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uc3m PHD

Surrogate-Assisted Structural Optimization Framework for Composite Airframes

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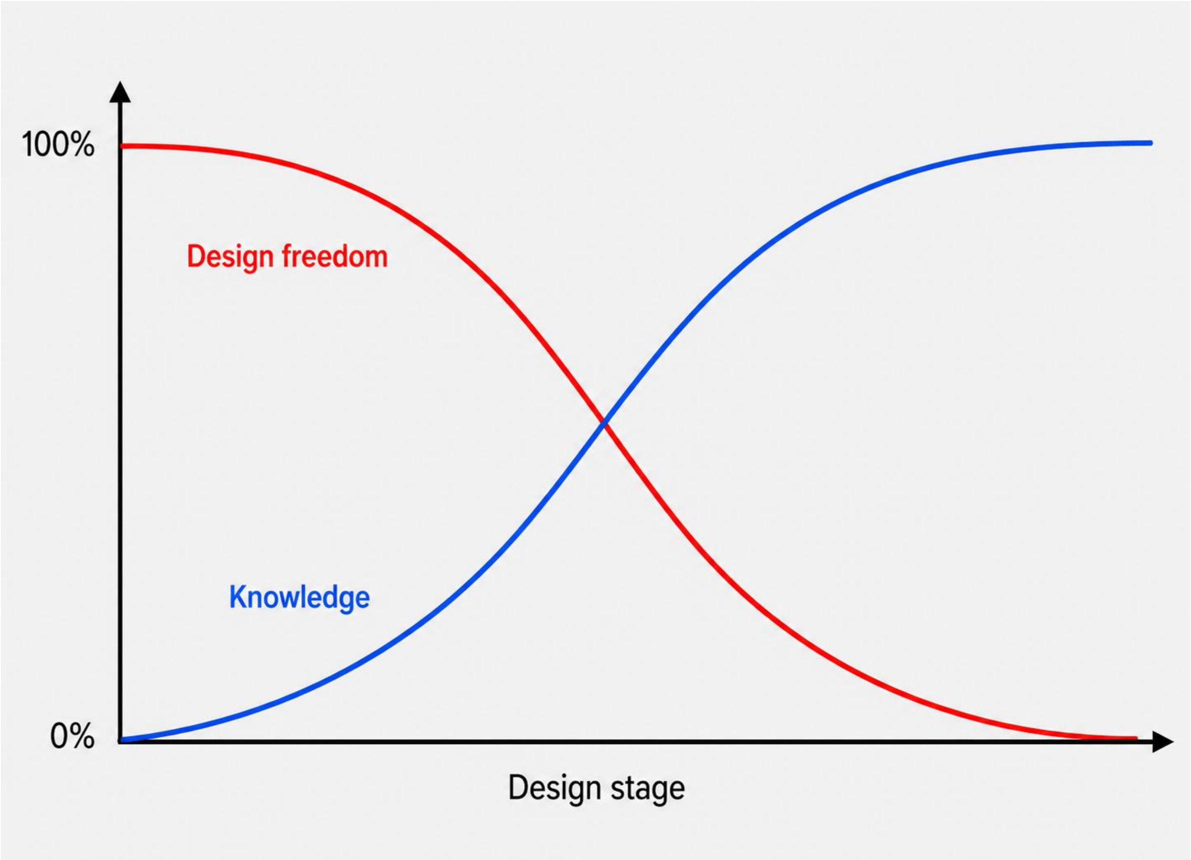
Motivation: why early structural design needs better tools

Problem

- Important design choices are made early, when we have still limited information
- Conceptual stage decisions are dominated by empirical rules and older designs
- Current methods are not sufficient for novel designs and composite structures

Solution

- Use physics-based (Finite Element) simulations and optimization early



But 2 main bottlenecks:

- Manual model creation is slow **-> design exploration is limited**.
- Multiple optimization runs **are computationally expensive.**

Main question

Can we use efficiently FE models and optimization for early design exploration?

Research gaps

Gap 1: Automation

Few workflows with **parametric GFEM** of composite structures within an **automated optimization framework**

Gap 2: Coupled Optimization

Coupled **structural layout** (e.g. number of ribs) and **sizing optimization** is rare

Mixed-integer optimization is challenging

Gap 3: Data efficiency

Optimization runs are computationally expensive, so **evaluations must be limited**

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Objective and methodology

PhD objective

Develop a framework for **efficient early-stage Finite Element** modeling and **surrogate-based optimization** of composite airframes

Step 1

Parametric GFEM

Python framework for automated model generation

Step 2

Surrogate modeling

Train GP surrogate on a small layout dataset

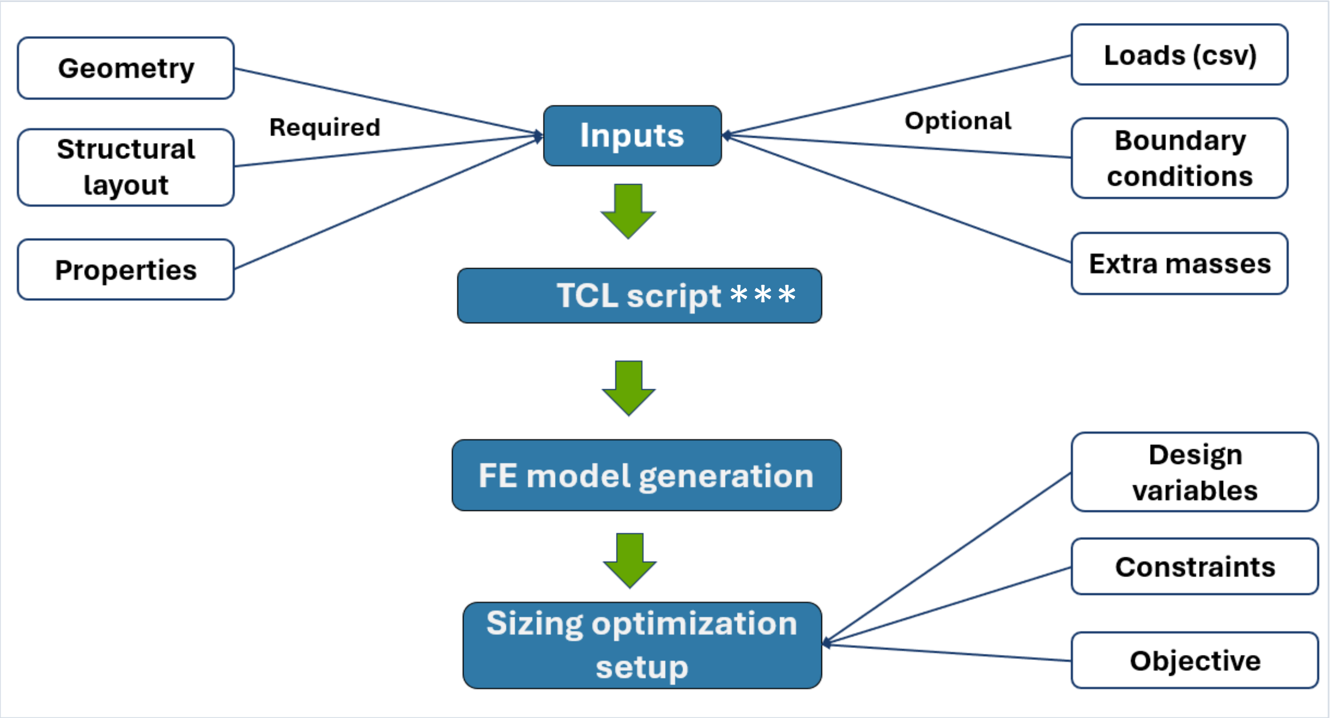
Step 3

Bayesian optimization

Use the surrogate to select new layouts and find minimum mass

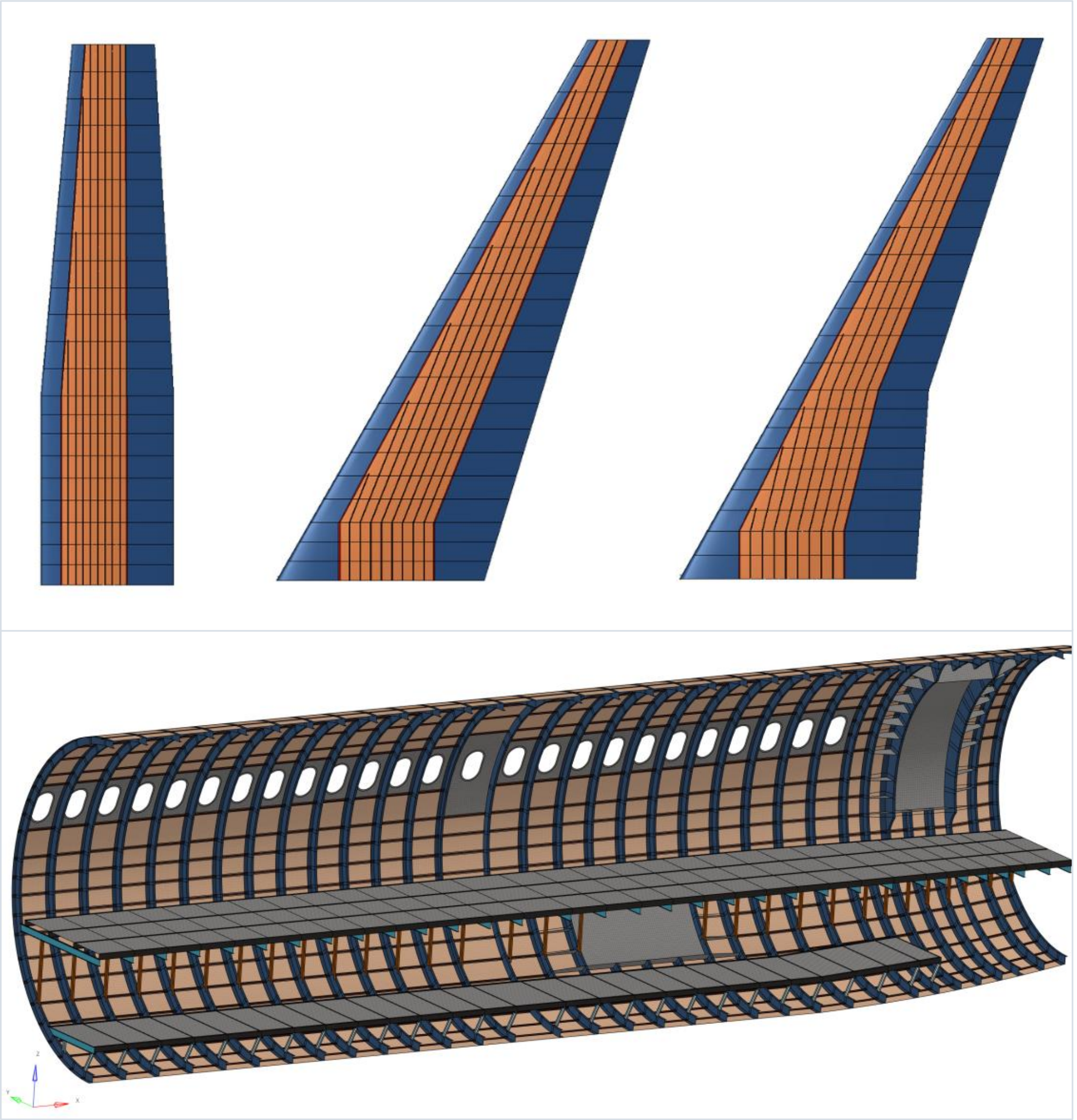
Automated parametric FE model generation

Model generation workflow (Python)



****Hypermesh command language*

Example wing and fuselage models generated



Application on benchmark wingbox optimization

Main question

Can we solve the coupled **layout-sizing optimization** problem of a composite wingbox efficiently using **surrogate-based optimization in a nested loop**

Related dissemination

Parametric Framework for Automated Structural Layout Modelling and Optimization of Composite Airframe

Presented in Scitech 2026 – submitted to Journal

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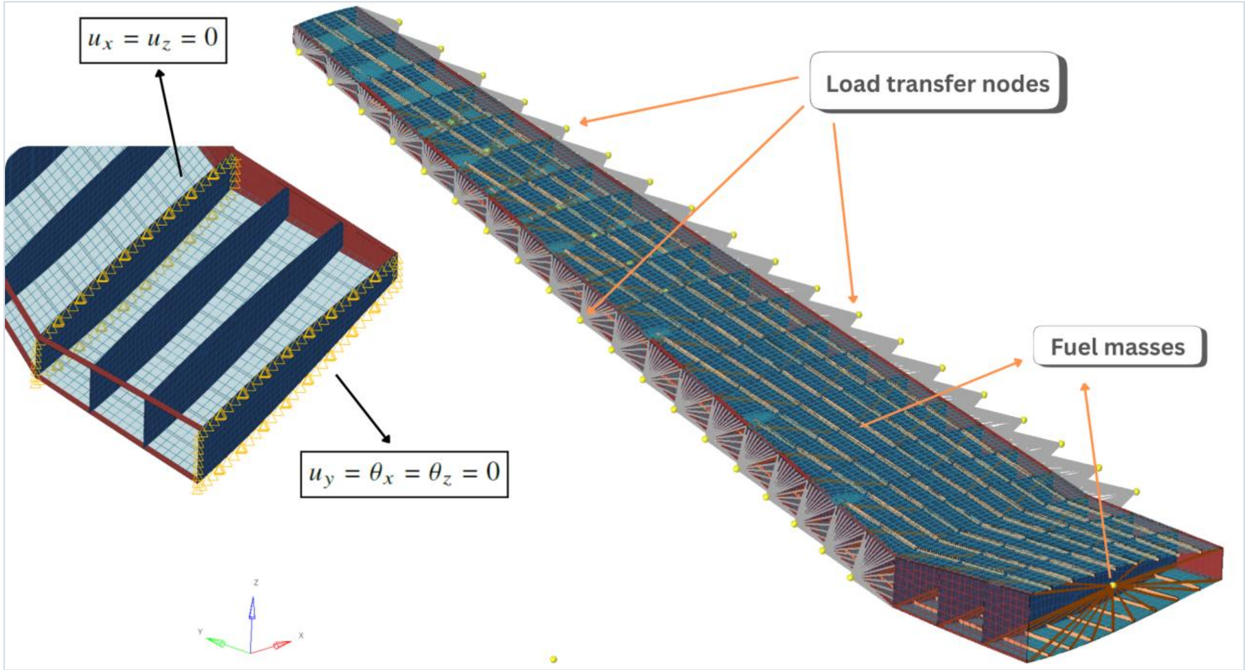
Baseline model: STW composite wingbox (Gray 2024)



Model highlights

- Sizing components (9): **upper/lower skins, ribs, upper/lower stringers, front/rear spar webs and caps.**

- **Symmetry conditions** at root, **no x,z displacements** at wing-fuselage intersection

- **2D shell FE mesh** with connected interfaces and component offsets.

- Loads: **+2.5g pull-up** and **-1g pull-down**: AVL pressures transferred to the wingbox.

Nested formulation: layout outside, sizing inside

Outer-loop layout variables

3 mixed-integer variables

Number of ribs and stringers (integers) + width of spar caps (continuous).

Inner-loop sizing variables

75 sizing variables - 3 optimization zones

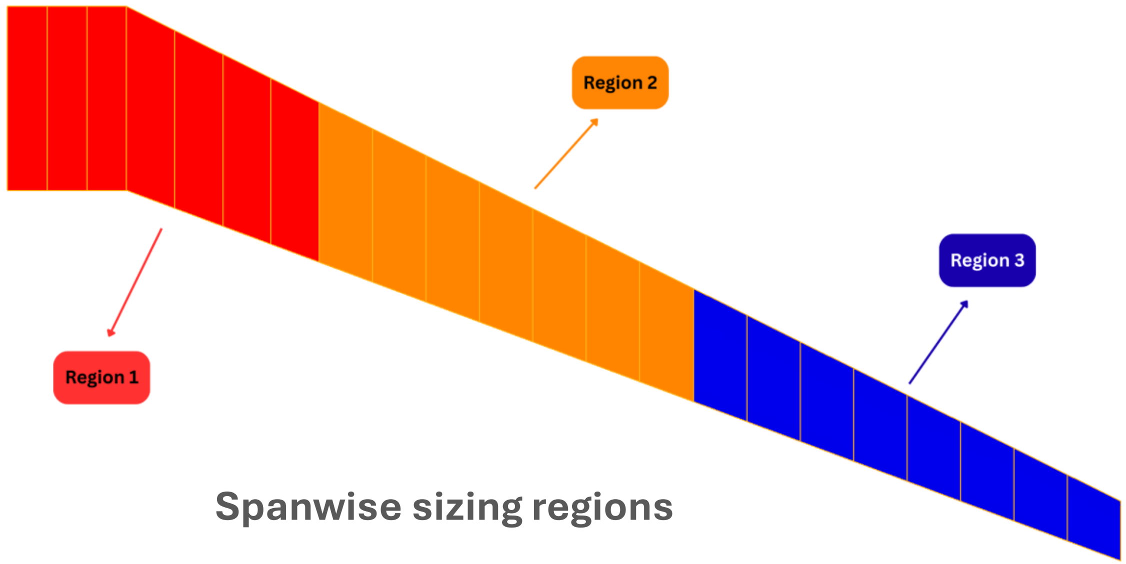
Composite ply-thicknesses for [0, ±45, 90) + rib thicknesses.

Optimization Objective

Minimum feasible mass

Multiple OptiStruct sizing runs for each design (**Gradient-based** algorithm)

Structural constraints: composite principal **strains**, aluminum rib **stresses**, linear **buckling**, ply-percentage and manufacturing thickness constraints.

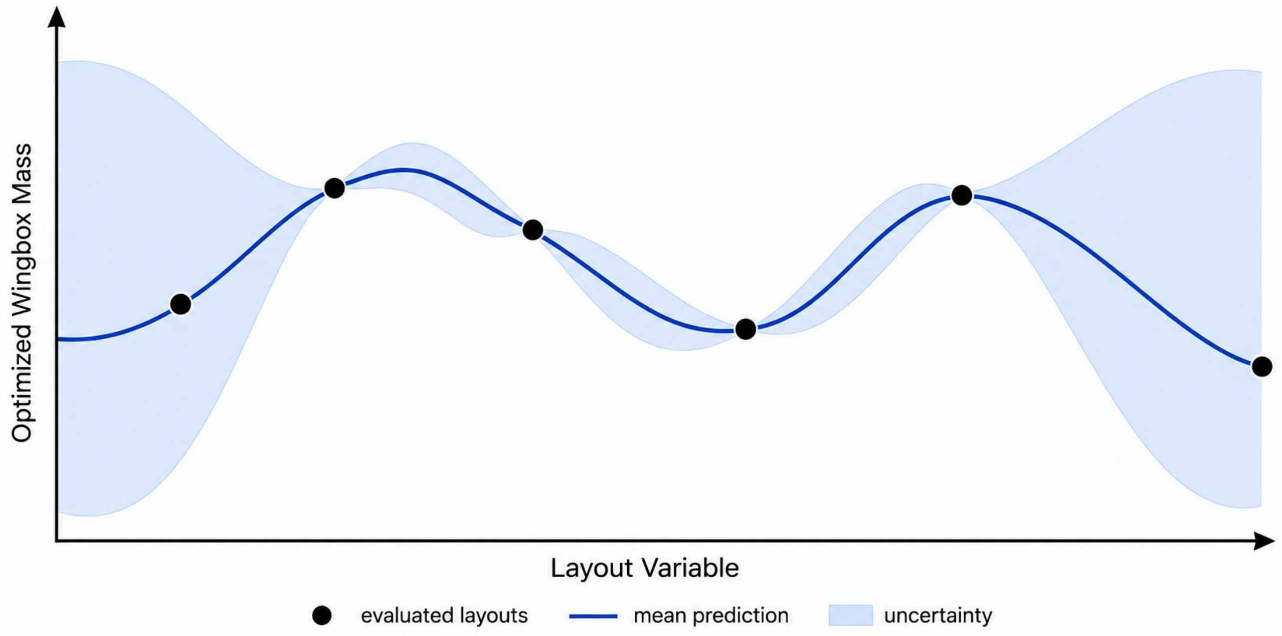


Spanwise sizing regions

Surrogate model: Outer-loop response

Surrogate formulation

- **Predict the minimum mass for each layout** without running sizing optimization
- **Inputs-output: $x = (N_{ribs}, N_{str}, w_{cap}) \rightarrow M_{min}$**



Gaussian Process Regression (GPR)

- **Multivariate Gaussian distribution** over possible functions
- Provides **mean + uncertainty** prediction

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

mean + covariance (kernel)

Why GPR?

- Good predictions with **limited data**
- Uncertainty quantification enables **Bayesian Optimization**

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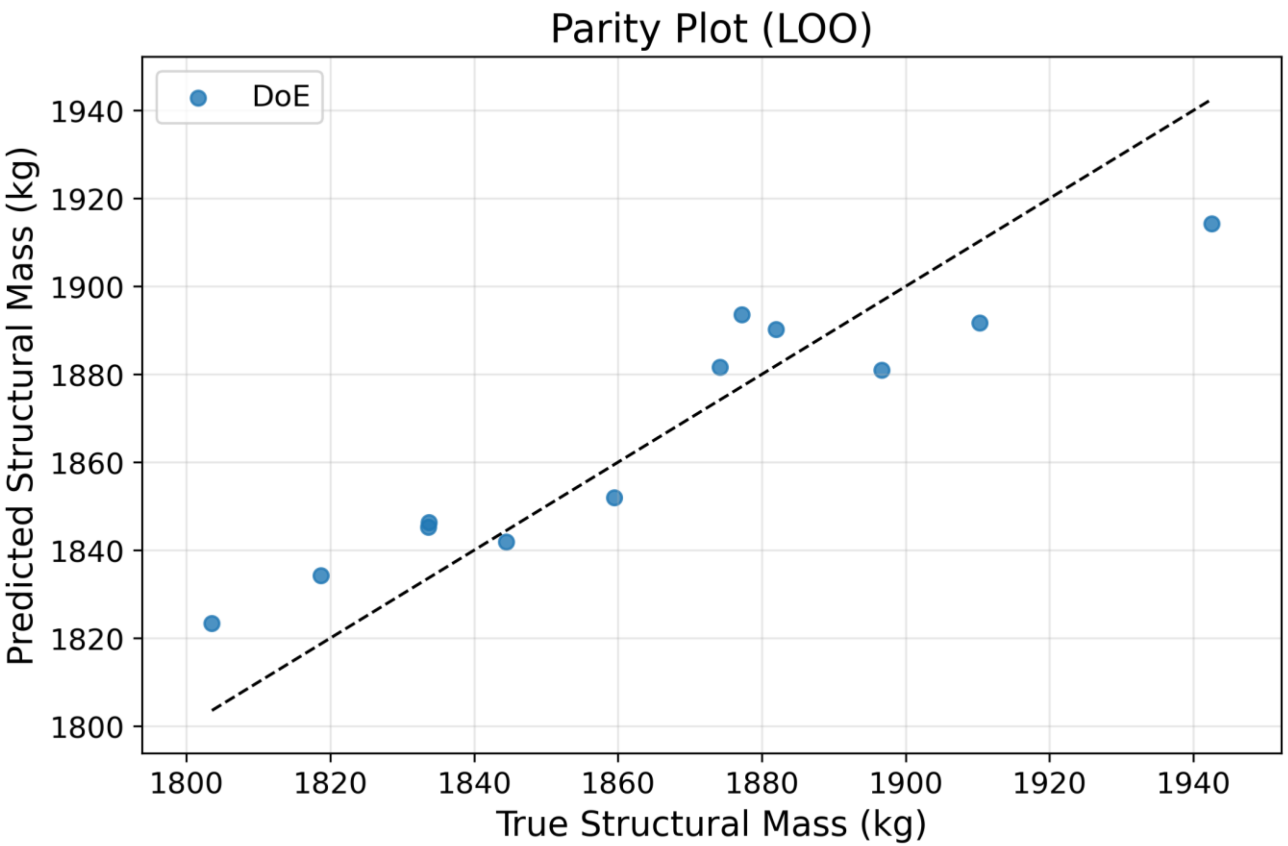
Initial dataset (12 layouts) and GP model training

Dataset generation

A **Latin Hypercube Sampling (LHS)** method is used to select 12 **space-filling** designs for surrogate training



LHS samples	RMSE [kg]	MAE [kg]	R^2
N = 12	15.2	13.7	0.845

Table: LOO error metrics for the GP surrogate on the initial dataset

Main remarks

- Model fits the data very well
- Error metrics possibly **"underestimate"** the actual variability from local minima convergence (gradient-based sizing)

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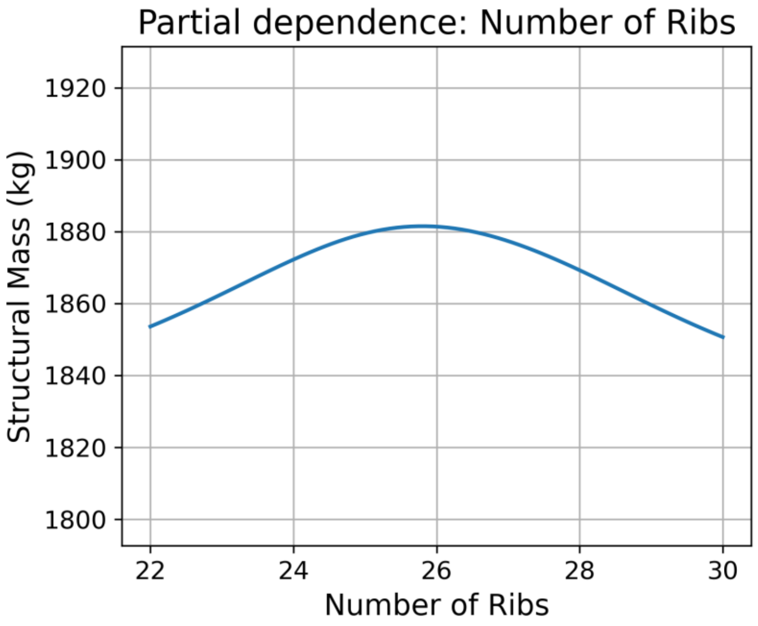
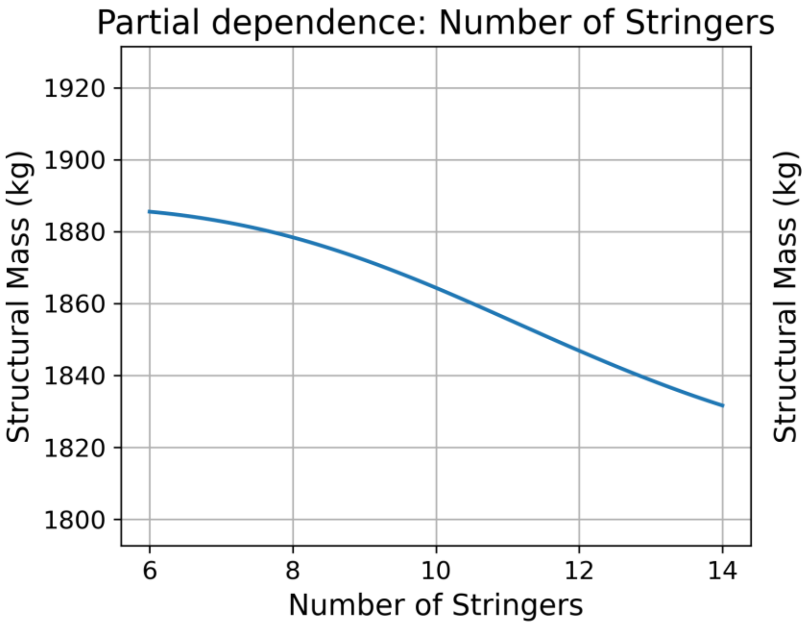
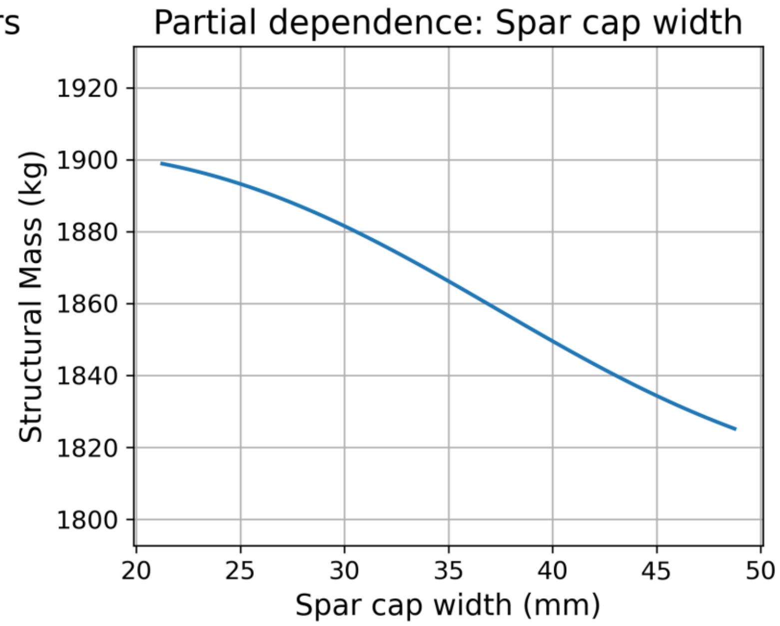
Partial dependence plots: structural trends







Effect of ribs

Weaker influence on the mass – non-monotonic trend

Effect of stringers

More stringers reduce overall mass - **improved buckling support**

Effect of spar caps

Thicker caps result in mass reduction - improved **bending resistance**

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Bayesian optimization: how the next layouts are selected

Bayesian Optimization loop

Layout dataset

GP model: mean + uncertainty

Expected Improvement (EI) maximization

New batch of layouts

Update

EI balances exploitation (low mass) and exploration (uncertainty)

EI ≈ improvement probability × improvement amount

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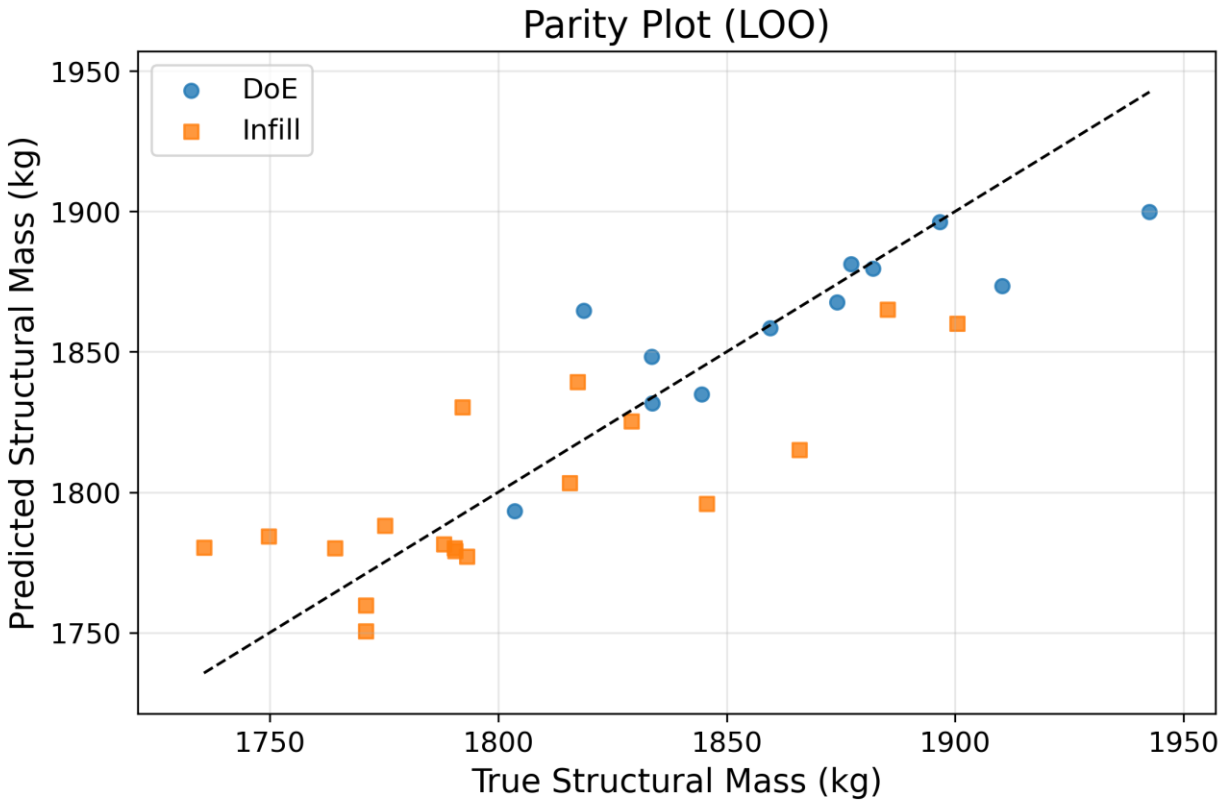
Bayesian optimization: infill and updated fit

Updated Parity plot with infill points (30 total):



Bayesian Optimization (BO) results:

Initial LHS	Infill	Best Layout (Nribs, Nstr, wcap)	Mass [kg]
12	18	**(23, 13, 50)**	1735.6

Table: Best wingbox layout design found after the BO

Dataset	RMSE [kg]	MAE [kg]	R^2
12	15.2	13.7	0.845
12 + 18 infill	25.6	19.9	0.752

Table: LOO error metrics for the GP surrogates before and after infill points

Main remarks

- Updated LOO errors are larger after the new data – but possibly more realistic
- Infill points mainly clustered in the low-mass region due to exploitation

Comparison with MIDACO: same optimum region at lower cost

MIDACO (Mixed-Integer Distributed Ant Colony Optimization)

A **derivative-free evolutionary algorithm** for mixed-integer black-box optimization problems

Nested Bayesian Optimization

Best mass found
1735.6 kg
Best layout
23, 13, 50 mm
30 layout evaluations

Nested Optimization with MIDACO

Best mass found
1732.2 kg
Best layout
23, 13, 48.6 mm
152 layout evaluations

Main conclusions

Effectively the **same layout** is found across BO and MIDACO, mass differences mainly due to thickness distribution from inner-loop sizing

The computational cost of MIDACO is **5 times higher** compared to the BO approach

Conclusions: returning to the original goals

Goal 1: Automate models

- Robust **parametric** GFEM generation for **composite airframe**
- **Automated sizing optimization** setup

Goal 2: Couple layout + sizing

- **Nested layout + sizing optimization** framework

Goal 3: Reduce cost

- Train **GP surrogate** model
- **Bayesian optimization** to search optimum efficiently

Future work and dissemination

Next research steps

- Investigate scalable constrained surrogate-based optimization approaches trained with analysis data
- Include laminate stacking sequence optimization
- Expand the optimization framework to include the fuselage

Dissemination / achievements

- AIAA SciTech 2026 proceedings paper.
- EASN / MDPI Engineering Proceedings paper.
- AIAA journal manuscript under review.

Planned / potential conferences

ECCOMAS 2026
Munich, July 2026 – accepted for presentation

ICAS 2026
Sydney, 2026 — accepted; potential presentation and proceedings

Scitech 2027
Orlando, 2026 – submitted; potential presentation and proceedings

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Thank you!
Questions?

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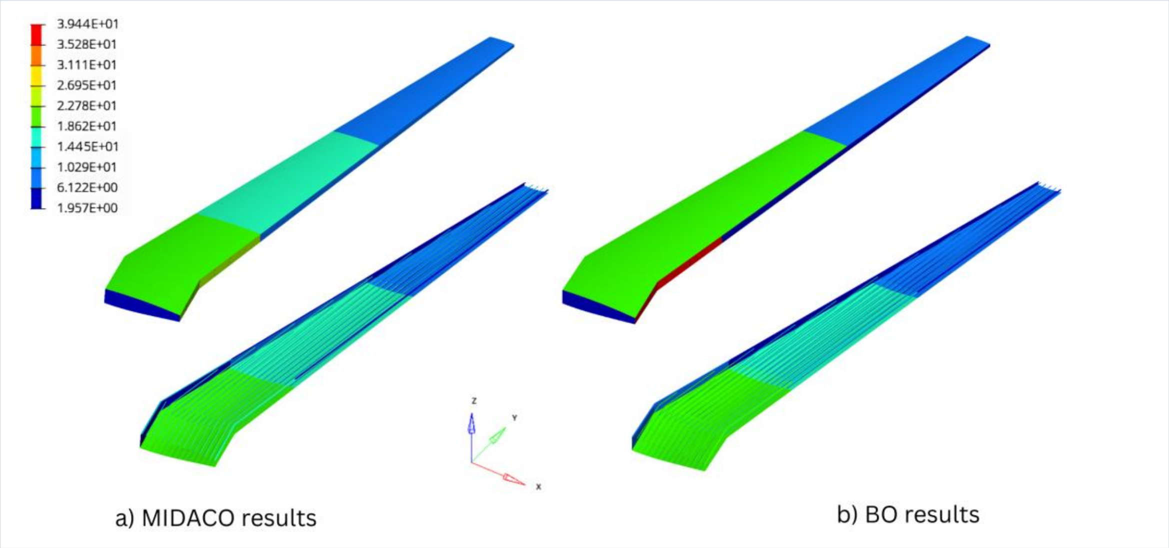
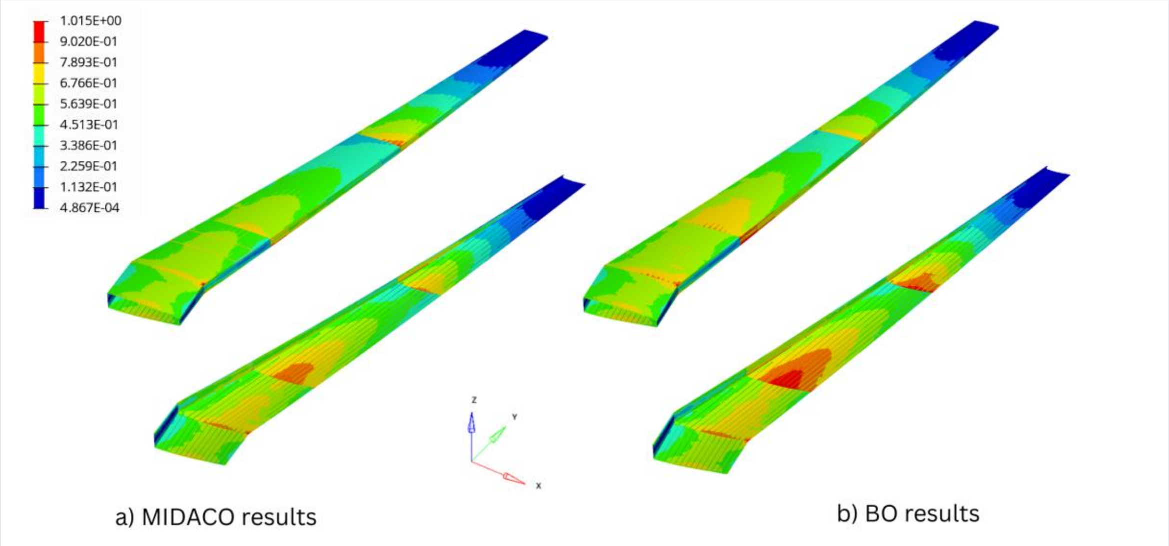
TIFON – Artificial Intelligence for Design and Manufacturing (AIDme) PLEC2023-010251

Structural interpretation: what the optimum looks like



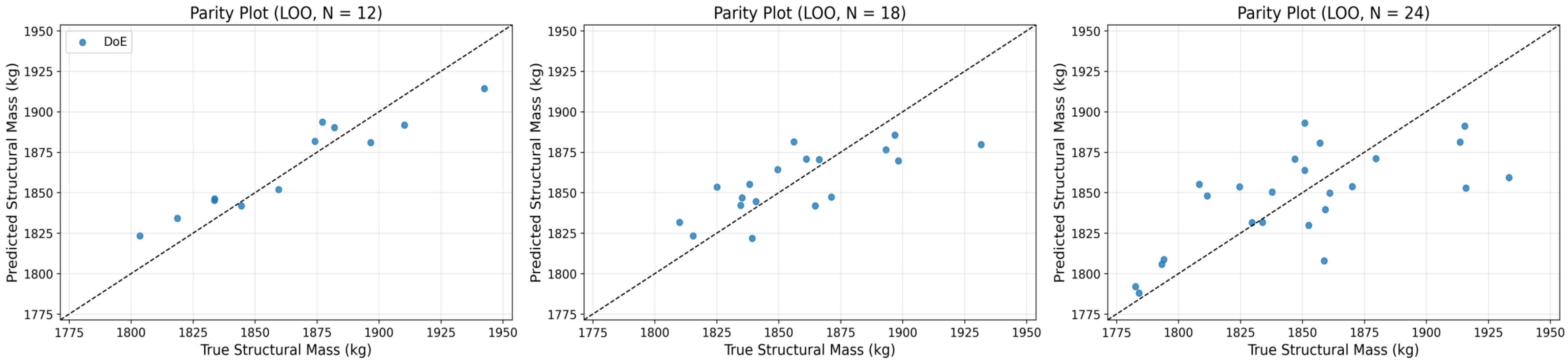


Thickness taper along the span due to bending loads

Stress concentrations near the kink – higher thickness

Aluminum ribs have a secondary role – low thickness

Fitted GP surrogate models for each layout dataset (12, 18, 24 samples)



Main remarks

- The 12-point surrogate is **overconfident** and smooth – low errors
- The 18- and 24-point surrogates are "rougher", revealing more **solver variability** and local variations

Leave-one-out error metrics

Good when we want to use all the data for training

Initial DoE	RMSE [kg]	MAE [kg]	R^2
N = 12	15.2	13.7	0.845
N = 18	21.2	18.0	0.534
N = 24	31.0	24.8	0.439

Table: LOO error metrics for the three surrogates fitted on initial datasets.

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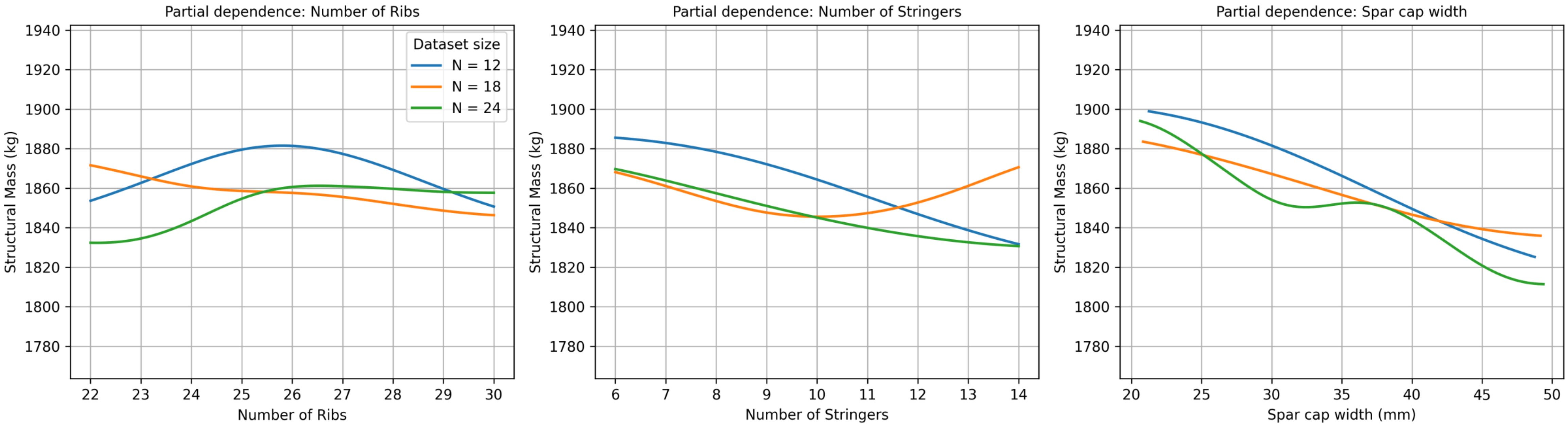
Initial DoE surrogate: structural trends



Effect of ribs

Weaker influence on the mass – models struggle to find a consistent trend

Effect of stringers

More stringers **improve buckling** – effect can be non-monotonic

Effect of spar caps

Thicker caps result in mass reduction - improved **bending resistance**

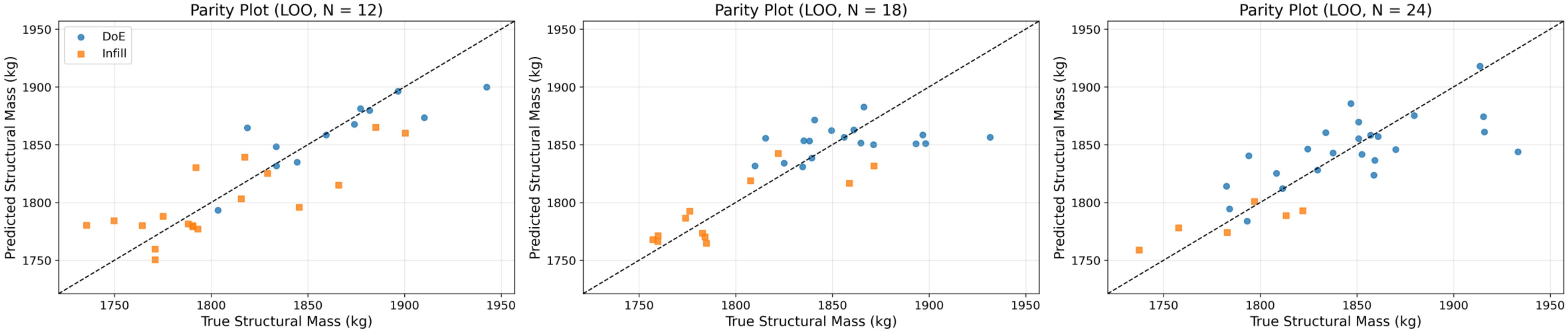
Bayesian optimization: infill and updated fit

BO studies: best layouts and updated surrogate errors

All studies use 30 total layout evaluations

Study	Infill	Best layout (Nribs, Nstr, wcap)	Mass [kg]	RMSE [kg]	MAE [kg]	R^2
12 + 18	18	(23, 13, 50)	1735.6	25.6	19.9	0.752
18 + 12	12	(29, 14, 50)	1757.1	26.6	20.7	0.653
24 + 6	6	(23, 13, 50)	1737.4	28.5	21.1	0.630

Updated LOO parity plots after infill points



Main remarks

- All BO studies recover roughly the same layout (18+12 study stuck in local optimum)
- Updated LOO errors more comparable between surrogates after infill points

Staged multistart strategy against local minima