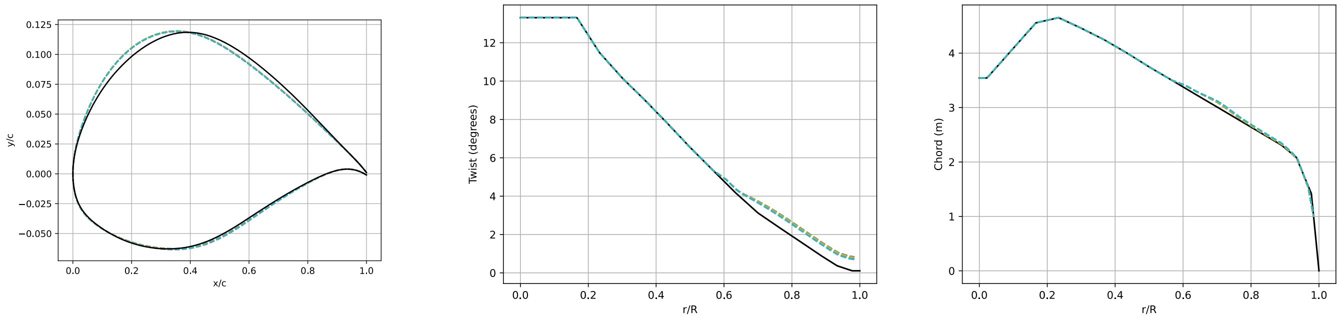


Match target outputs within error thresholds →

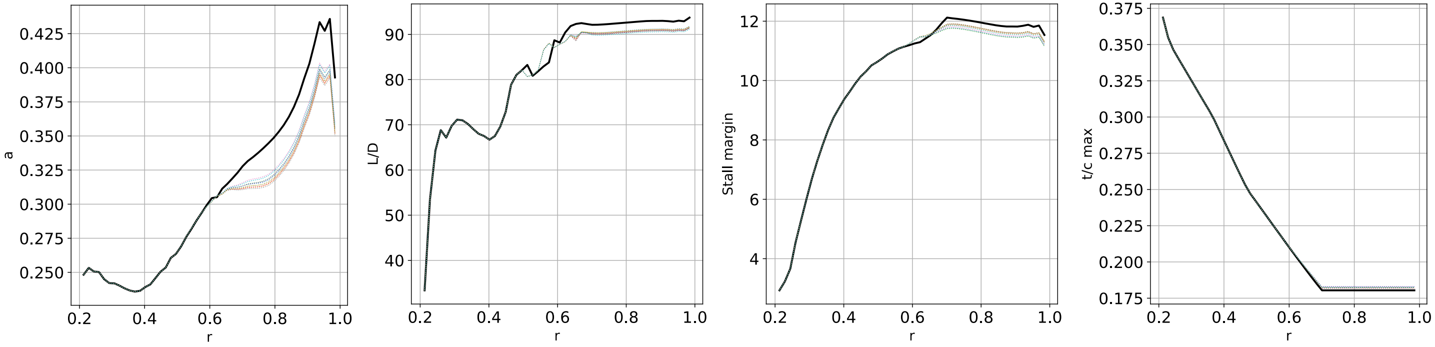


Results – Scenario 2 – BEM

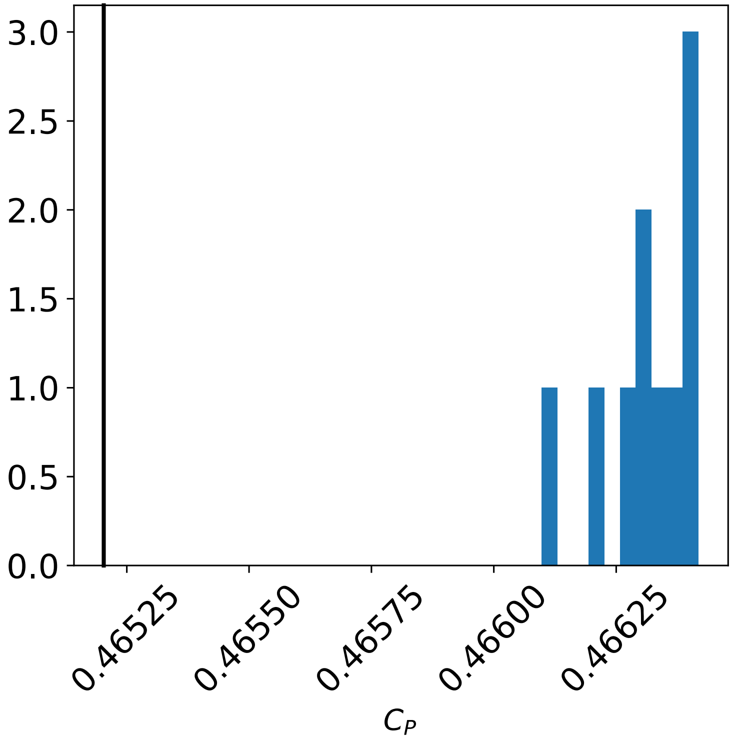
Ten generated blade designs →

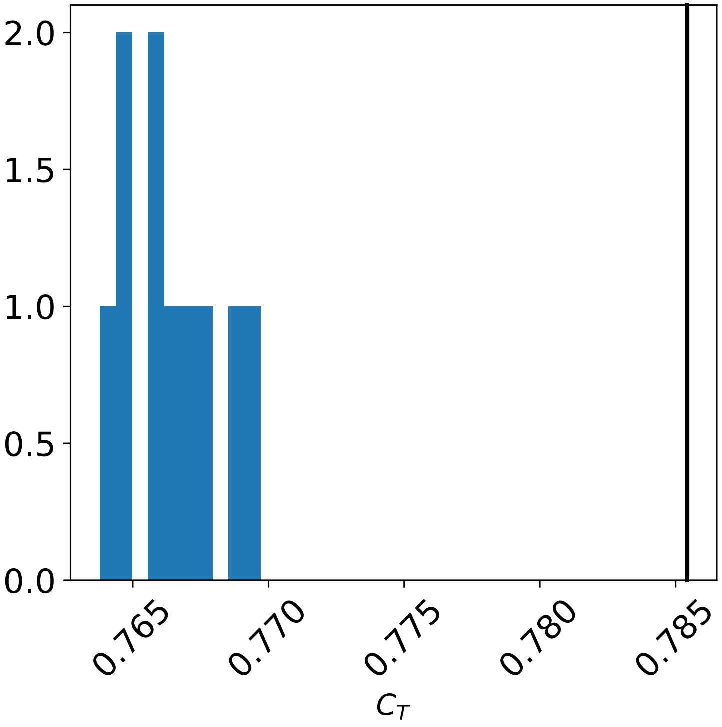


Match target outputs within error thresholds →



Results – Scenario 2 – BEM





Conclusion & Next Steps

- Used invertible neural network (INN) architecture to perform design of the outboard section of the blade
  - Learns a bijection between inputs and outputs
  - Relies on Grassmann airfoil shape representations and KL expansions for blade span profile quantities
- Next steps: Perform full 3D blade shape design using the INN framework
  - Used PGA perturbations to sample new blade shapes
  - Used Mercury 3D CFD framework to evaluate over 5,000 blades
  - Train the INN using this data and validate the generated designs

Thanks!

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