Toward a Self-Aware Aircraft:

Data-Driven Decisions, Adaptive Reduced Models, and Digital Twins

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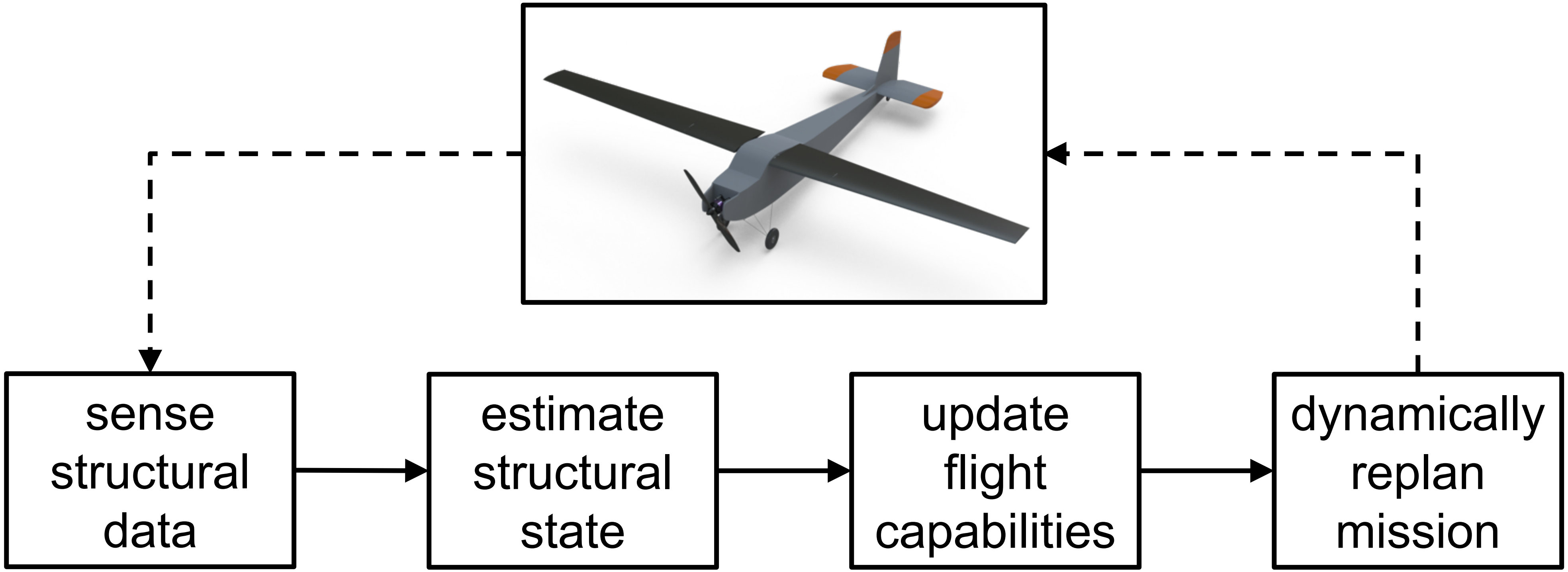
Motivation: Enabling a self-aware aircraft

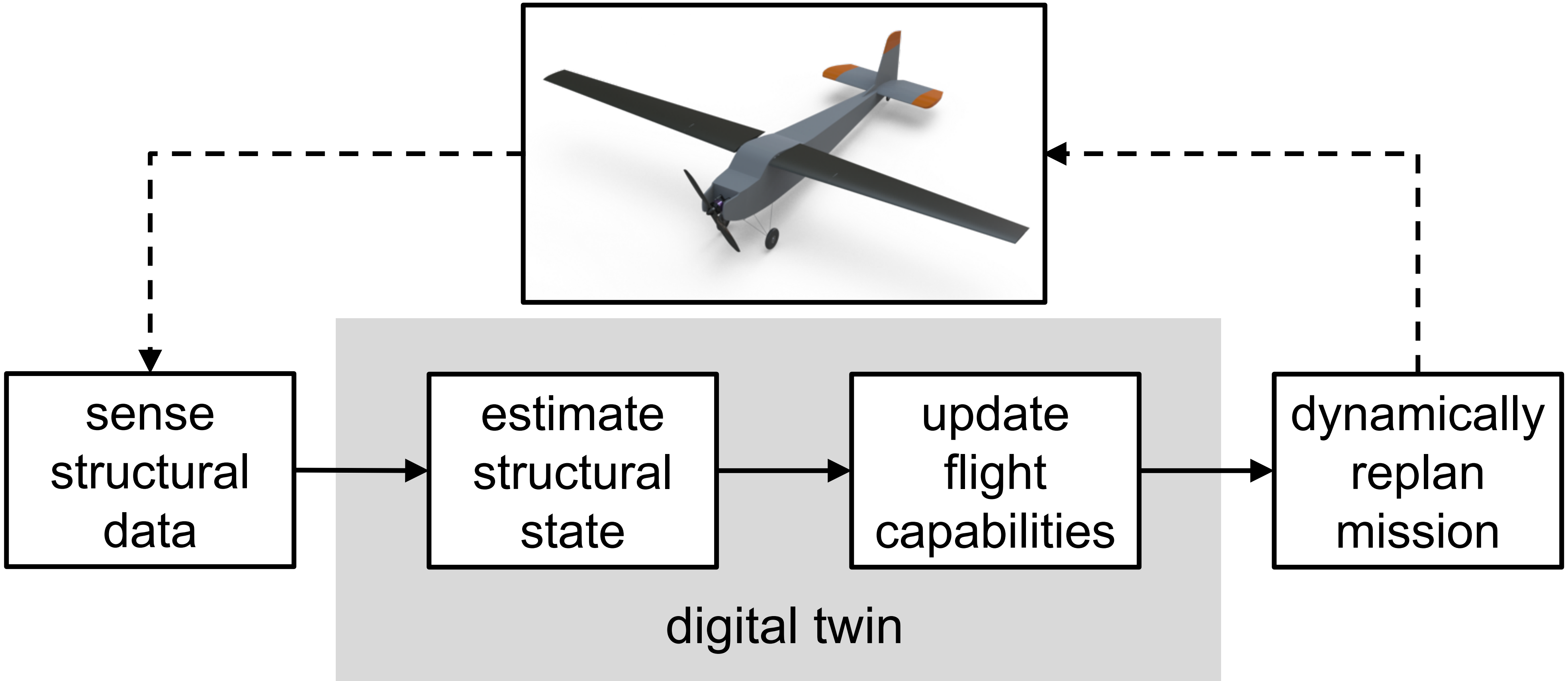


An aircraft that can **sense changes** in its own internal state, **and adapt accordingly**

Prior work has shown that this provides[Singh 2017]

- Increased survivability
- Increased utilization

Motivation: Enabling a self-aware aircraft



Our approach:

Create a **digital twin** that **adapts to the evolving structural health** of the UAV, providing **near real-time capability estimates** that enable **dynamic decision-making.**

The need for physics-based digital twins

Such critical decisions require digital twins that are

- Predictive
- Reliable
- Explainable

Physics-based models provide this

- Simulate new, previously unseen scenarios
- Obey the laws of physics
- Quantifiable error/uncertainty
- Parameters represent real-world quantities

But…

- Typically slow to evaluate, challenging to update

Reduced-order models provide low-cost physics-based approximations that enable digital twins

Reduced basis (RB) method: powerful certified reduced models for a wide range of PDEs

Limitations of a traditional RB method:

1. Training the reduced model requires many solutions of a costly full-order FE model
   - **Even a single FE solution may be prohibitively expensive in many industrial contexts**

2. Restricted to relatively few parameters
   - **Large assets require many parameters, both the offline and online cost largely eliminate any benefit of model order reduction**

3. Only admits parametrizations which induce continuous dependence of the PDE solution on parameters
   - **Unable to incorporate variations in topology, geometry, meshes**

Outline

1. Motivation: Physics-based digital twins

2. Approach: Component-based reduced-order models

3. Results: Toward a self-aware UAV

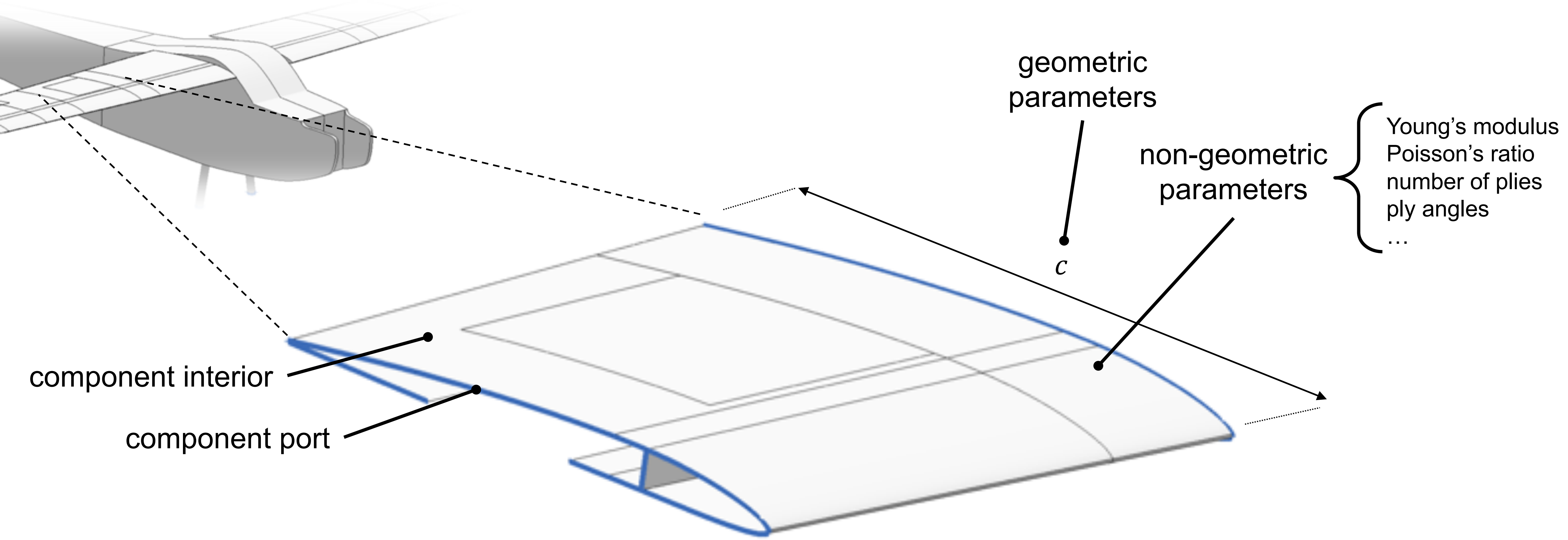
The Static-Condensation Reduced-Basis-Element (SCRBE) method

Based on research from the last ~15 years with many contributors—
SCRBE developed by Huynh, Knezevic, and Patera [Huynh 2013]

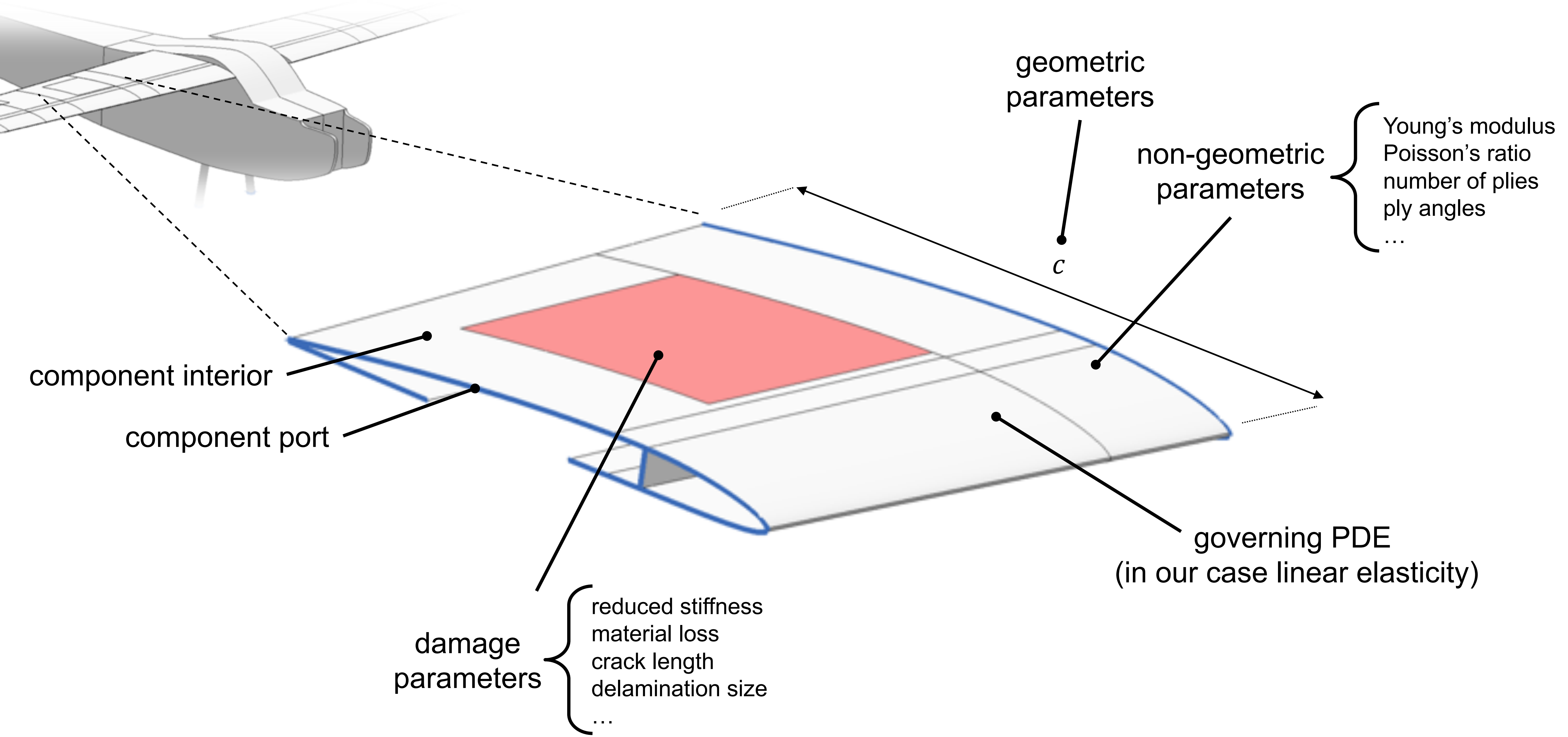
Why take a component-based approach? **"Divide and conquer"**

1. Divide model into components
2. Train reduced models at component-level
3. Assemble reduced models and rapidly solve

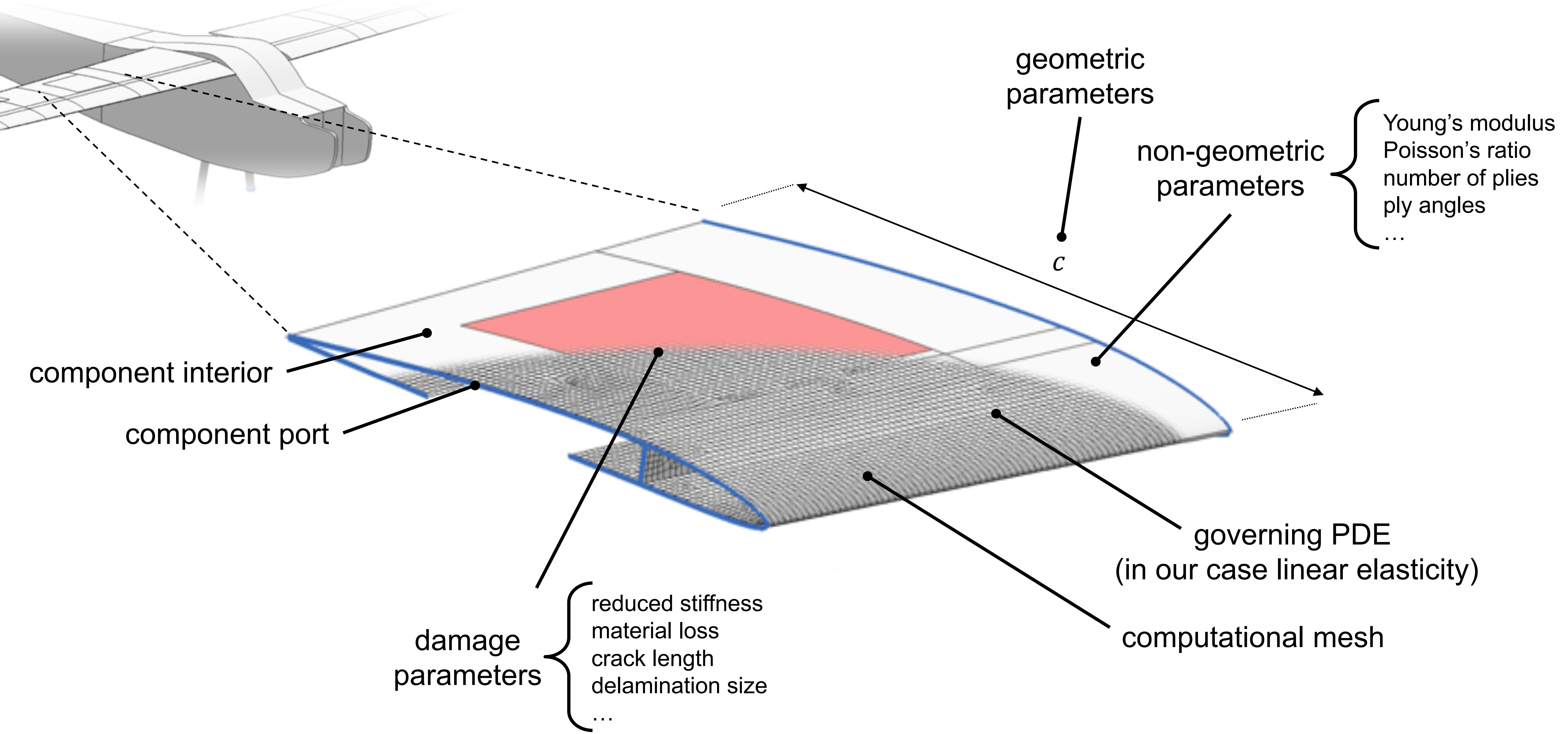
Example component: section of a wing



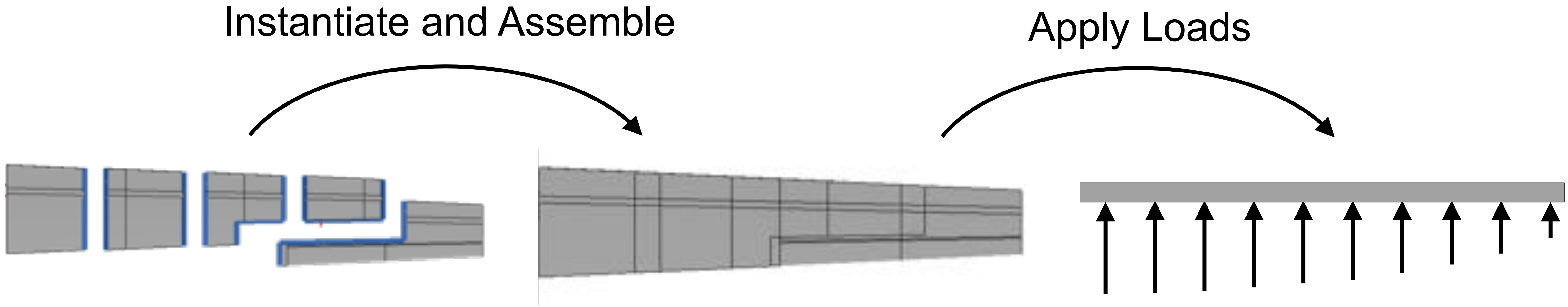
Example component: section of a wing



Example component: section of a wing



From components to systems



component parameters μ_c + assembly parameters μ_a + load parameters μ_l =

system parameters

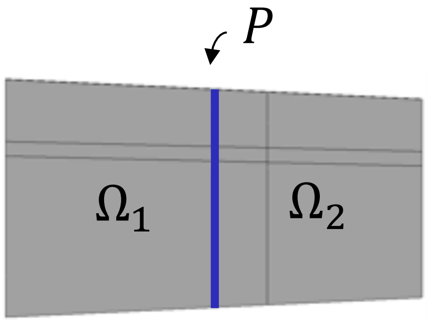
$$\mu = [\mu_c,\ \mu_a,\ \mu_l]$$

Solving a component-based model

Start with the usual finite element problem statement:

Find $u_h \in V_h$ such that $a(u_h, v\,;\mu) = f(v;\mu) \quad \forall \quad v \in V_h$

$$\begin{array}{r} \text{port DOFs} \rightarrow \\ \text{Interior DOFs} \rightarrow \\ \text{Interior DOFs} \rightarrow \end{array} \begin{bmatrix} A_{P,P} & A_{P,\Omega_1} & A_{P,\Omega_2} \\ A^T_{P,\Omega_1} & A_{\Omega_1,\Omega_1} & 0 \\ A^T_{P,\Omega_2} & 0 & A_{\Omega_2,\Omega_2} \end{bmatrix} \begin{bmatrix} \mathbb{U} \\ u_{\Omega_1} \\ u_{\Omega_2} \end{bmatrix} = \begin{bmatrix} f_P \\ f_{\Omega_1} \\ f_{\Omega_2} \end{bmatrix}$$



M port DOFs
N interior DOFs

Express interior DOFs in terms of port DOFs

$$A_{\Omega_i,\Omega_i} u_{\Omega_1} = f_{\Omega_1} - A^T_{P,\Omega_1}\mathbb{U} \quad \leftarrow$$

Solve on each component independently

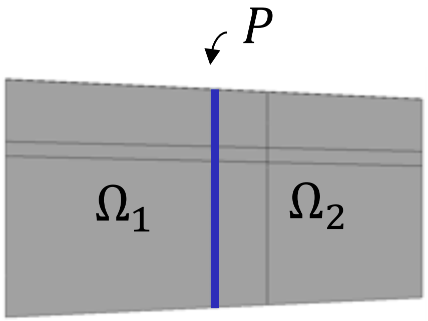
Substitute to get a system involving only port DOFs:

$$\mathbb{S}(\mu)\mathbb{U}(\mu) = \mathbb{F}(\mu)$$

Issue: Schur complement $\mathbb{S}$ **is large $(\mathrm{M}\times\mathrm{M})$, and expensive to compute**

Model reduction strategy

Model reduction occurs in two ways:



M port DOFs
N interior DOFs

i. <u>Port Reduction:</u>
Retain only the first m dominant modes at **component ports**

→ Reduces the size of $\mathbb{S}$:

$$\mathrm{M} \times \mathrm{M} \longrightarrow m \times m$$

ii. <u>Bubble Reduction:</u>
Replace the finite element space **inside each component** with an RB space of dimension n

→ Reduces the size of matrices required to compute entries of $\mathbb{S}$:

$$\mathrm{N} \times \mathrm{N} \longrightarrow n \times n$$

The benefits of SCRBE:

1. Model training can be performed using only small groups of components
   → Never have to solve full-system FE model

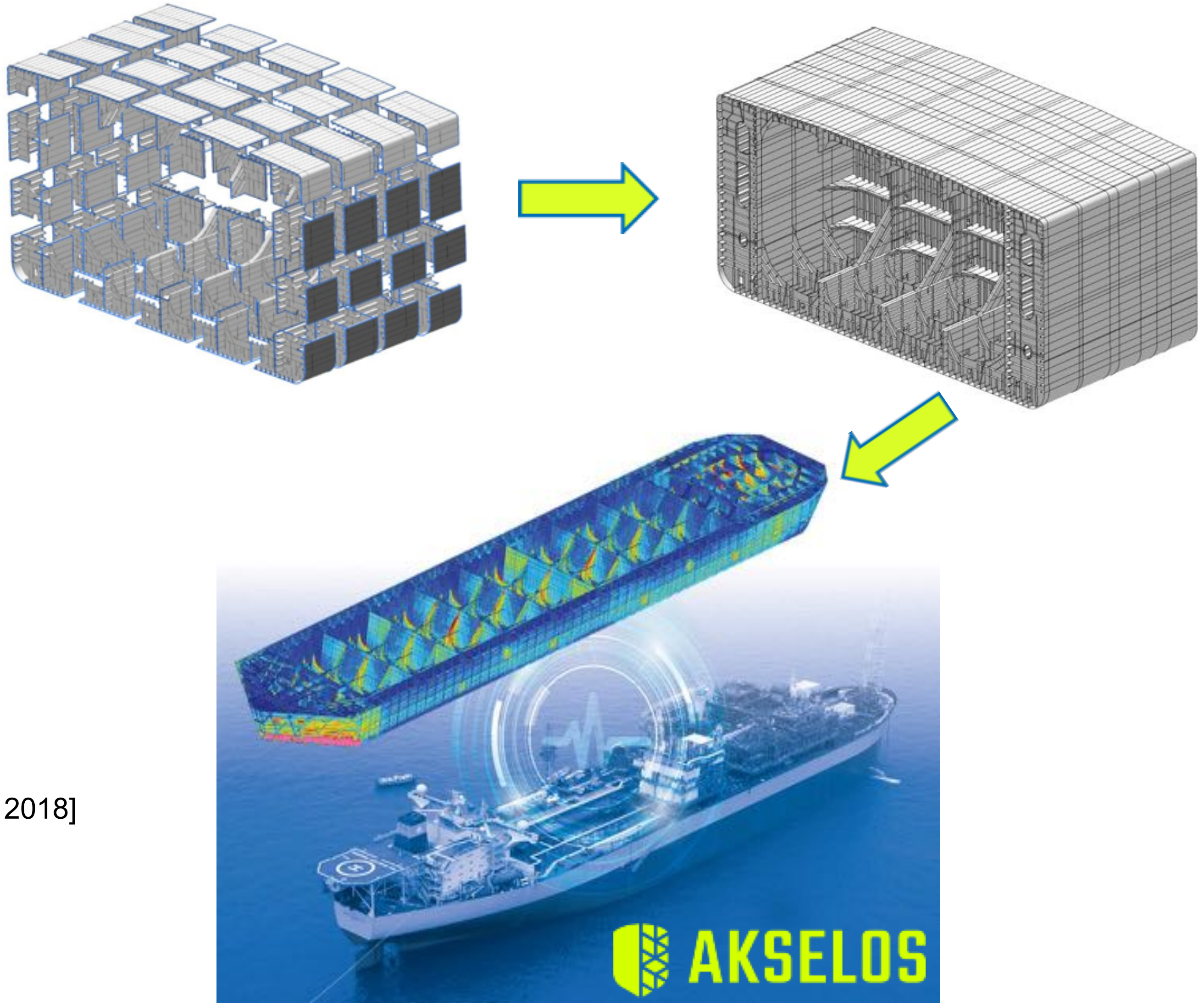
2. Component-wise RB admits a modest number of parameters per component
   → System may have many spatially distributed parameters

3. Component instantiation and replacement offers more flexible parametrization
   → Allows for changes to topology, geometry, meshes etc.

Implementation: RB-FEA and Akselos Integra

We are using the Akselos *Integra* software

- Implementation of patented **RB-FEA** algorithm, based heavily on SCRBE
- Enables **fast high-fidelity** structural analysis. Typically observe **1000x speedup** or more compared to FEA for large-scale models
- A posteriori **error indicators** [Huynh 2013]
- Hybrid solver for **local non-linearities** [Ballani 2018]
- Cloud-based **parallel solvers**



Graphic courtesy of David Knezevic, CTO Akselos, https://akselos.com/

Outline

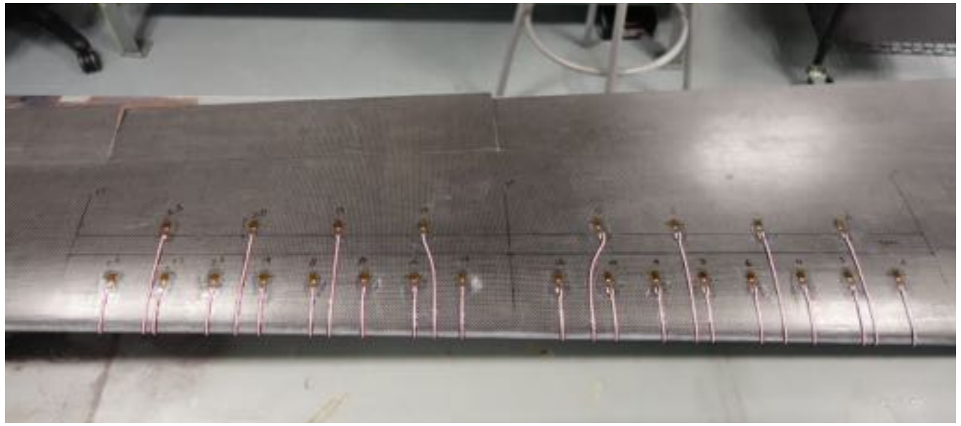
1. Motivation: Physics-based digital twins
2. Approach: Component-based reduced-order models
3. **Results: Toward a self-aware UAV**

Flight test vehicle

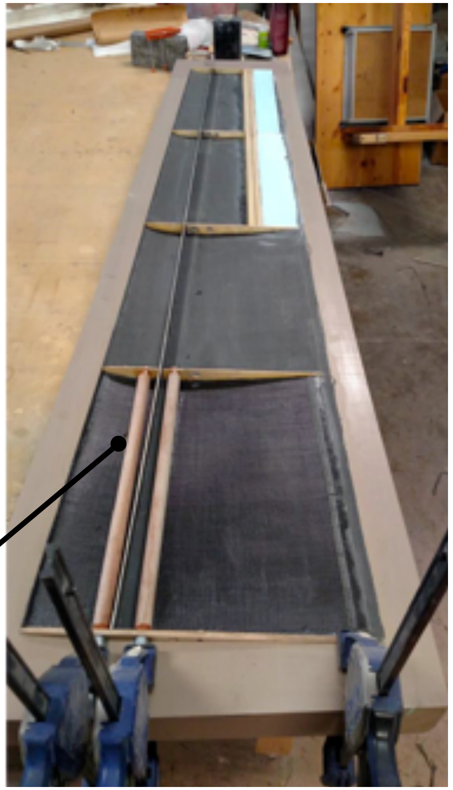
Customized 12ft Telemaster aircraft

Custom wing sets: pristine & damaged

Accelerometers + vibration sensors
24 strain gauges per wing

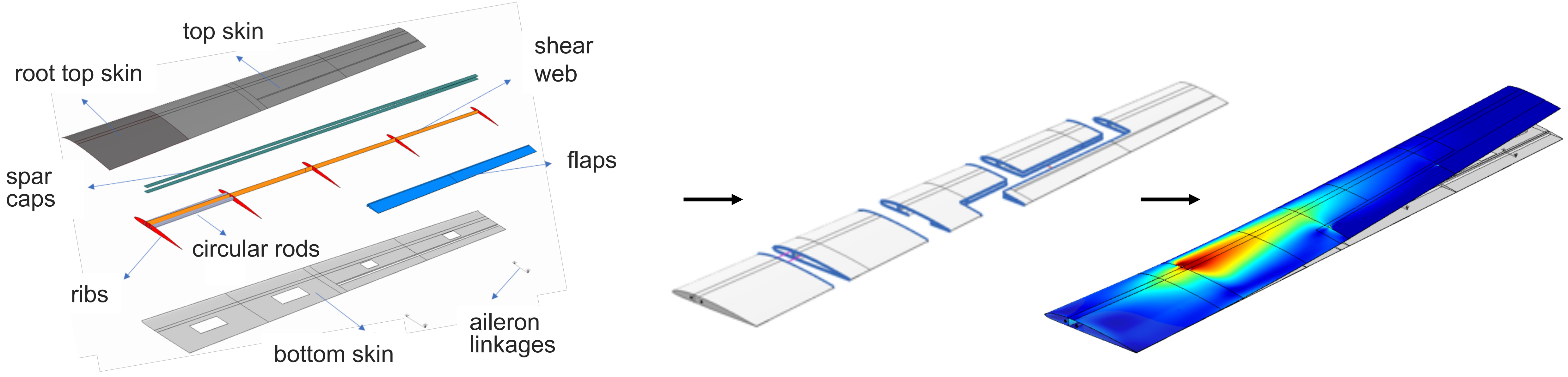


Internal structure



Component-based reduced-order model

- Multiple material types (carbon fiber, carbon rod, plywood, foam)
- Multiple element types (solid, shell, beam)



Performance:

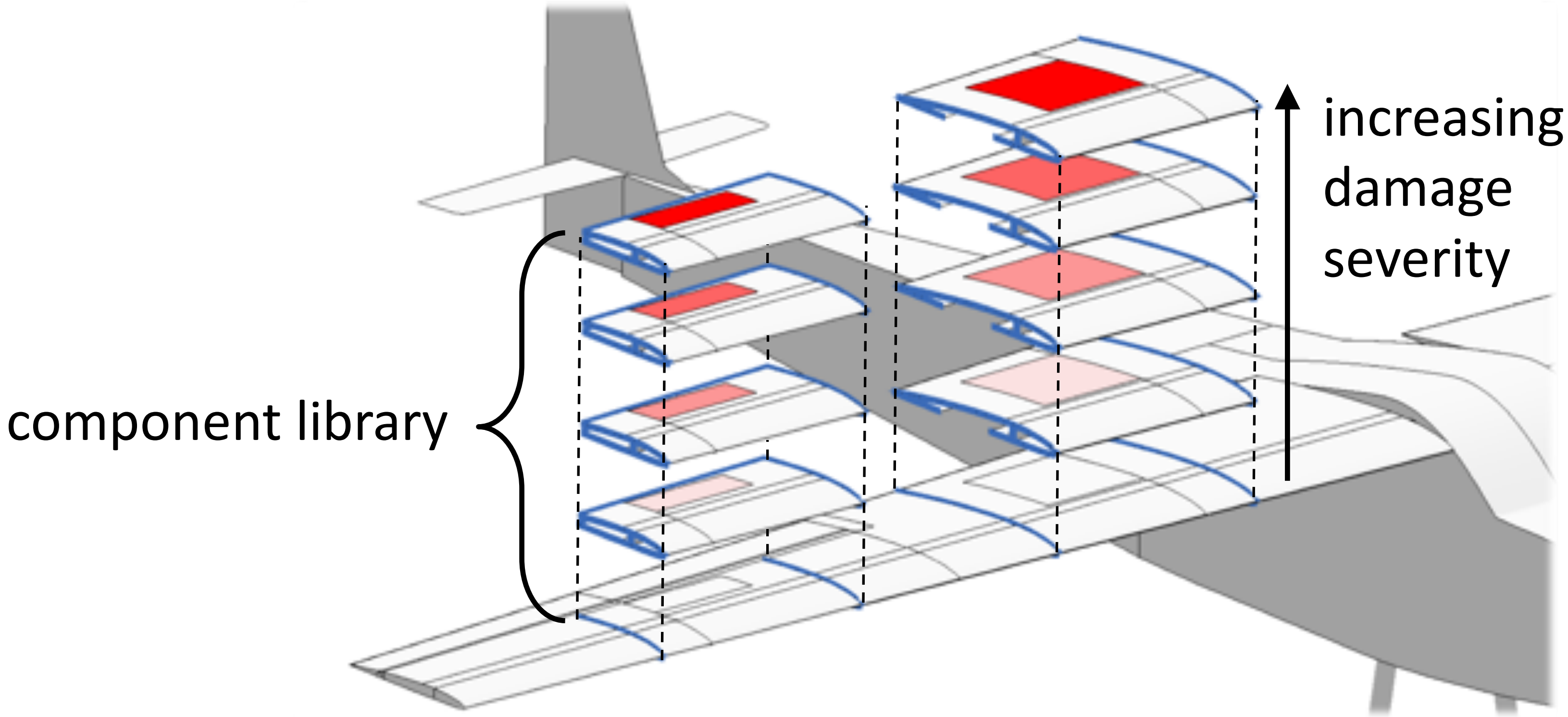
FEA:	387,906 dof	55 seconds
RB-FEA:	694 dof	0.03 seconds

→ 1000x speedup, 30 solves/second

From component-based model to digital twin

<u>Offline: Construct a library of damage states for each component</u>

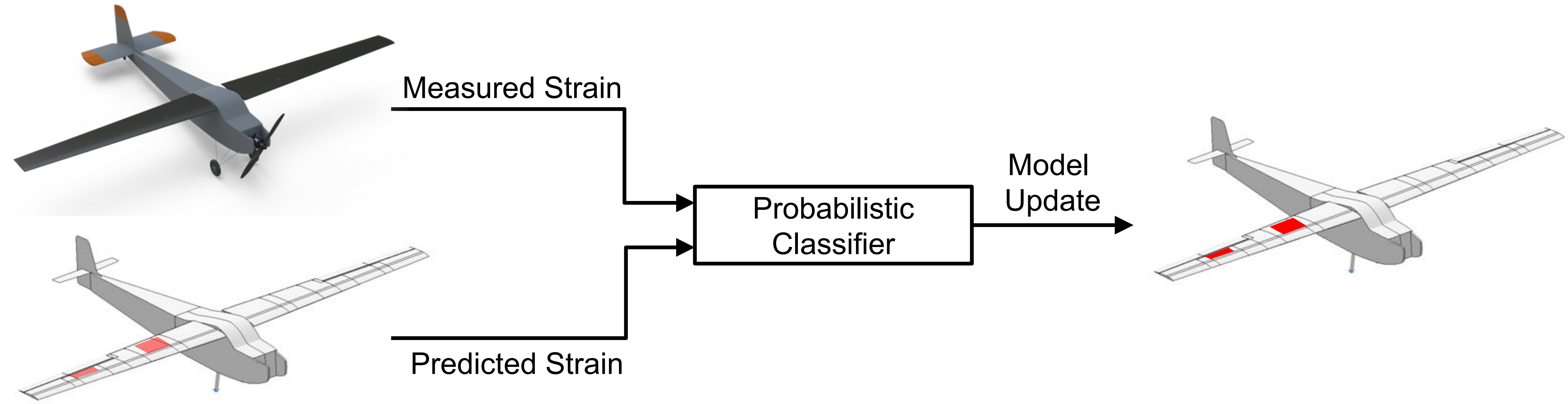
- Create multiple copies of each component
- Train components for parameter ranges of interest
- Compute associated aircraft structural load constraints



From component-based model to digital twin

<u>Online: Solve a classification problem to estimate the UAV state</u>

Use sensor data to perform probabilistic classification of aircraft state into model library entries



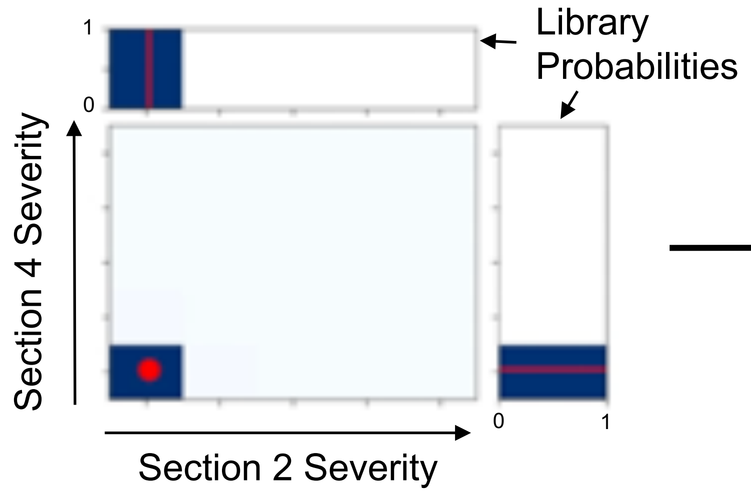
Rapid RB-FEA model evaluation provides near real-time digital twin updates

→ near real-time capability updates

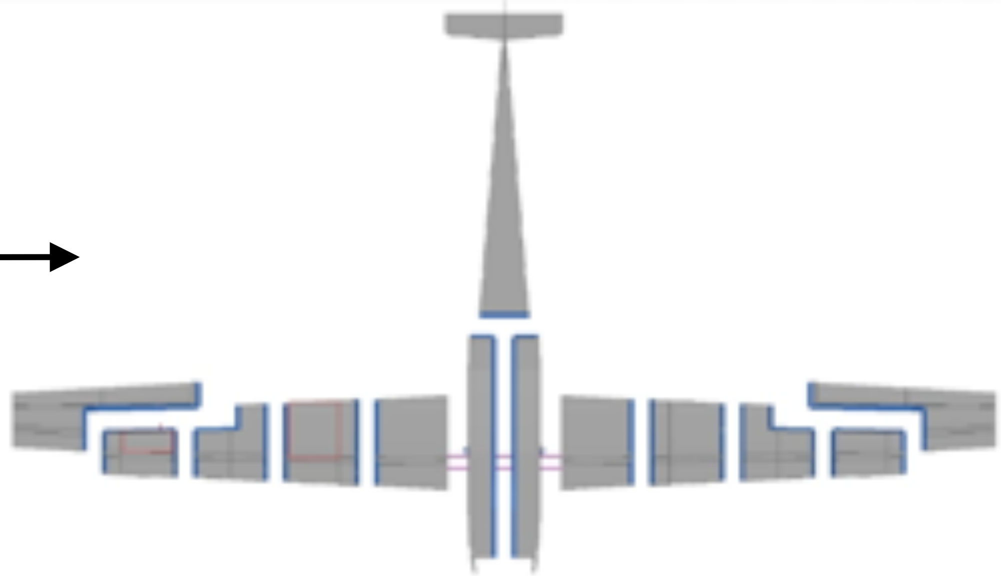
Simulation results

Classifier output:

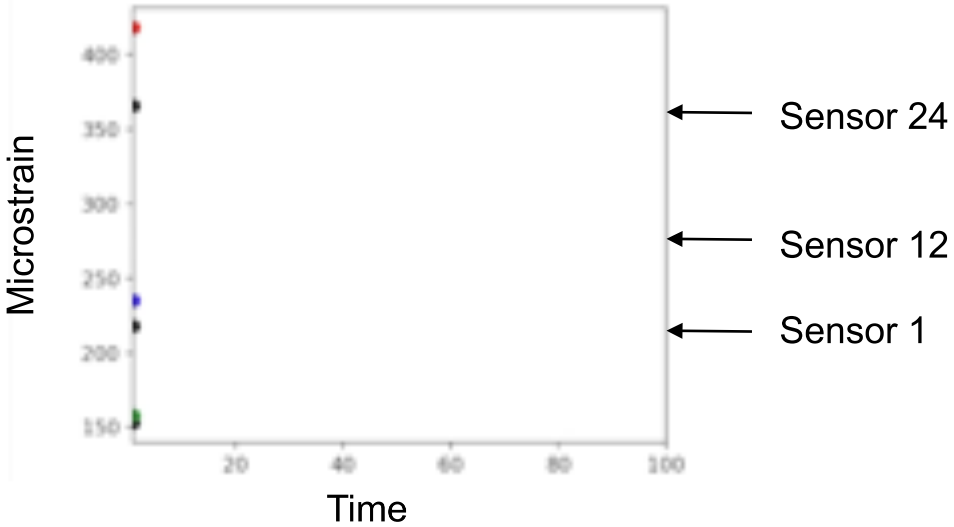
= ground truth



UAV Digital Twin:



Strain Measurements:



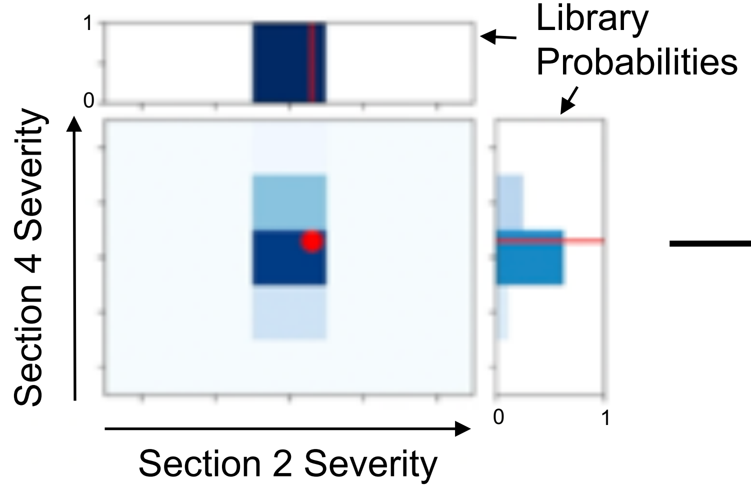
Estimated Capability:

Max. Load Factor: 3.0

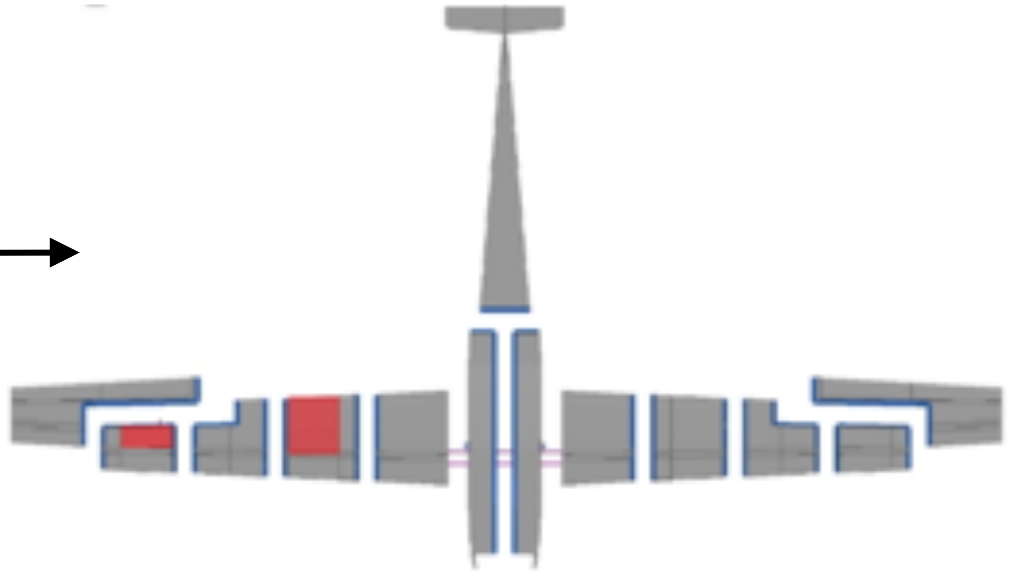
Simulation results

= ground truth

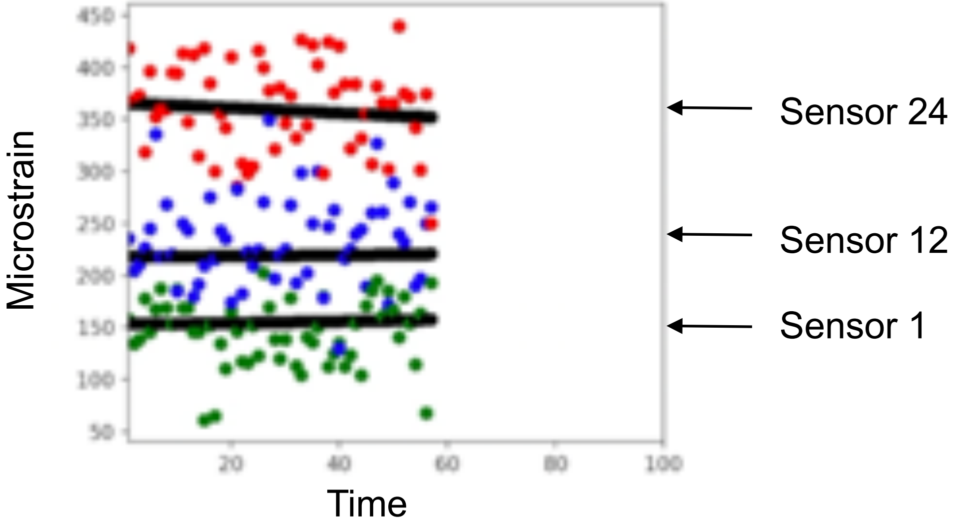
Classifier output:



UAV Digital Twin:



Strain Measurements:



Estimated Capability:

Max. Load Factor: 2.9

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Questions?

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