Toward Predictive Digital Twins

via component-based reduced-order models and interpretable machine learning

Michael Kapteyn*, Dr. David Knezevic, Prof. Karen Willcox

AIAA SciTech | Paper AIAA-2020-0418 | January 6, 2020

MIT AEROASTRO

Massachusetts Institute of Technology

Outline

1 Motivation

Predictive digital twins inform critical decision-making

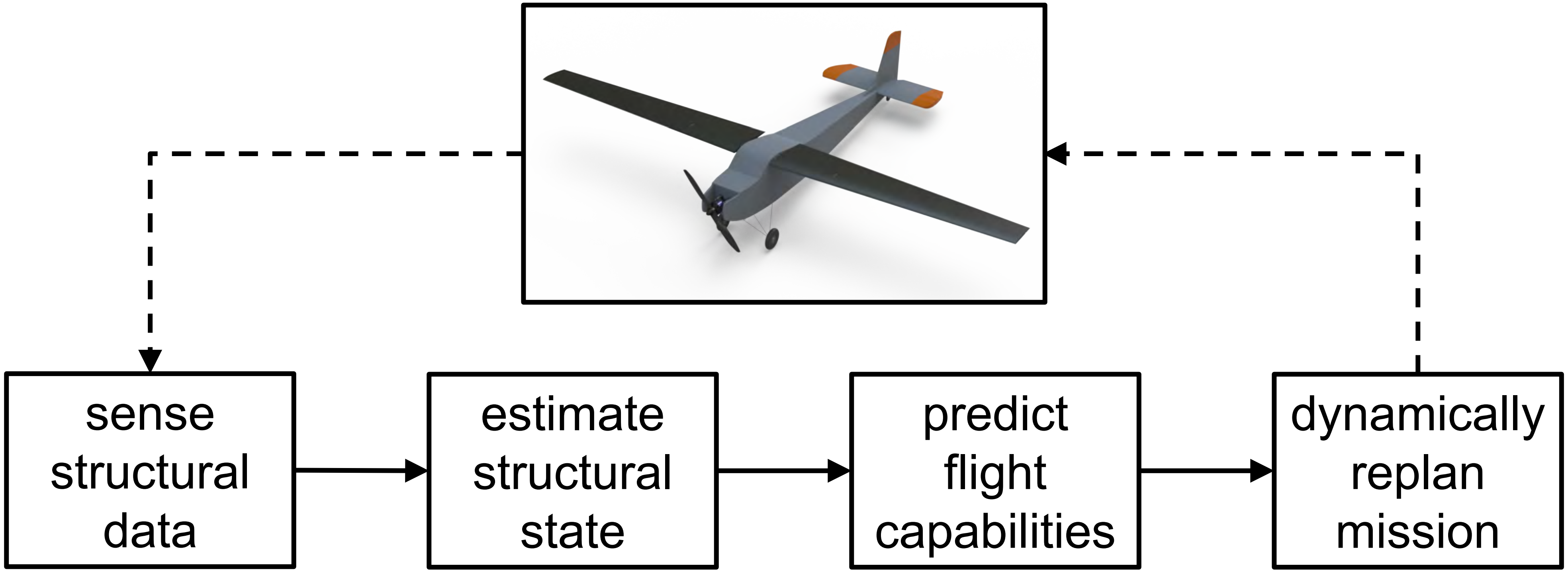
2 Methodology

Interpretable data-driven adaptation of scalable reduced-order models

3 Results

Enabling a self-aware UAV: progress and outlook

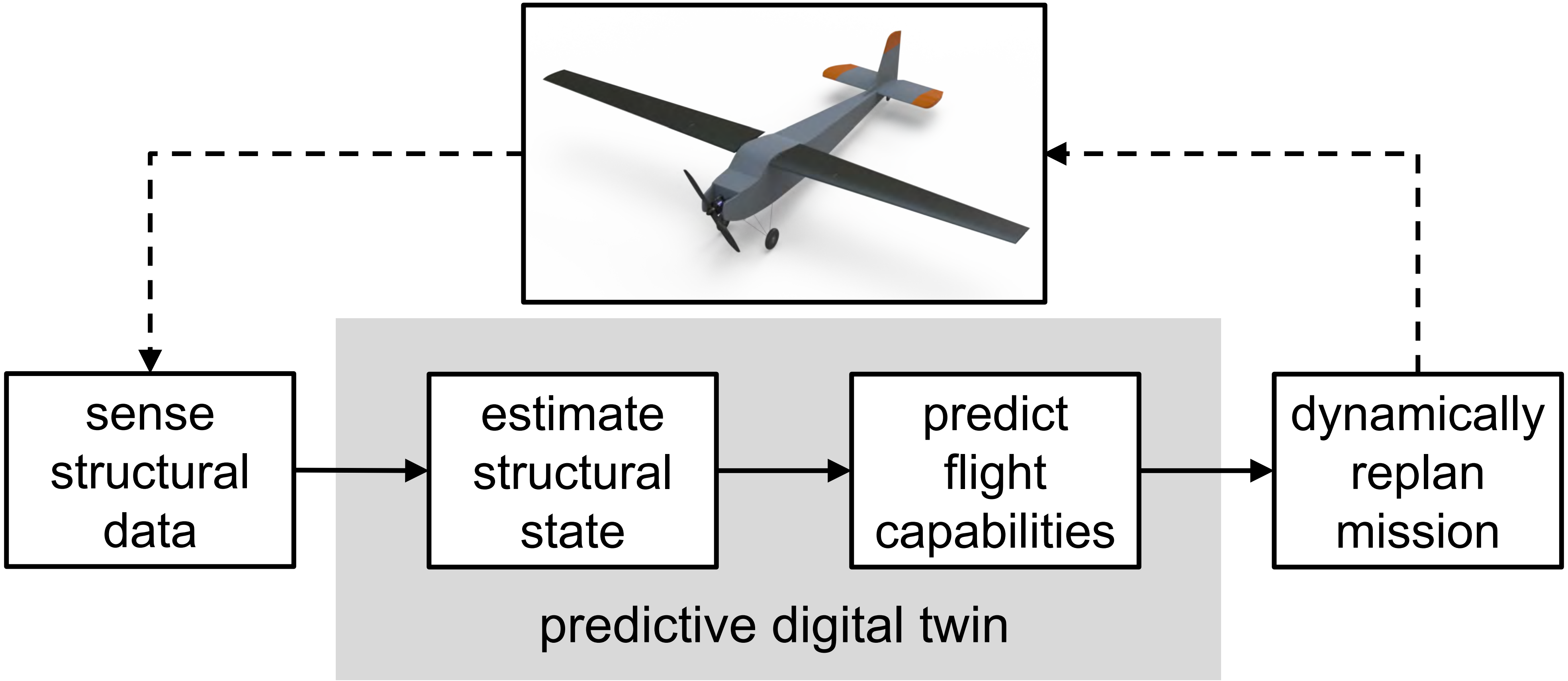
Motivation: Enabling a **self-aware aircraft**



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

Prior work has shown that this provides [Kordonowy 2011, Singh 2017]
- Increased survivability
- Increased utilization

Motivation: Enabling a **self-aware aircraft**



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

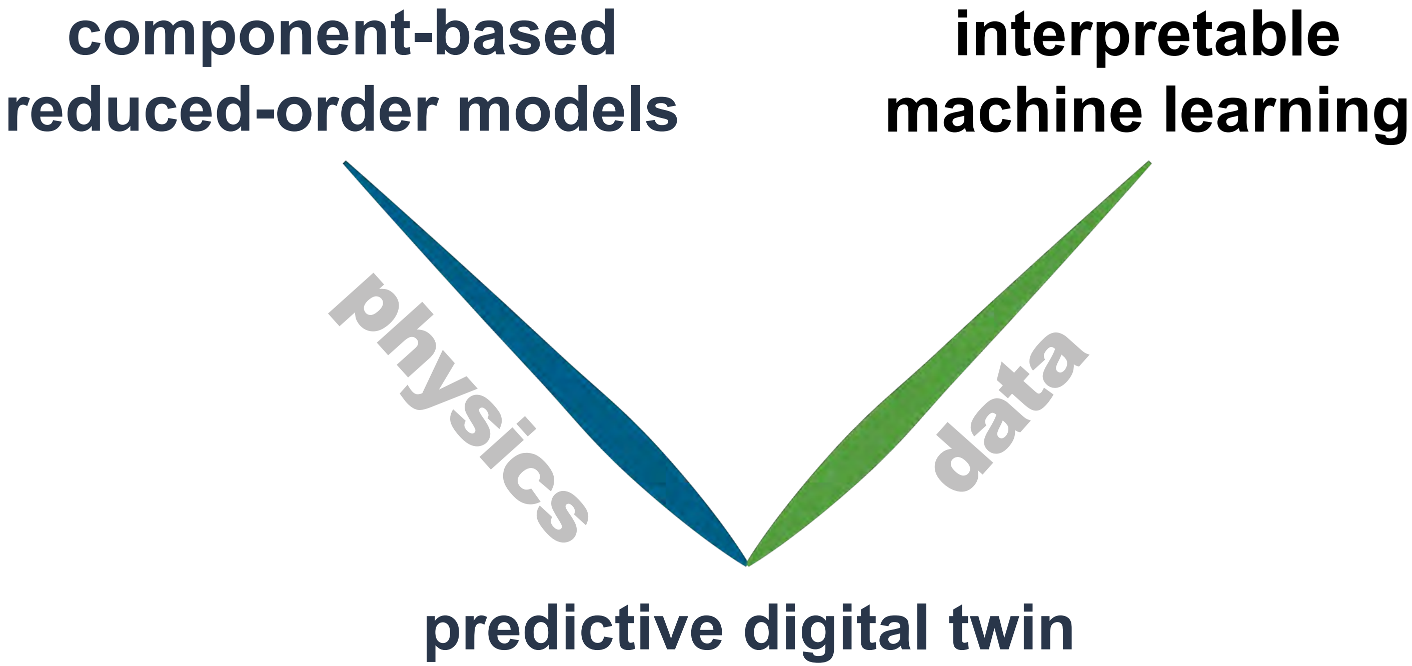
Flight test vehicle

Customized 12ft Telemaster aircraft:

- Complex structure with multiple materials
- Custom wing sets: pristine & damaged
- Custom sensor suite

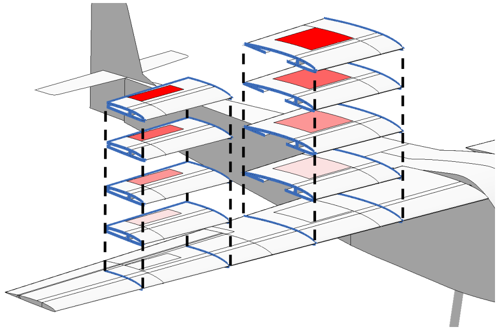
*One of the authors has a family member who is co-founder of Divinio. Purchase of the sensors for use in the research was reviewed and approved in compliance with all applicable MIT policies and procedures.

High-consequence decisions require digital twins that are **predictive • reliable • explainable**

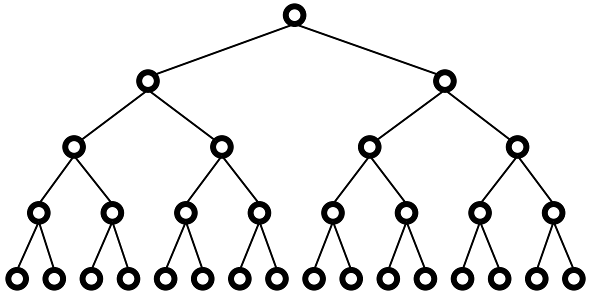


Our approach: **data-driven adaptation** of **component-based reduced-order models**

Offline:



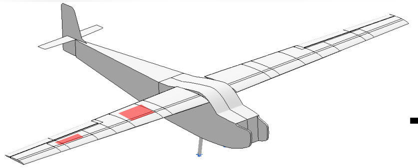
Construct library of reduced-order models representing different asset states



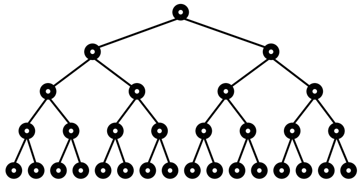
Use model library to train a classifier that predicts asset state based on sensor data

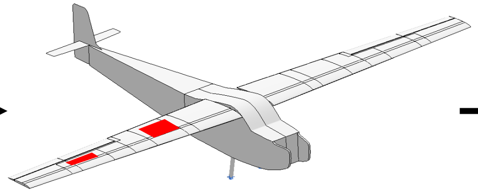
Online:

sensor data



current digital twin



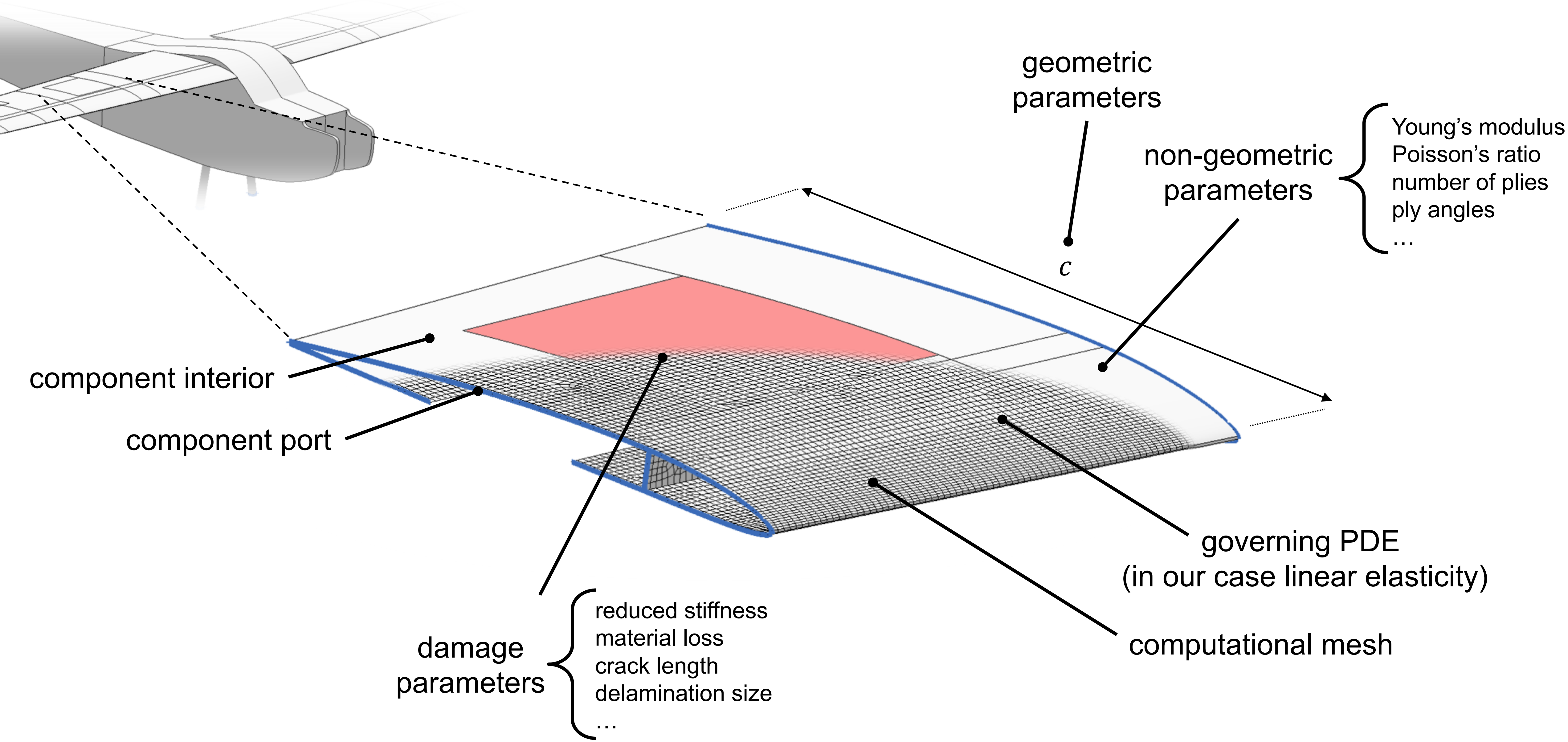


updated digital twin

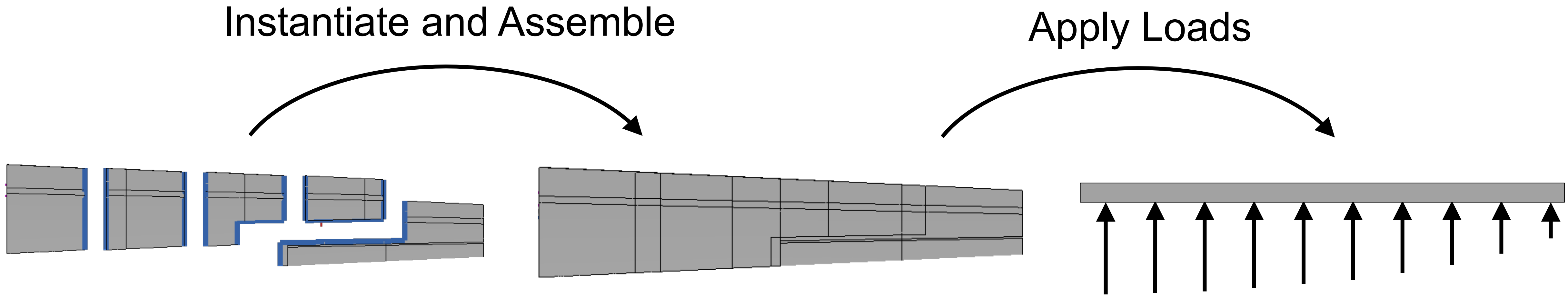
Analysis,
Prediction,
Optimization

Component-based reduced-order model library

Example component: section of a wing



From components to systems

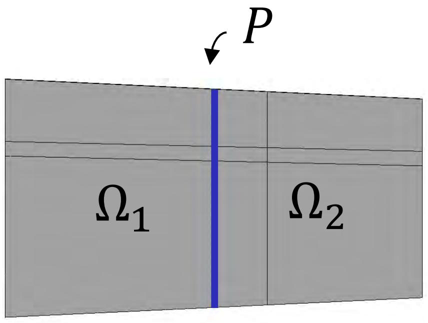


component parameters μ_c + assembly parameters μ_a + load parameters μ_l =

system parameters

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

Solving a component-based model



M port DOFs
N interior DOFs

Start with the usual finite element problem statement:

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

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

Express interior DOFs in terms of port DOFs

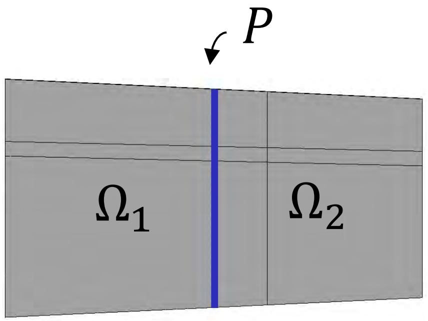
$$A_{\Omega_i,\Omega_i} u_{\Omega_1} = f_{\Omega_1} - A^T_{P,\Omega_1} \mathbb{U} \longleftarrow$$ Solve on each component independently

Substitute to get a system involving only port DOFs:

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

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

Model reduction strategy



M port DOFs
N interior DOFs

Static-condensation reduced-basis-element (SCRBE) method:
[Huynh 2013]

i. Port Reduction:
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. Component Interior Reduction:
Replace the finite element space **inside each component** with a reduced basis (RB) space of dimension n

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

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

How does SCRBE meet the demands of a digital twin?

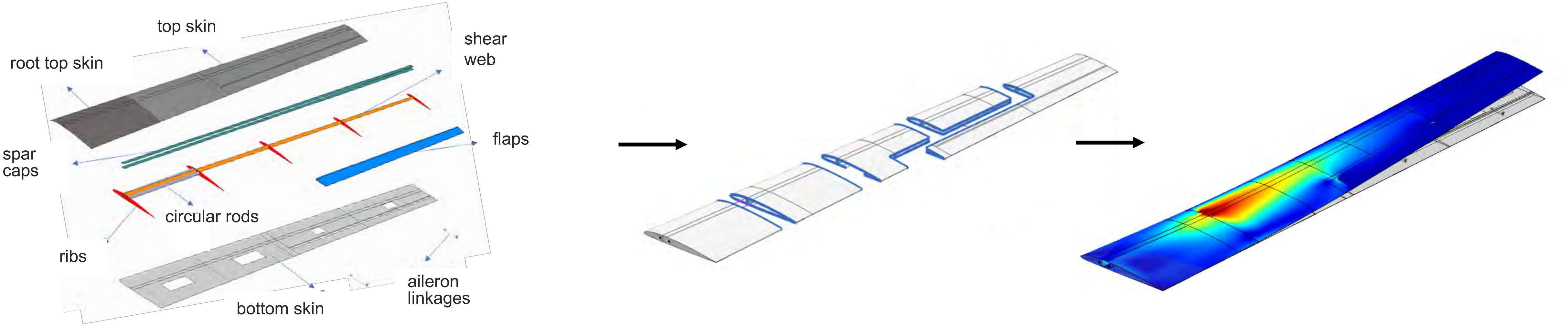
1. Model training can be performed using only small groups of components
   ▸ **Never have to solve full-system FE model**

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 expressive adaptation: changes to topology, meshes etc.**

- Cloud-based **parallel solvers**
- Equipped with a posteriori **error indicators**
- Extends to both **modal** and **dynamic** analysis [Vallaghé 2015]
- Hybrid solver incorporates **local non-linearities**
- Recourse to full **non-linear FEA** if required

How does SCRBE meet the demands of a digital twin?



Performance:

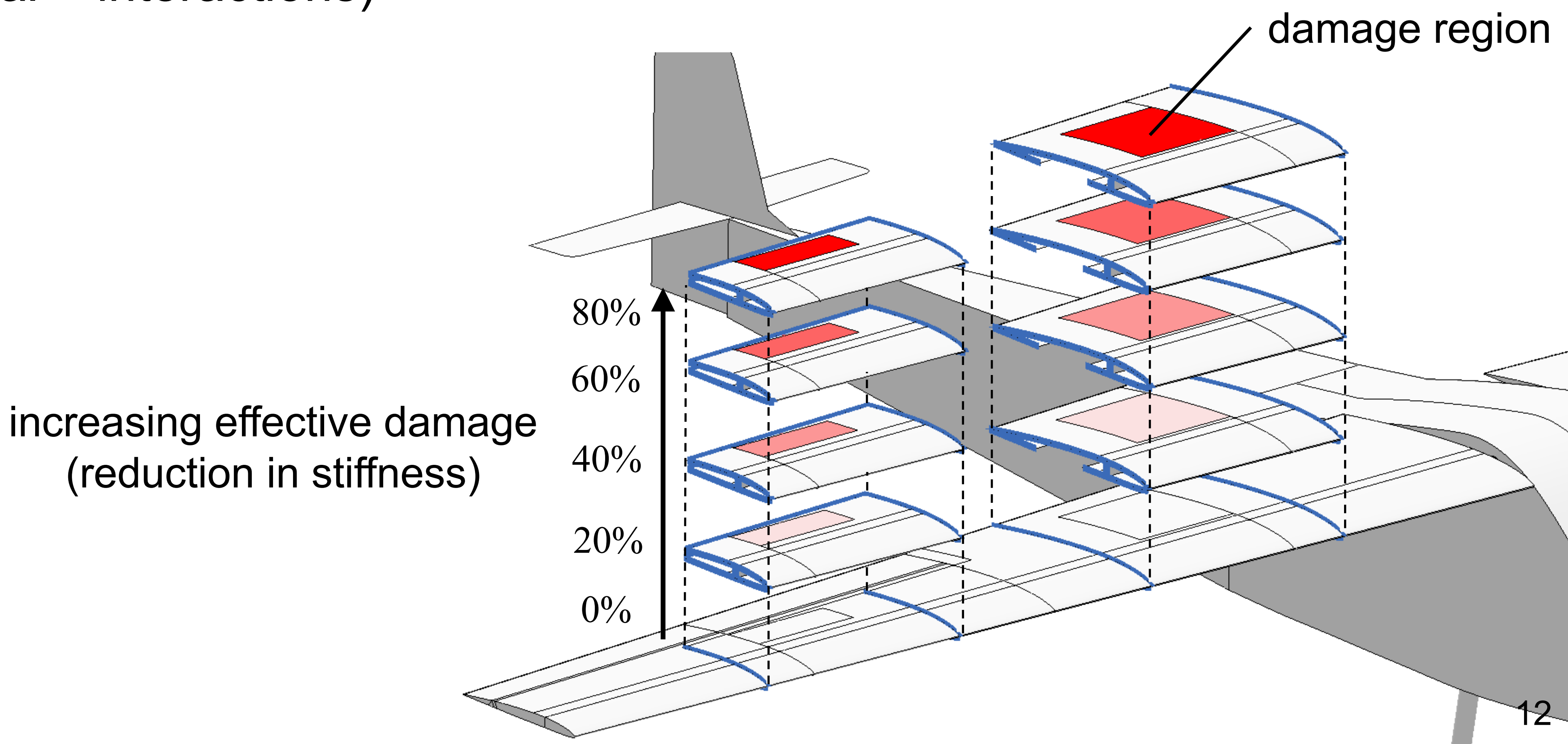
FEA:	387,906 dof	55 seconds
SCRBE:	694 dof	0.03 seconds

▸ **1000x speedup, solve in near real-time**

From component-based model to digital twin: Constructing a model library

Offline: Construct a library of damage states for each component

1. Create multiple copies of each component
2. Train components for parameter ranges of interest (local + interactions)

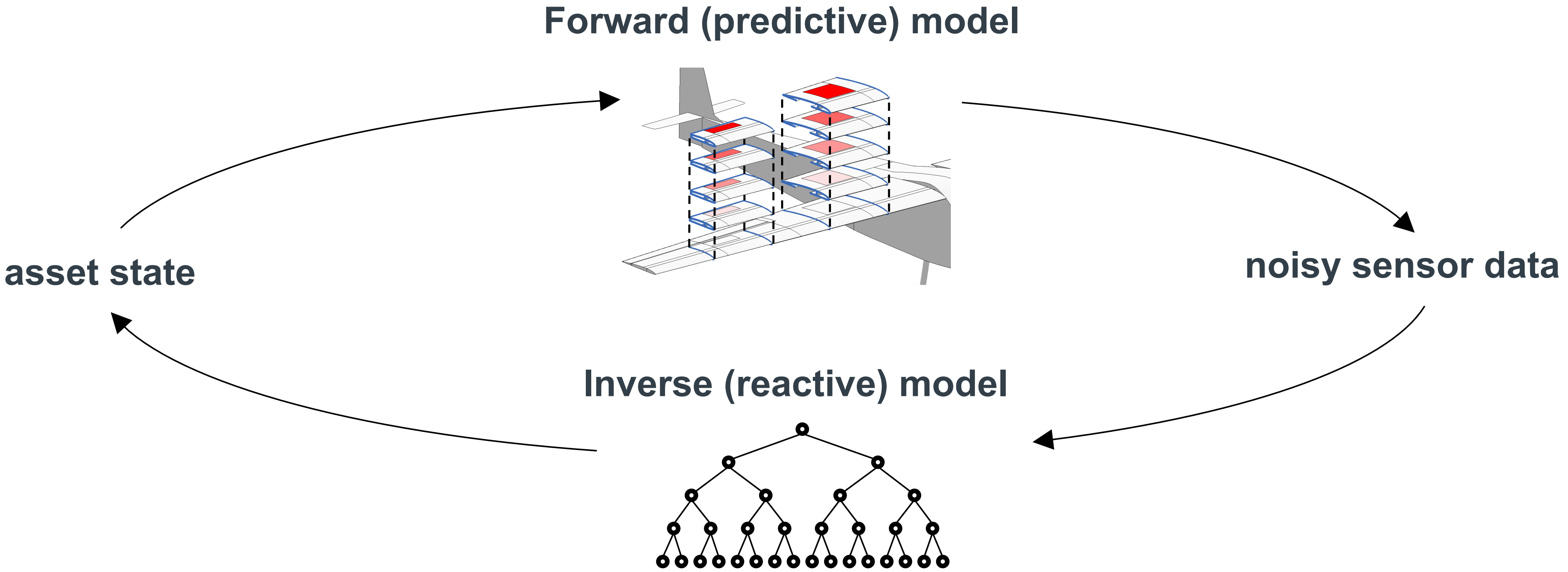


Interpretable machine learning

Onboard sensors inform which model is used in the digital twin

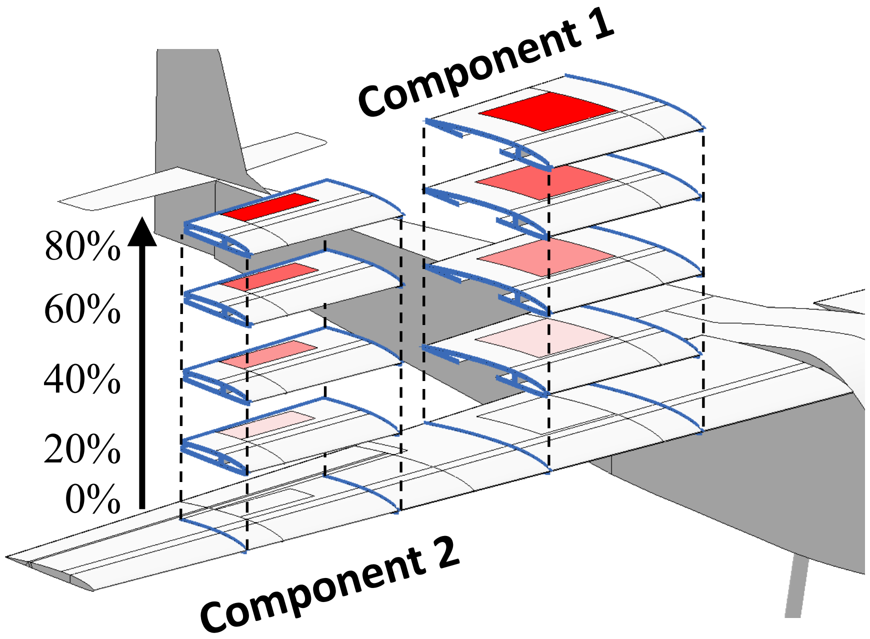
Data-driven digital twin:

Onboard sensors are used to select a reduced-order model from the library



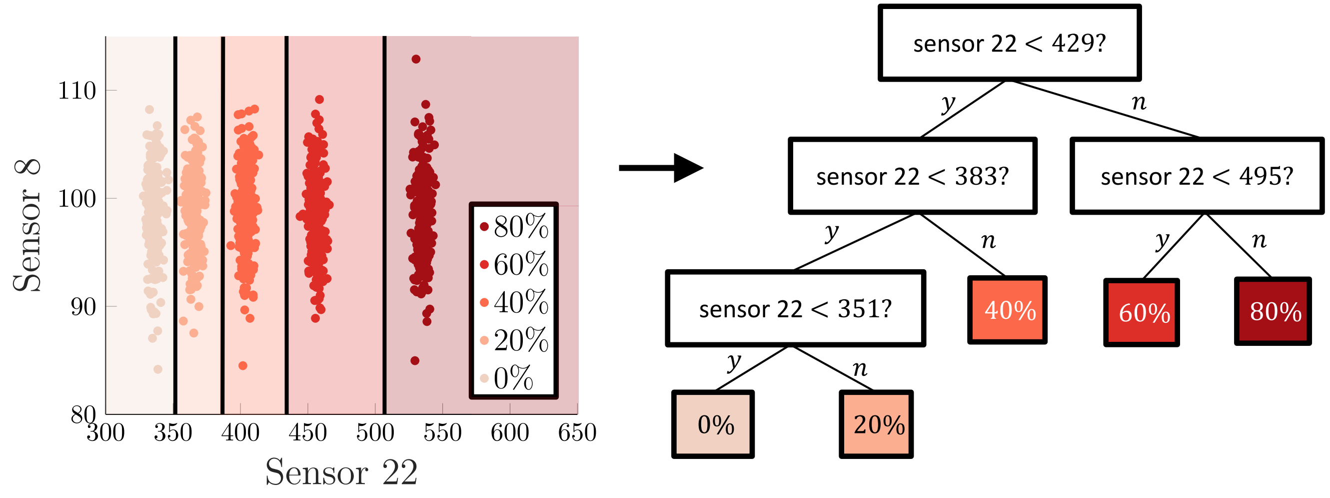
- Use **predictive models** to **generate training data**
- Use **machine learning** to train an **interpretable, explainable reactive model**

From component-based model to digital twin: Interpretable machine learning

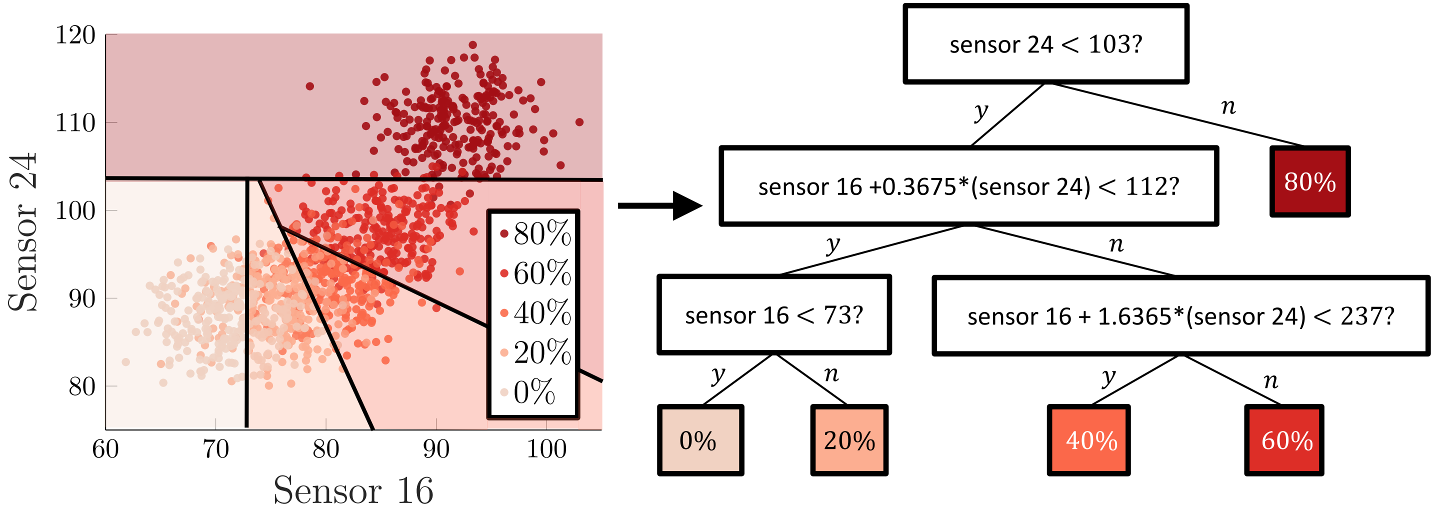


- Highly interpretable
- Natural framework for sensor selection
- Rapid online classification
- As expressive as standard neural networks

Component 1



Component 2



From component-based model to digital twin: Interpretable machine learning

Goal: Find a partitioning of the space of possible sensor measurements, and assign to each partition the library model that best explains the measurements

Optimal Classification Trees [Bertsimas, 2019] uses mixed-integer optimization techniques to find a partition in the form of an optimal binary tree, T:

tradeoff parameter

$$\min_{\mathrm{T}} \quad \underbrace{\mathrm{R}(\mathrm{T})}_{\text{error on training data}} + \overbrace{\alpha}^{\text{tradeoff parameter}} \underbrace{|\mathrm{T}|}_{\text{complexity of the tree}}$$

error on training data

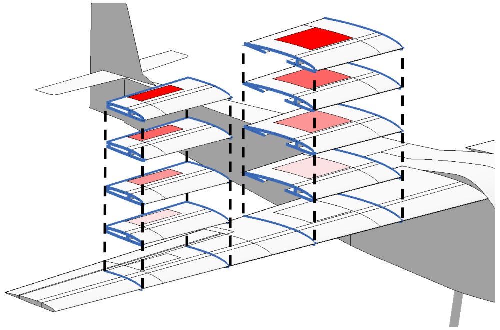
complexity of the tree

- ✚ Globally optimal
- ✚ Scalable
- ✚ Naturally extends to hyperplane splits

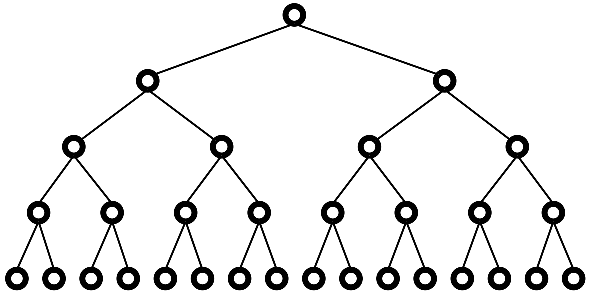
Interpretable AI

Recall our approach: **data-driven adaptation** of **component-based reduced-order models**

Offline:



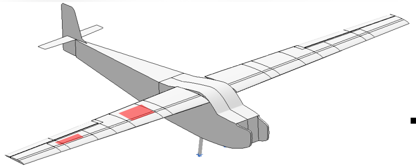
Construct library of reduced-order models representing different asset states



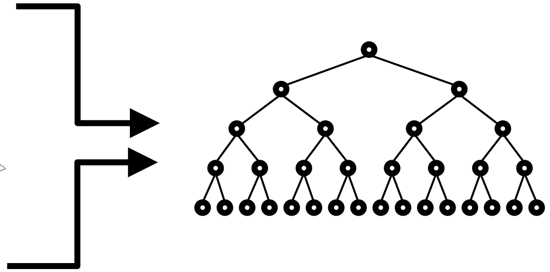
Use model library to train a classifier that predicts asset state based on sensor data

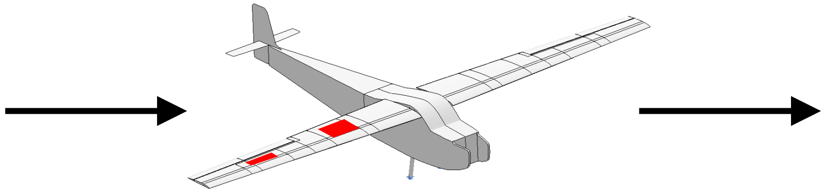
Online:

sensor data



current digital twin





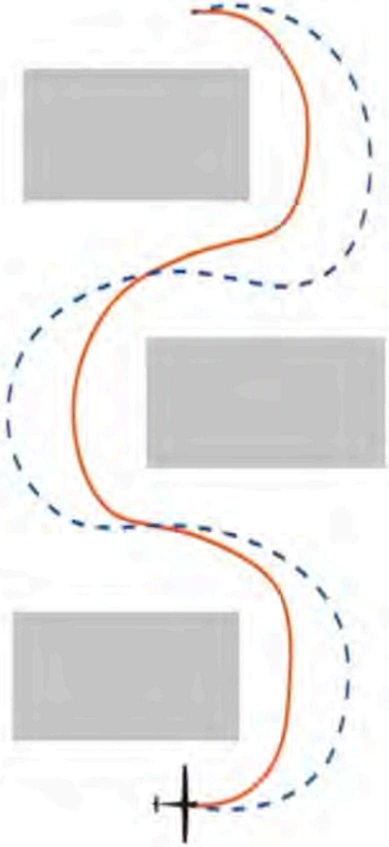
updated digital twin

Analysis,
Prediction,
Optimization

Flight of the UAV

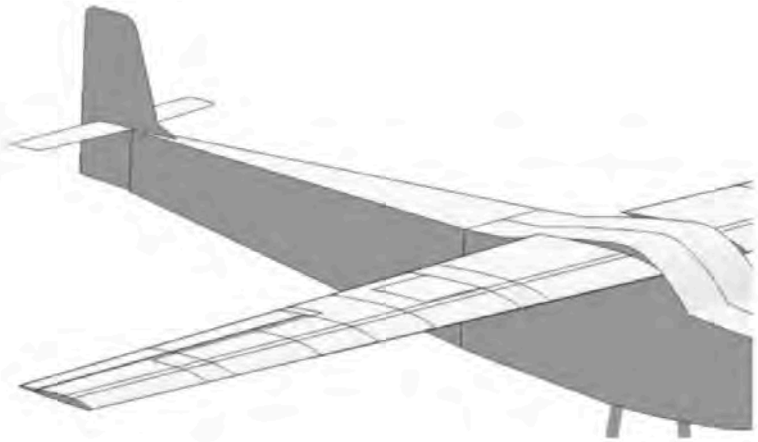
Aggressive flight path

Conservative flight path



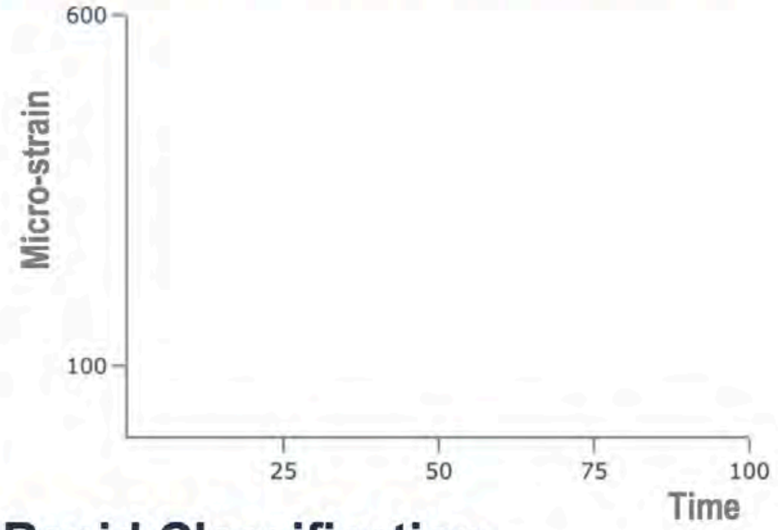
Health estimates

Less damage | More damage

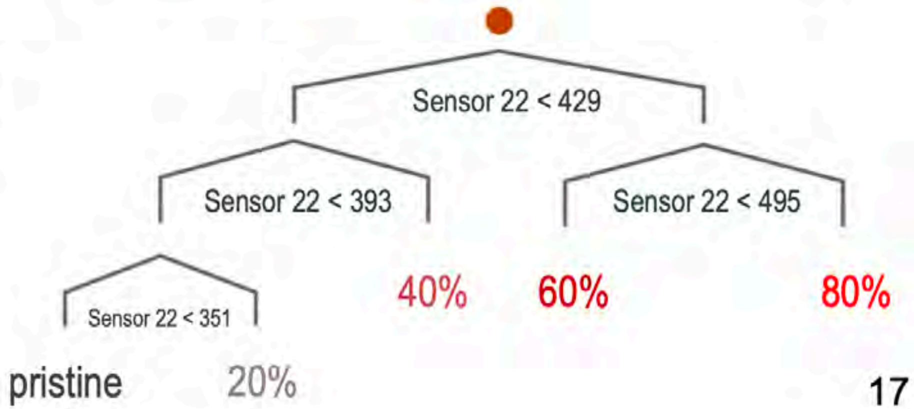


Strain Measurements

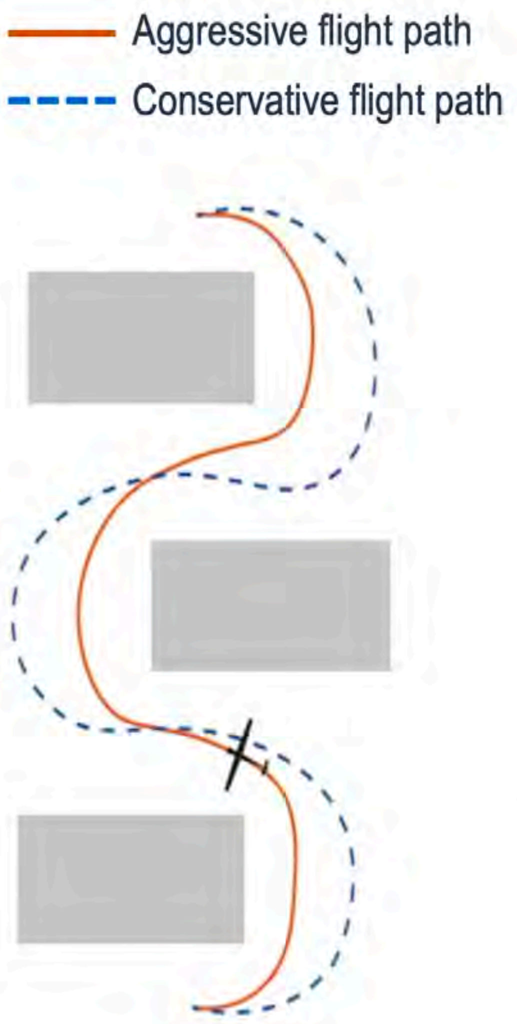
Sensor 22 Sensor 12 Sensor 24



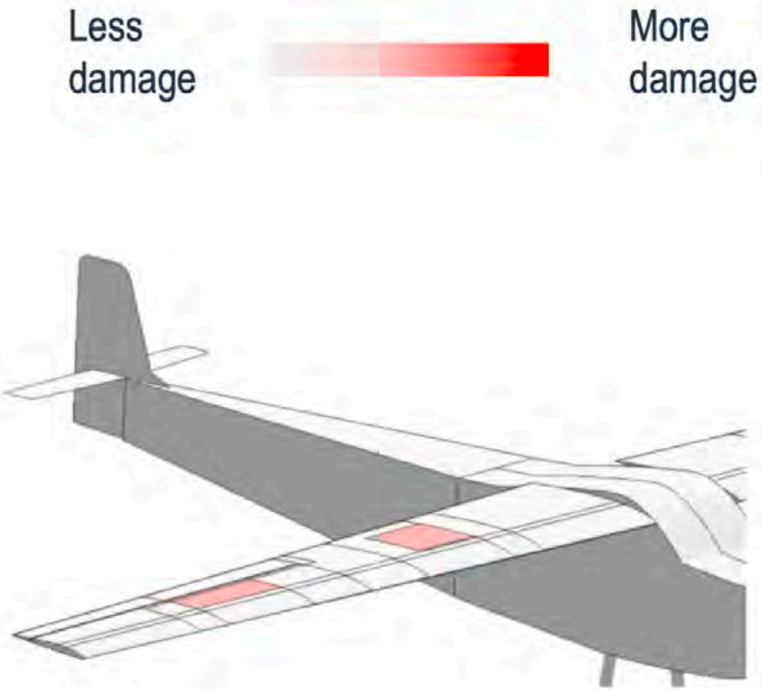
Rapid Classification



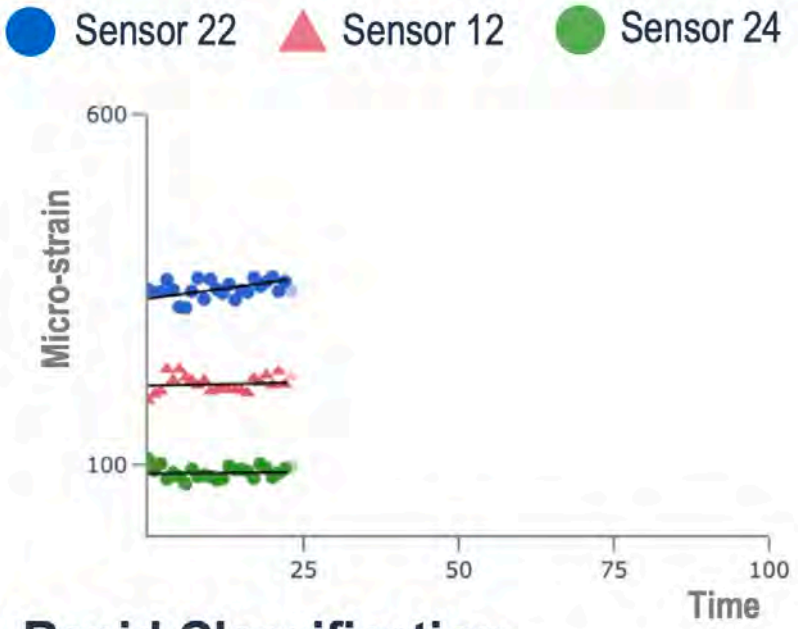
Flight of the UAV



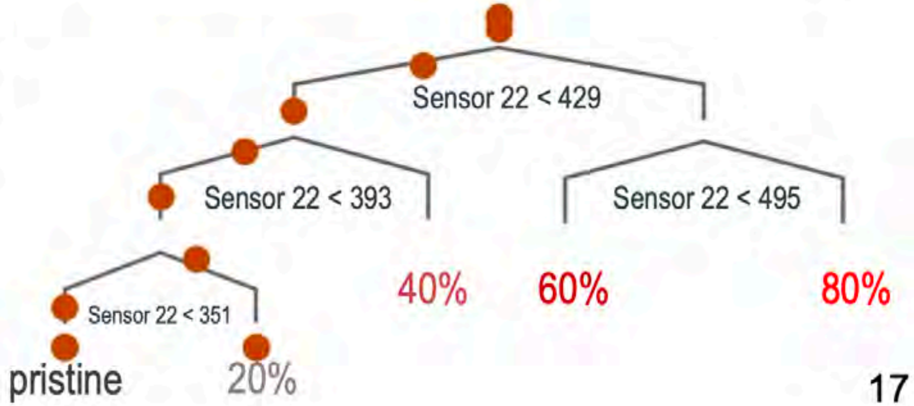
Health estimates



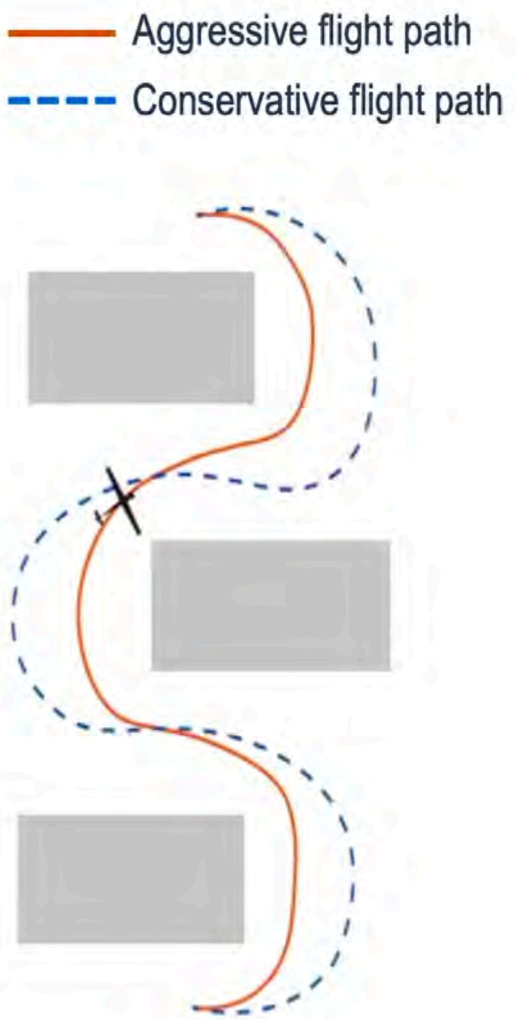
Strain Measurements



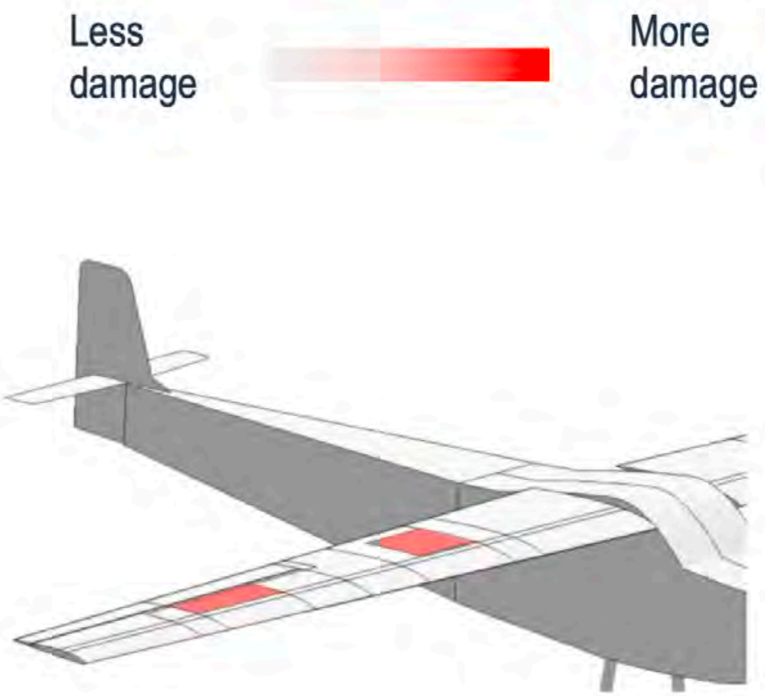
Rapid Classification



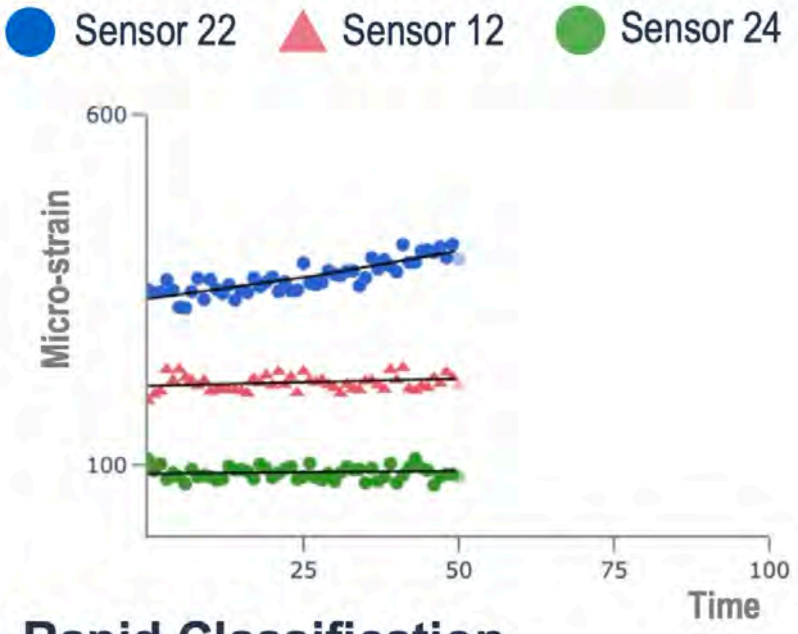
Flight of the UAV



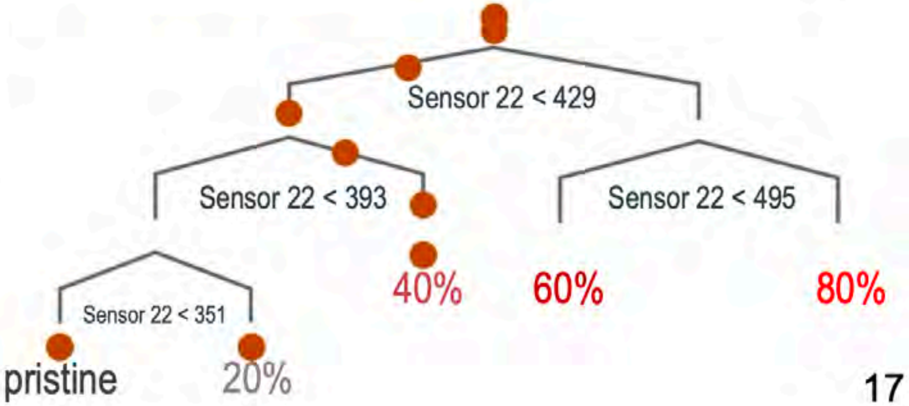
Health estimates



Strain Measurements

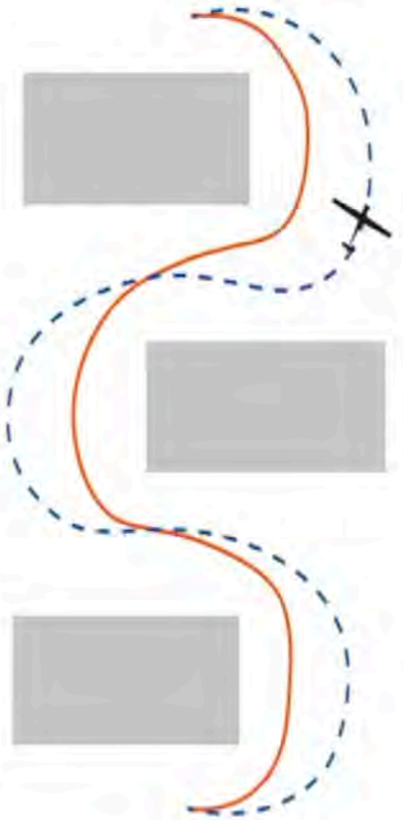


Rapid Classification



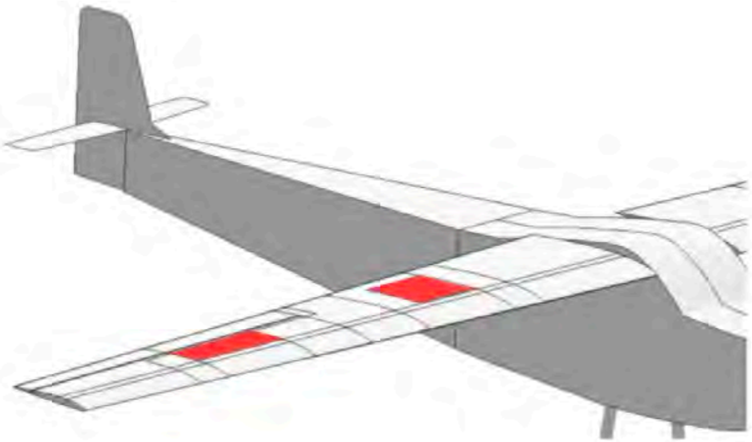
Flight of the UAV

Aggressive flight path
Conservative flight path



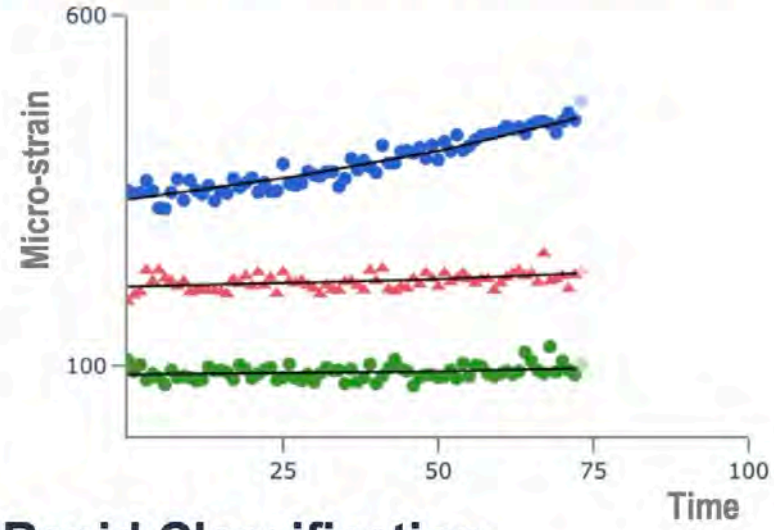
Health estimates

Less damage  More damage

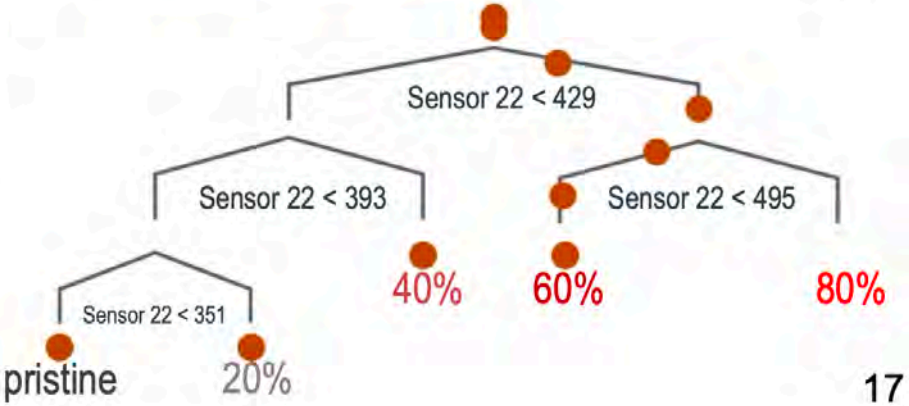


Strain Measurements

Sensor 22 Sensor 12 Sensor 24



Rapid Classification



Combining component-based **reduced-order models** and **interpretable machine learning** enables **predictive digital twins**

Future Work

- Test with **experimental data**
- Incorporate **multimodal observations**
- **Flight demonstration**

Open challenges

- Improving **damage models**
- Accounting for **model uncertainty** and **inadequacy**

High-consequence decisions require digital twins that are

predictive • reliable • explainable

component-based
reduced-order models

interpretable
machine learning

predictive digital twin

For a project overview, slides, and the full paper, visit https://kiwi.oden.utexas.edu/research/digital-twin

Funding acknowledgements:

- Air Force Office of Scientific Research (AFOSR) Dynamic Data-Driven Application Systems (DDDAS)
- The Boeing Company
- SUTD-MIT International Design Centre

References

[Kordonowy 2011] Kordonowy, D., and Toupet, O., "Composite airframe condition-aware maneuverability and survivability for unmanned aerial vehicles." *Infotech@ Aerospace* 2011, 2011-1496.

[Singh 2017] Singh, V., and Willcox, K.E., "Methodology for Path Planning with Dynamic Data-Driven Flight Capability Estimation." *AIAA Journal* (2017): 2727-2738.

[Vallaghé 2015] Vallaghé, S., et al. "Component-based reduced basis for parametrized symmetric eigenproblems." *Advanced Modeling and Simulation in Engineering Sciences* 2.1 (2015): 7.

[Huynh 2013] Huynh, D.B.P., D.J. Knezevic, and A.T. Patera. "A static condensation reduced basis element method: approximation and a posteriori error estimation." *ESAIM: Mathematical Modelling and Numerical Analysis* 47.1 (2013): 213-251.

[Bertsimas 2019] Bertsimas, D., and Dunn, J., "Machine Learning under a Modern Optimization Lens." Dynamic Ideas (2018).