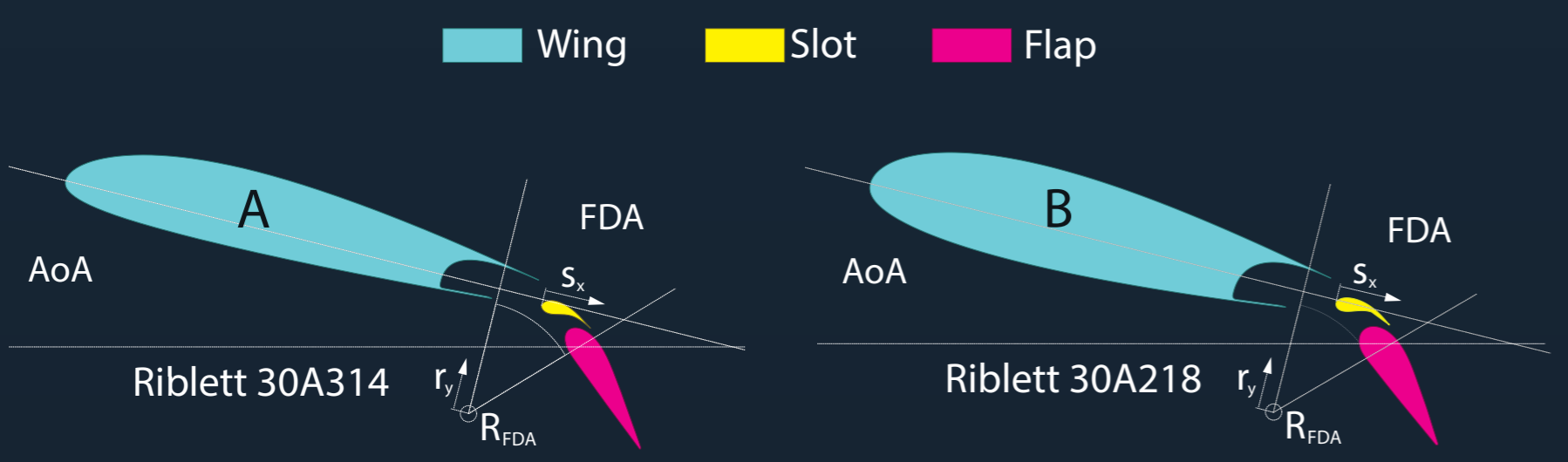


## Problem and Motivation

Designing high-lift systems for small custom-built aircraft requires balancing conflicting aerodynamic objectives—maximizing lift for safe low-speed operation. Traditional CFD-based optimization of flap shapes and configurations is computationally expensive and too slow for extensive design exploration. This limits the ability to fully exploit the design space and achieve optimal performance. To overcome this, we leverage AI-based surrogate models trained on high-fidelity CFD data, enabling rapid evaluation and efficient shape optimization of flap systems. This approach significantly accelerates the design cycle while improving low-speed performance, safety, and overall aircraft efficiency.

## 1. Wing Geometry Definition



### Slot geometry parametrization using the Kulfan CST

$$y(x) = C(x)S(x) + \delta_{LE}(1-x) + \delta_{TE}x$$

$$C(x) = x^{N_1}(1-x)^{N_2}$$

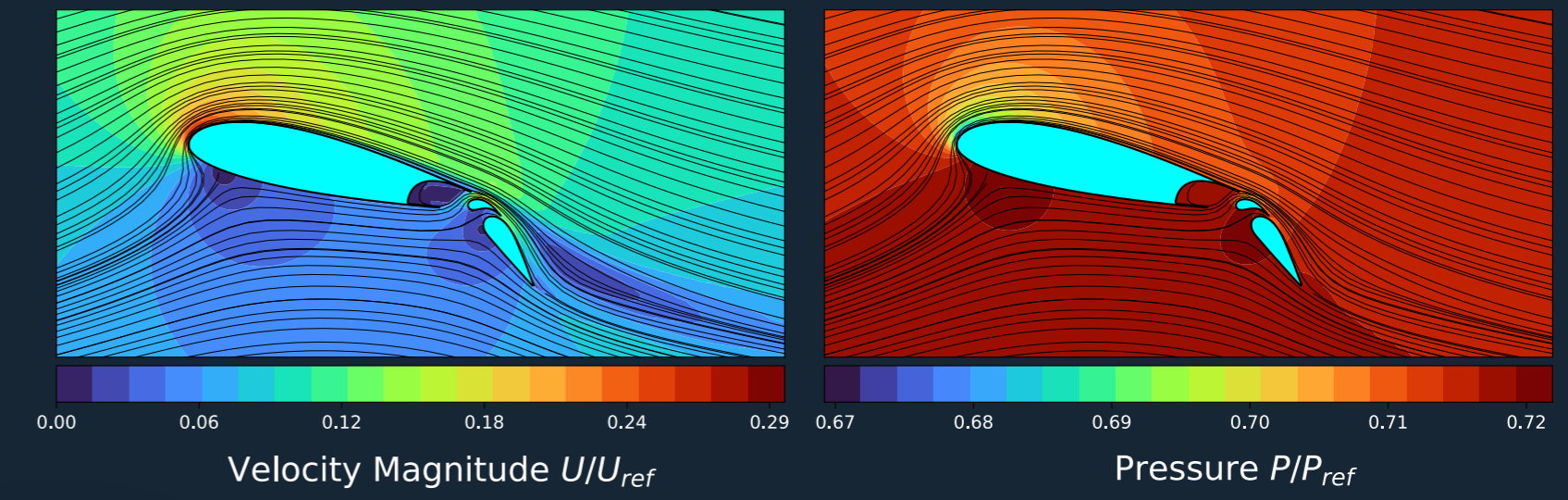
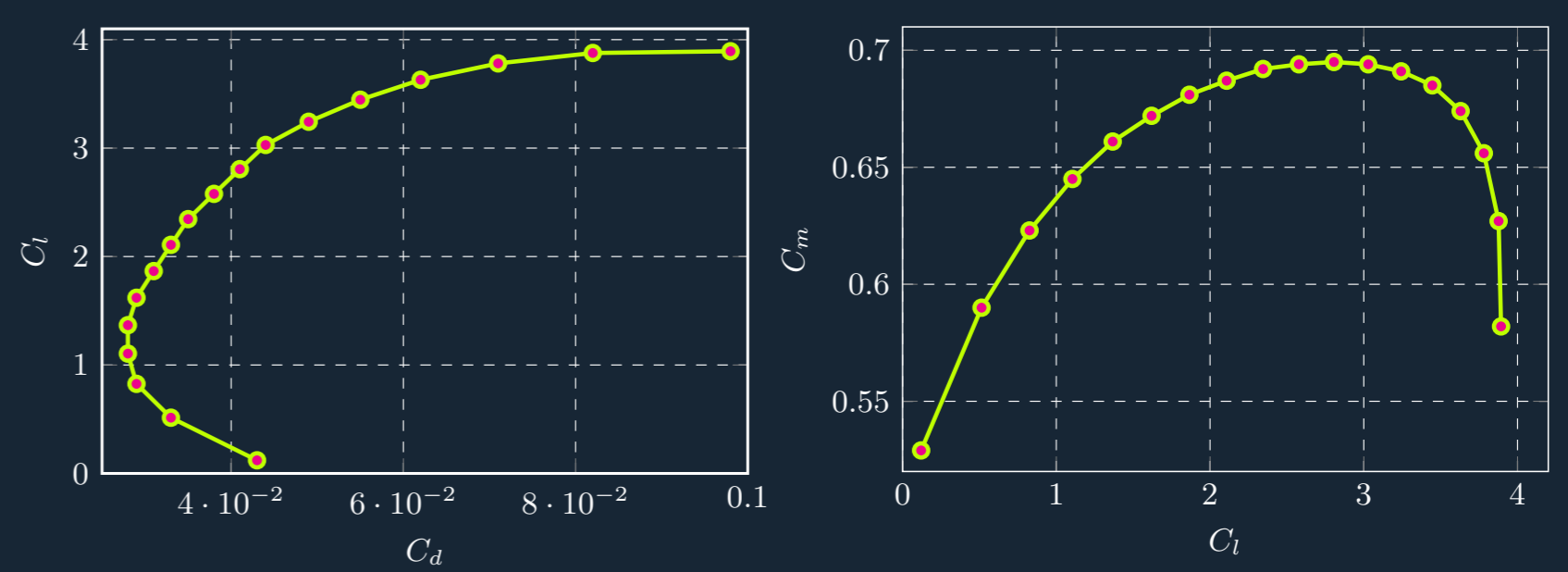
$$S(x) = \sum_{i=0}^M w_i B_i(x)$$

$$B_i(x) = \binom{M}{i} x^i (1-x)^{M-i}$$

### 15 parameters

$\delta_{LE}, \delta_{TE}, r_y, s_x, AoA, FDA,$   
 $\{w_i^{(w)}\}_{i=1}^3, \{w_j^{(l)}\}_{j=1}^6$

## 2. Data Generation



$$e_i = |y_i - \hat{y}_i| \quad \bar{e} = \frac{1}{n} \sum_{i=1}^n e_i$$

$$e_i^{(\%)} = 100 \cdot \frac{|y_i - \hat{y}_i|}{y_{max} - y_{min}}$$

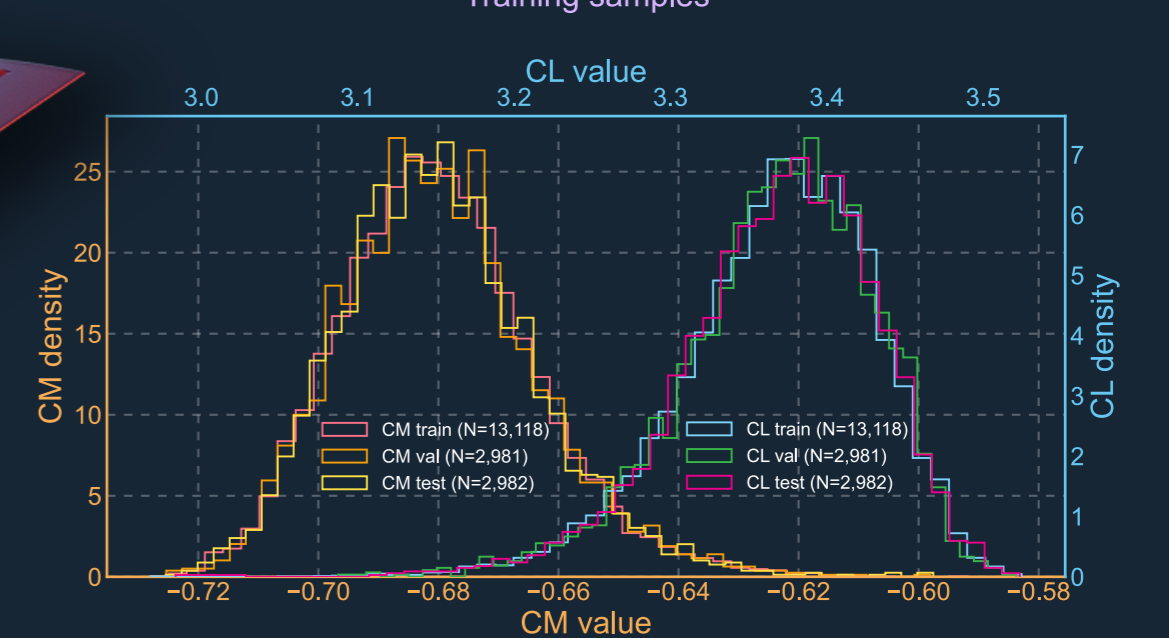
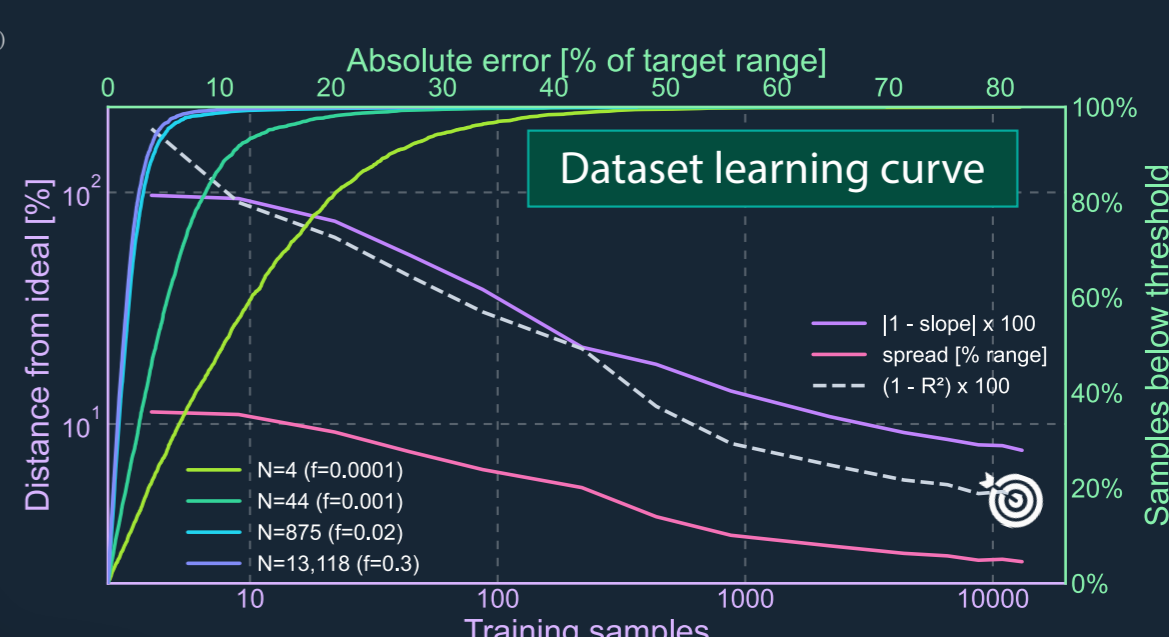
$$spread = \sqrt{\frac{1}{n} \sum_{i=1}^n (e_i^{(\%)} - \bar{e}^{(\%)})^2}$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

$$\hat{r}^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

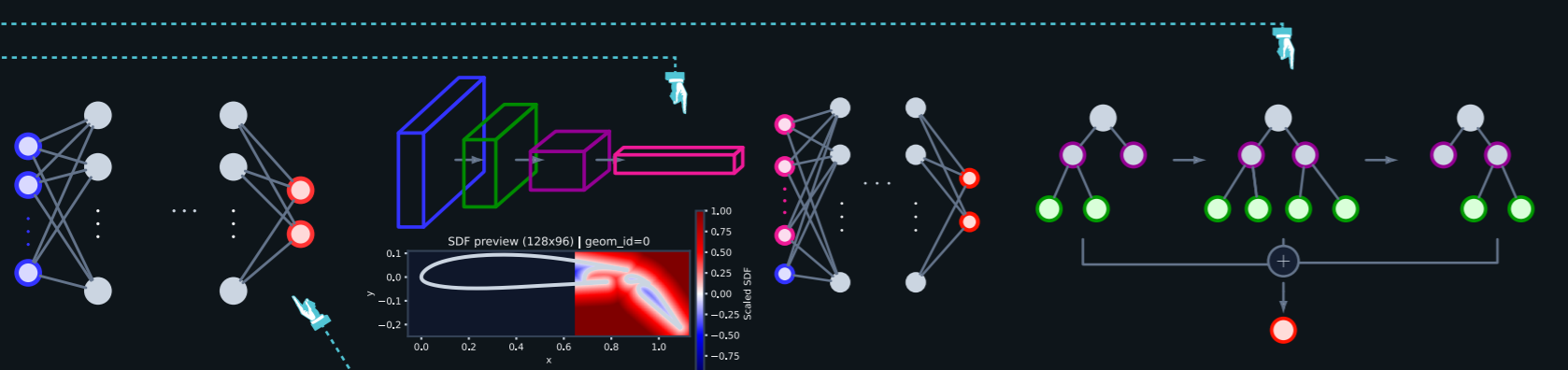
$$\hat{x}_i = \frac{x_i - \mu}{\sigma}$$

$$\mathbb{E}[\hat{x}_i] \approx 0 \quad \text{Var}(\hat{x}_i) \approx 1$$



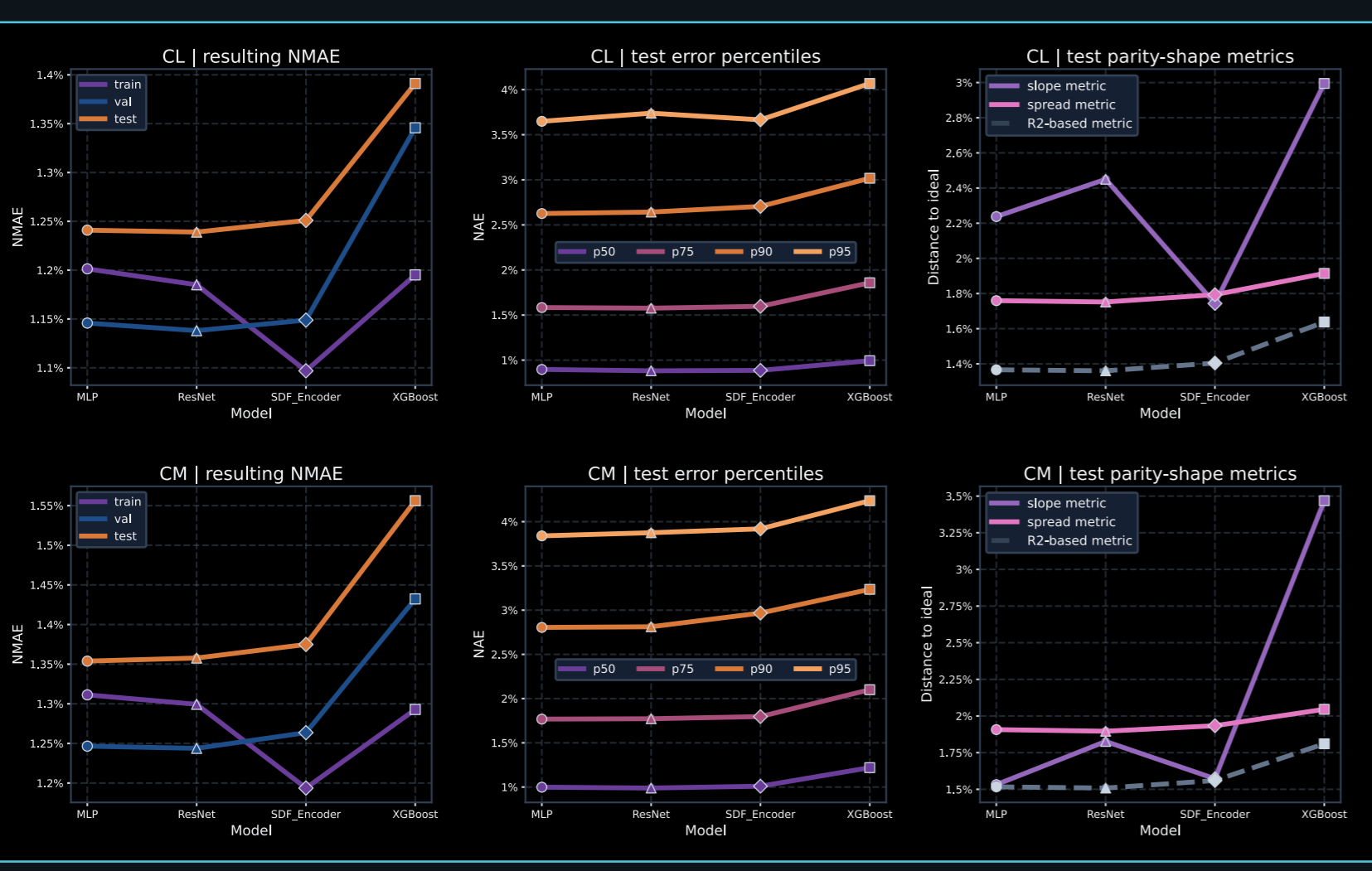
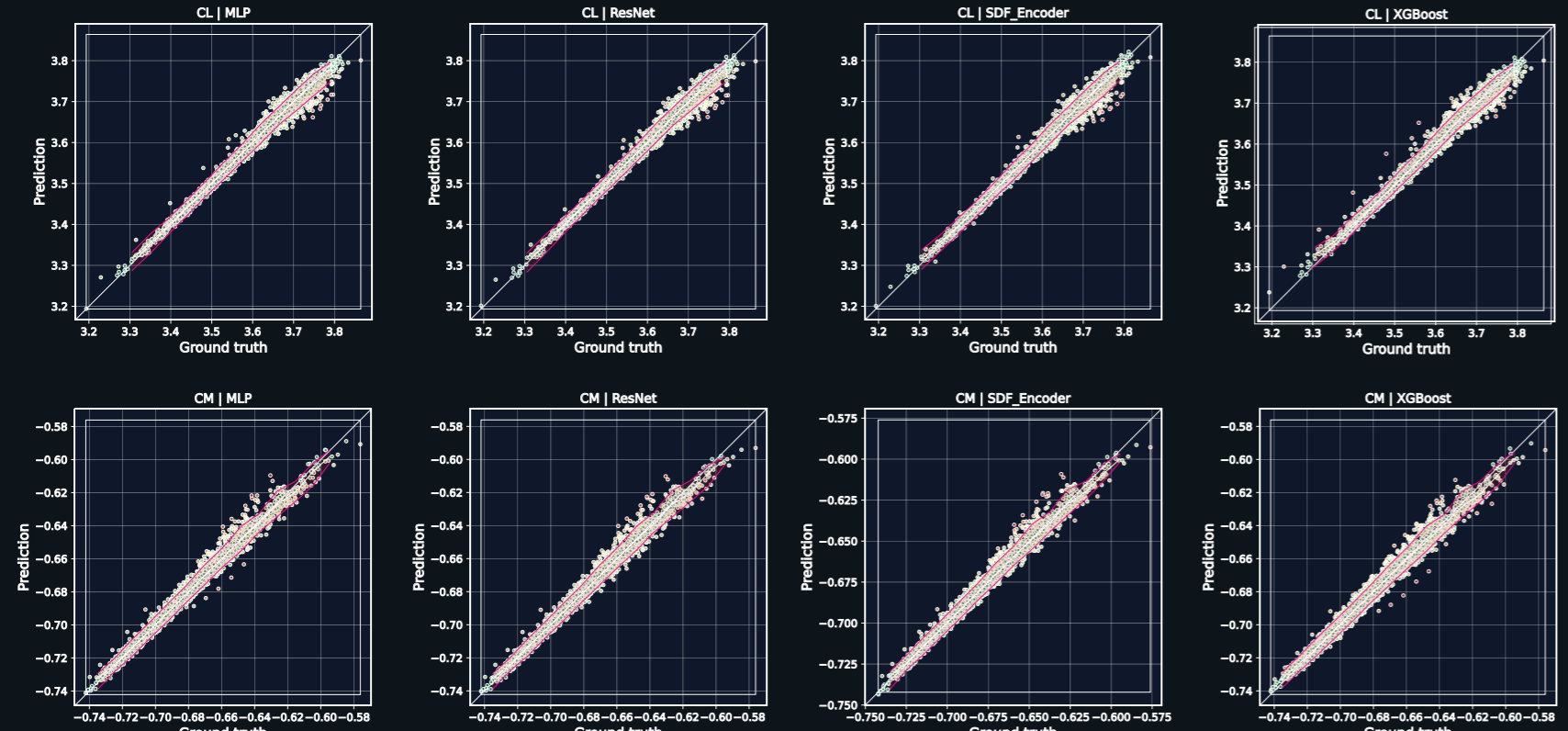
The aerodynamic response of each generated configuration was evaluated using compressible CFD simulations with the RANS SST turbulence model. For each case, lift, pitching moment, and pressure coefficient distribution were extracted. The analysis was performed at sea-level conditions, corresponding to  $M = 0.15$  and  $Re = 3.5 \times 10^6$ , for angles of attack ranging from  $6^\circ$  to  $14^\circ$ .

## 3. Surrogate Models for Aerodynamic Coefficients

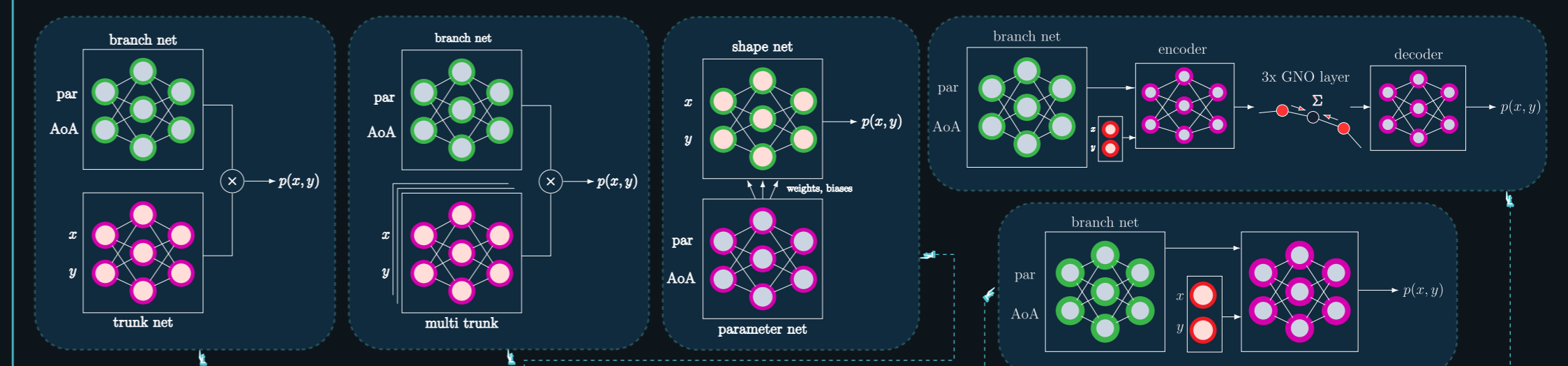


Model	CL				C M			
	p50	p75	p90	p95	p50	p75	p90	p95
MLP	0.897	1.583	2.626	3.649	0.998	1.768	2.805	3.839
ResNet	0.882	1.576	2.642	3.739	0.989	1.772	2.812	3.875
SDF Encoder	0.886	1.597	2.705	3.665	1.010	1.797	2.967	3.919
XGBoost	0.994	1.858	3.017	4.069	1.219	2.101	3.235	4.237

Test normalized absolute error (NAE) percentiles [%]

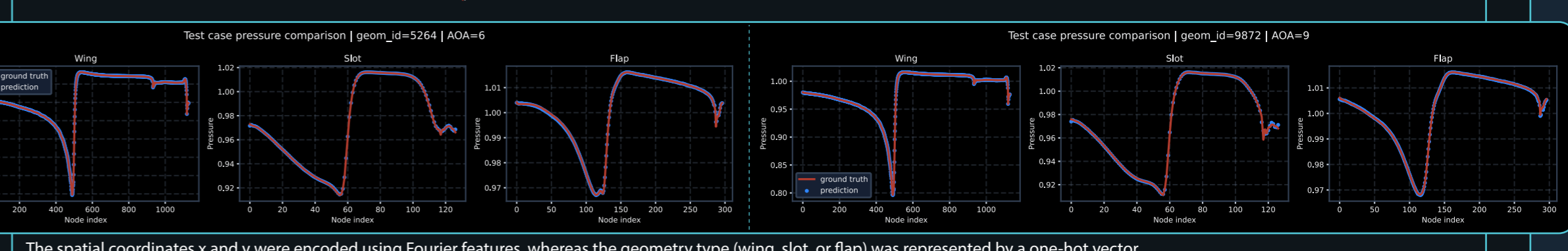
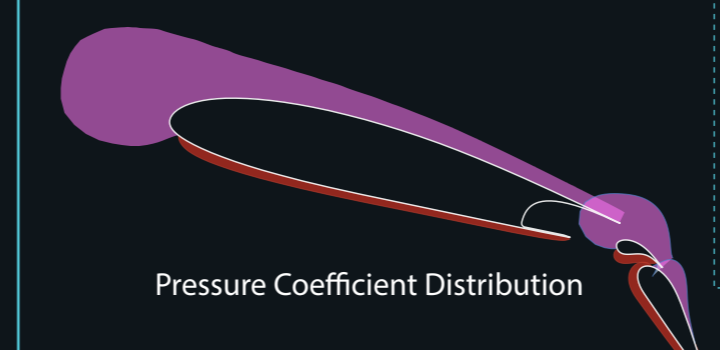


## 4. Surrogate Models for Pressure Coefficient Distribution



Test normalized absolute error (NAE) percentiles for surface pressure prediction [%]

Model	Wing				Slot				Flap			
	p50	p75	p90	p95	p50	p75	p90	p95	p50	p75	p90	p95
Conditioned MLP	0.123	0.144	0.169	0.188	0.769	0.935	1.140	1.312	0.759	0.862	0.999	1.106
NIF	0.044	0.063	0.092	0.117	0.303	0.385	0.525	0.651	0.198	0.255	0.338	0.417
DeepONet	0.082	0.108	0.140	0.162	0.520	0.635	0.801	0.950	0.402	0.488	0.596	0.695
MultiTrunk DeepONet	0.053	0.076	0.104	0.126	0.440	0.559	0.722	0.846	0.257	0.323	0.412	0.500
GNO	0.069	0.085	0.108	0.131	0.353	0.462	0.627	0.756	0.456	0.535	0.638	0.732



The spatial coordinates x and y were encoded using Fourier features, whereas the geometry type (wing, slot, or flap) was represented by a one-hot vector.

## 5. Genetic Algorithm Based Shape Optimization

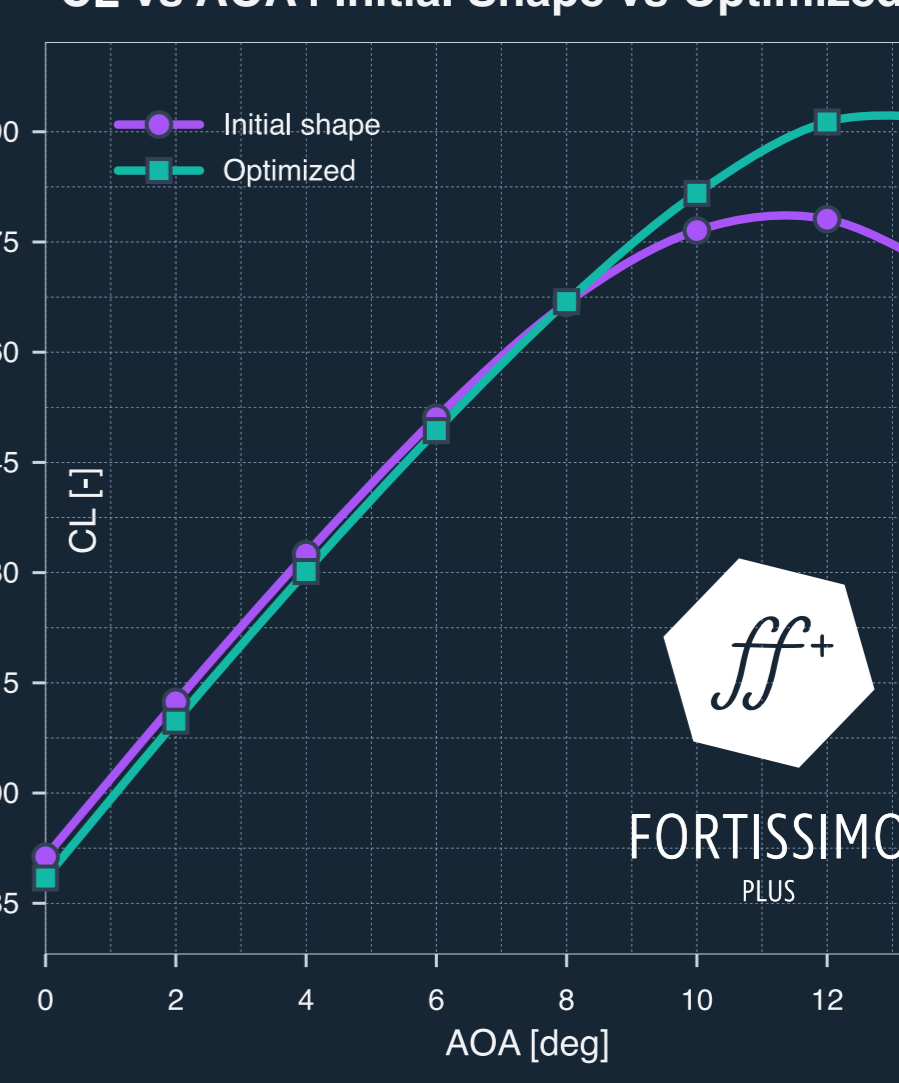
Evolutionary optimization in a normalized design space. Candidate designs are evaluated via a surrogate model, enabling fast exploration without expensive simulations.

- Population size: 1000
- Generations: 800
- Independent runs: 10
- Selection: Tournament, size 10
- Crossover: Uniform,  $p = 0.7$
- Gene exchange: 0.6
- Mutation: Gaussian,  $p = 0.4$
- Gene mutation:  $\mu = 0.2, \sigma = 0.05$

### Objective Functions

- Lift maximization  
 $G_{lift} = -C_L$
  - Lift-Moment trade-off  
 $G_{lift+moment} = -C_L - \frac{C_M}{\kappa}$
- Balancing parameter:  $\kappa = 4.761$
  - Ensures comparable influence of lift and pitching moment

### CL vs AOA | Initial Shape vs Optimized



### GA optimization: CL evolution and Pareto fronts

