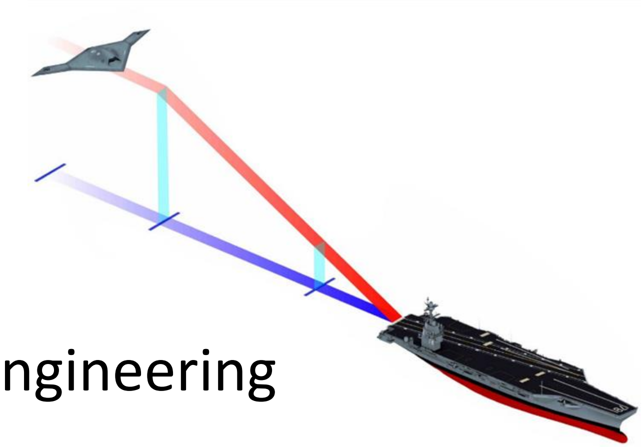
Stanford | ENGINEERING
Aeronautics & Astronautics

Digital What?



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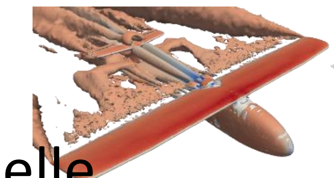
Marne La Vallee, France



Acknowledgements: AFOSR, Autodesk, ONR

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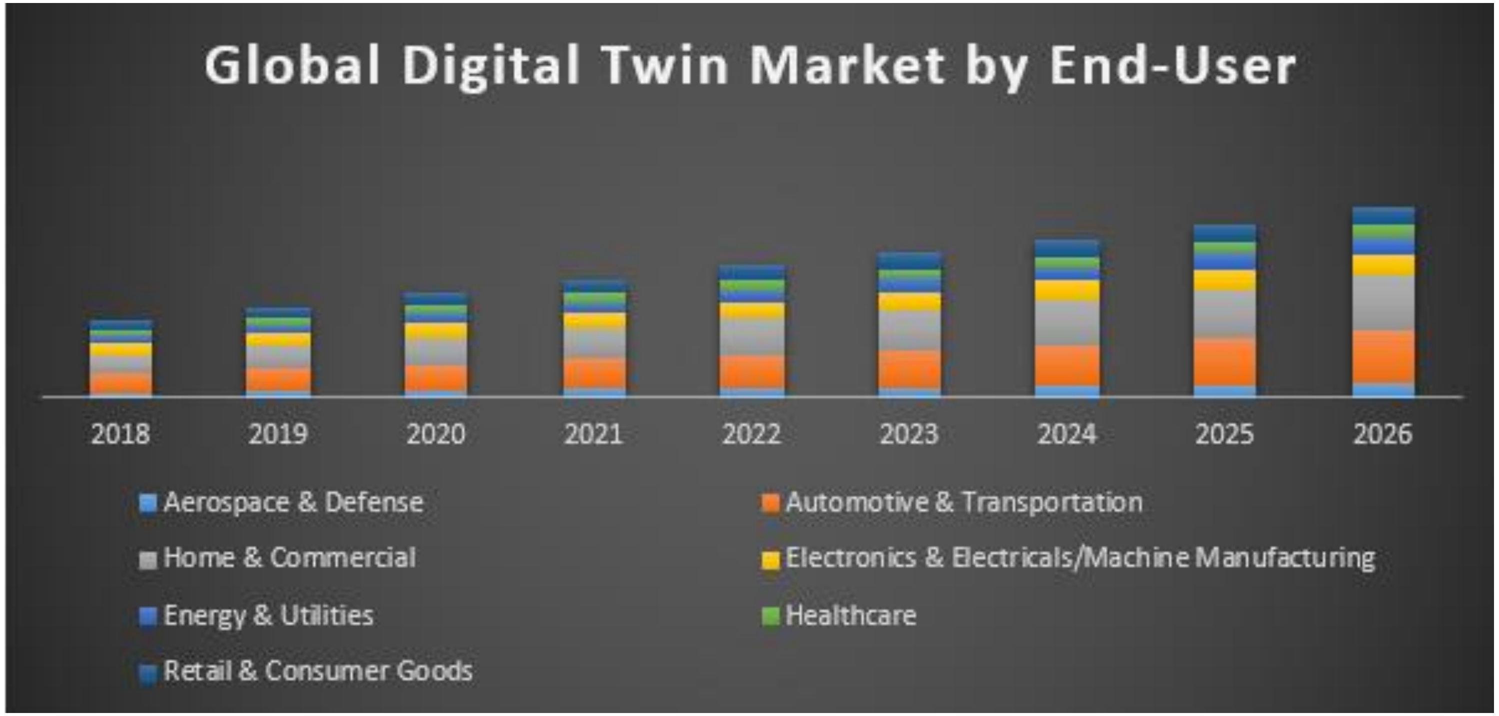
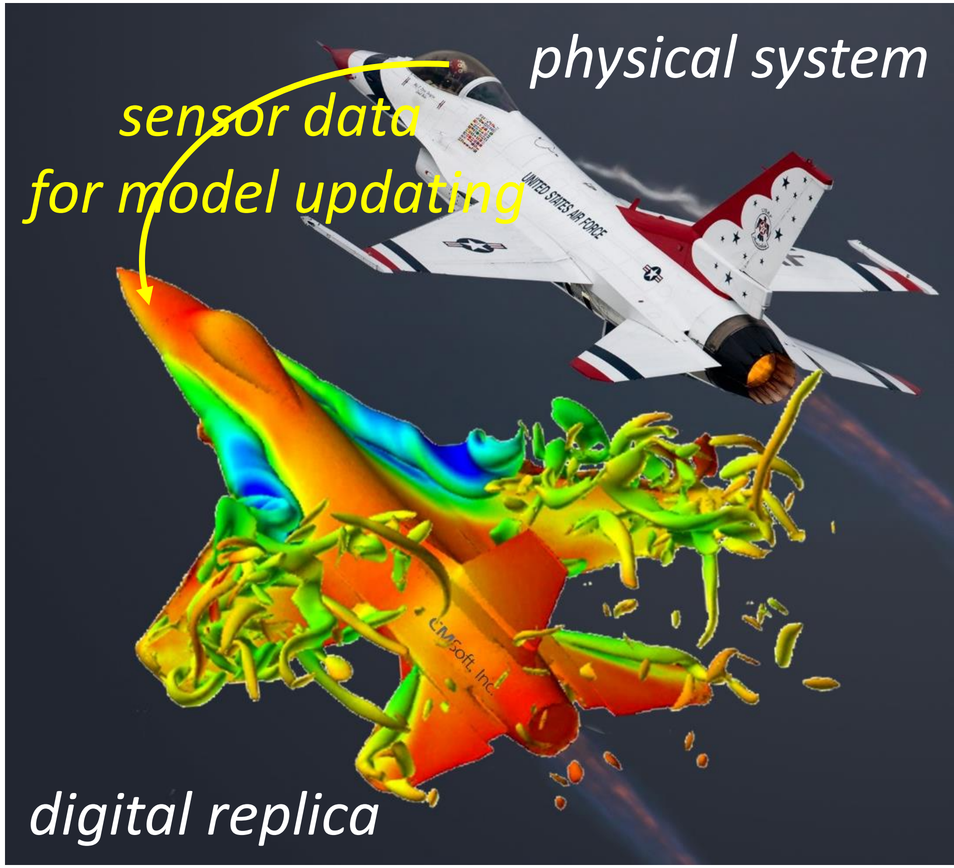


everyone claims to have/do the Digital part

*few talk about the __**Twin**__ part …*

Digital Twins (DTs)

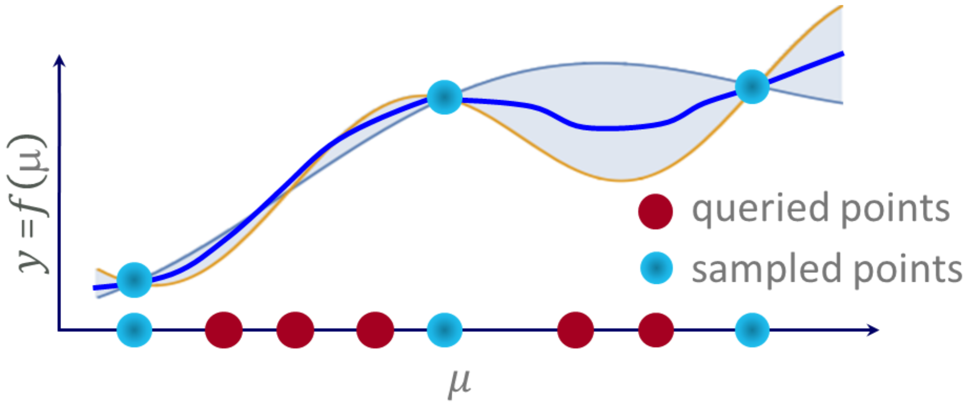
- **Digital twin prototype (DTP)**
  - design, analyses, and processes to ***realize*** a physical product → rebranding of old CAD and modeling and simulation
  - ***innovation:*** real-time (RT) counterpart (RT-DTP) for accelerating the objectives
- **Digital twin instance (DTI)**
  - digital twin of a specific instance of the product, ***after it is manufactured***
  - learn from data to perform model updating
- **Digital twin aggregate (DTA)**
  - aggregation of DTIs, allowing for larger sensor datasets and therefore enhanced learning and prognostic processes
- **Industry 4.0**
  - crisis management, predictive maintenance, quality control, warranty optimization



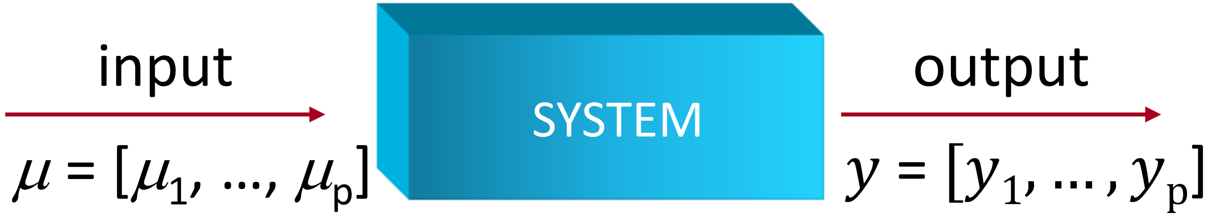
surrogate modeling for tractability and/or real-time performance

Data-Driven Surrogate Modeling

- **External representation**



- **Internal representation**

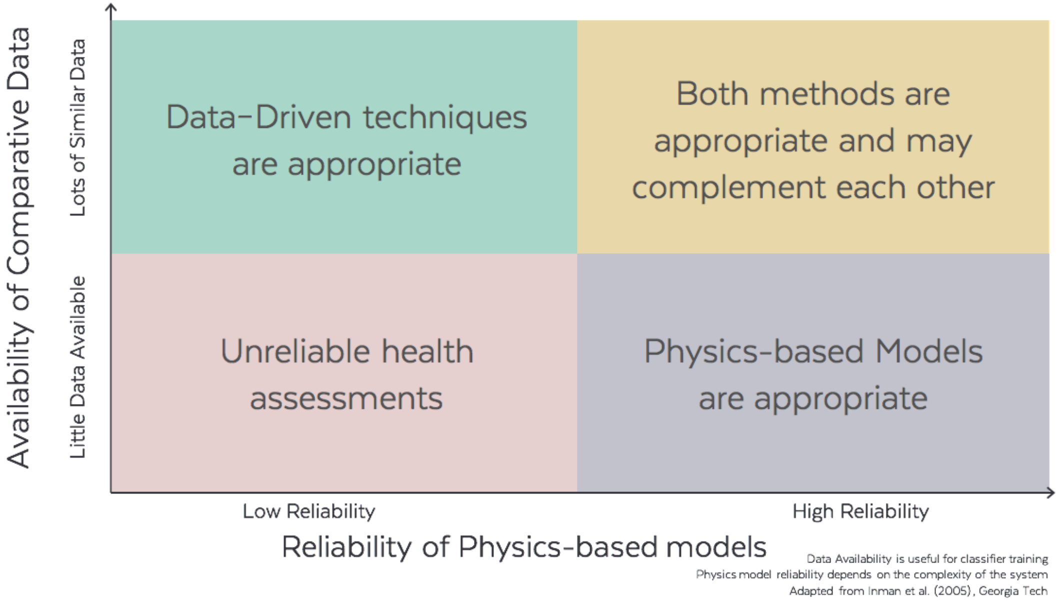


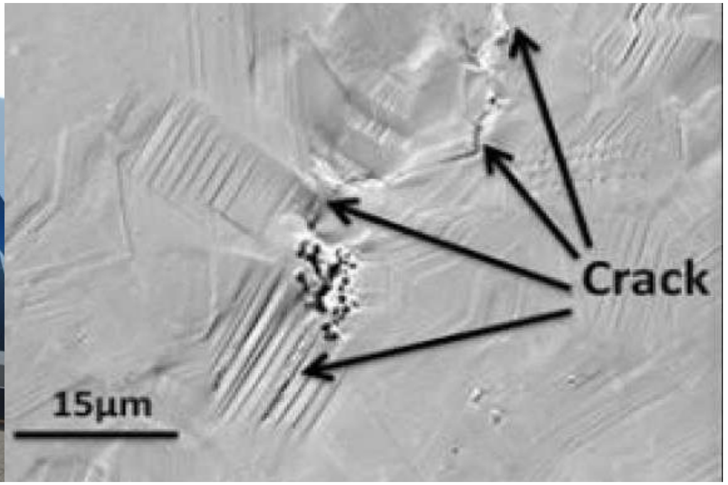
$y = f(\mu)$ via the post-processing of a ***physics-based***, high-fidelity model of the system

- **Examples and characterization**
  - Gaussian processes (GPs), regression artificial neural networks (ANNs)
  - ***a few, pre-determined, scalar quantities of interest (QoIs)***
  - ***real-time surrogate models*** of output(s)

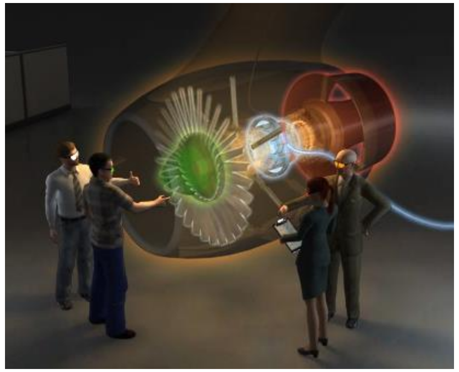
- **Examples and characterization**
  - projection-based reduced-order models (PROMs), simplified-physics models
  - ***many QoIs, determined via exploration***
  - ***QoIs can be spatio-temporal fields***
  - ***real-time surrogate models*** of systems

Purely Data-Driven vs Physics-Based Data-Driven Computational Modeling





- How to identify the QoIs (rare events, failure modes, multiple scales, …)?

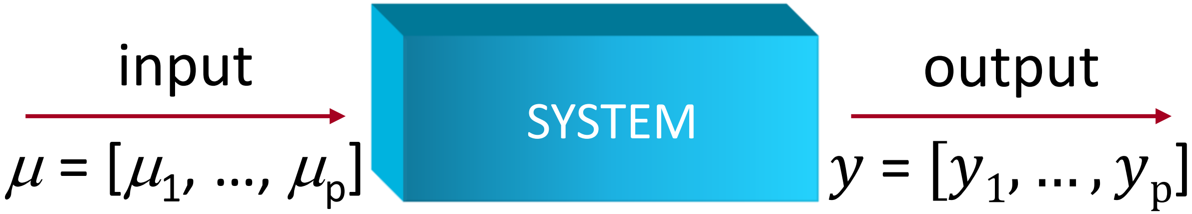


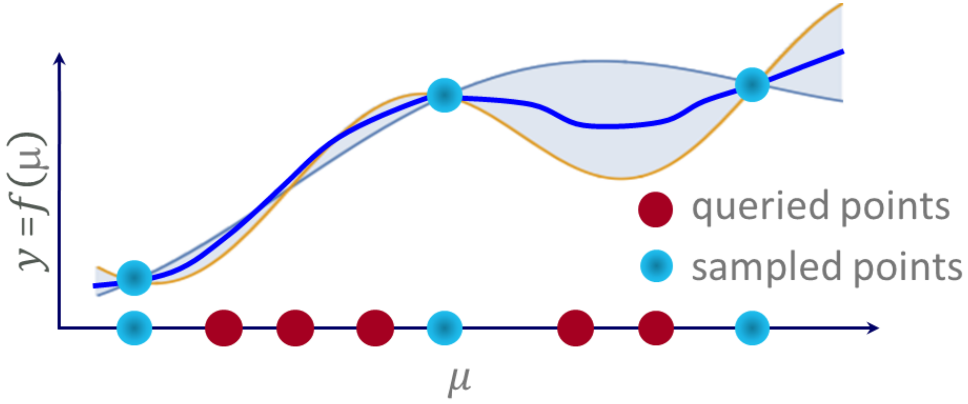
- $T < T_{cr}$
- $\nabla T < \nabla T_{cr}$

- Crack nucleates at the microscale, but online monitoring is performed at the macroscale
  → QoIs? amount of data? model reliability?

Surrogate Modeling

- **External representation**





- **Examples and characterization**
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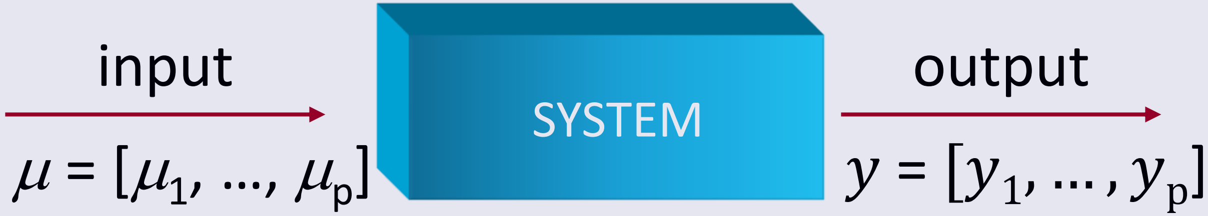
- Internal representation



$y = f(\mu)$ via the post-processing of a ***physics-based***, high-fidelity model of the system

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Danger

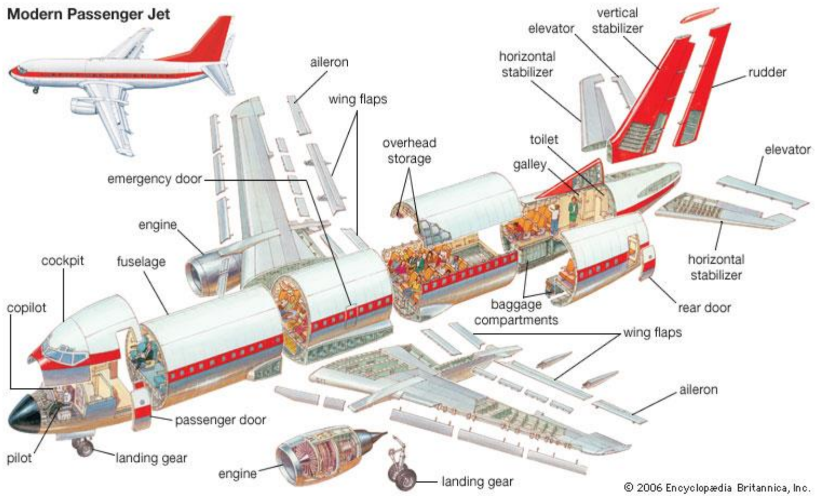
- **In general, there is not much information regarding how accurate a DT is, compared to its physical counterpart**

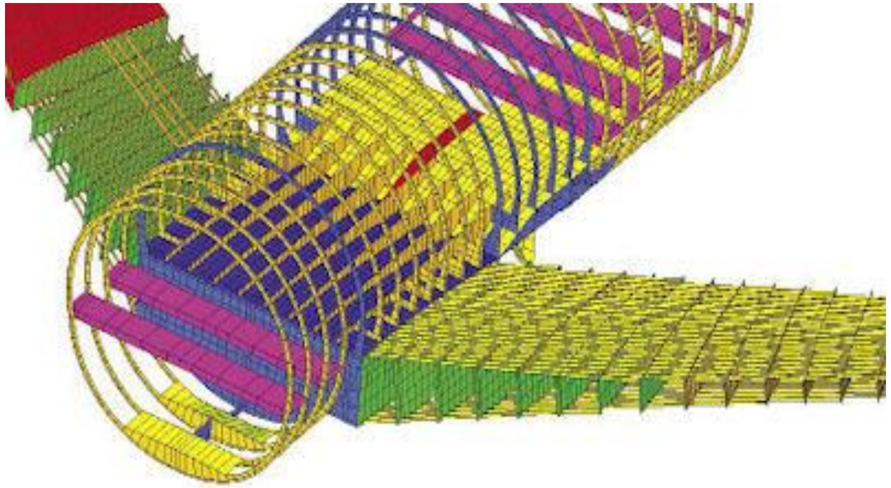
→ the biggest concern that most business owners interested in this technology have is the ***risk of misrepresenting*** the physical asset they want to replicate using a DT

- **Requirements for twinning**
  - ***high-fidelity modeling***, whether data-driven or physics-based-model-driven (DTP)
  - ***modeling and quantifying uncertainty*** – and particularly model-form uncertainty (MFU)
  - ***(non parametric) model updating***

Model-Form Uncertainty (MFU)

- **In general, once a model must be considered for any purpose, MFUs is unavoidable**





  - lack of knowledge of the true physics underlying the problem of interest
  - omission or truncation of modeling details, (e.g. in computational structural dynamics: constitutive, multi-scale, friction, homogenization, and free-play modeling errors)
- **Less studied in literature on uncertainty quantification (UQ) than parametric uncertainty**

UQ Using Surrogate Models

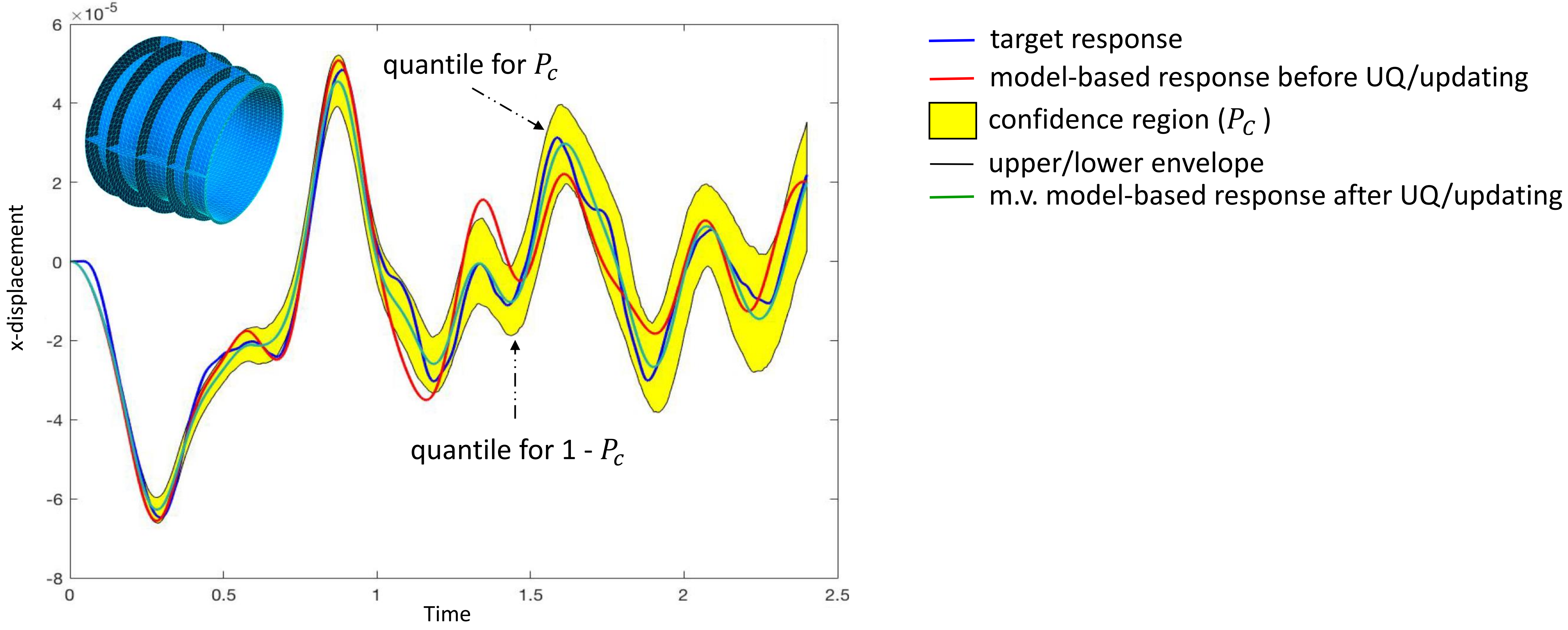
- **The typical method for UQ involves stochastic computations (e.g. Monte Carlo realizations):** thus, it calls for surrogate models in order to achieve computational tractability → ***additional MFU***

- **In the case of PROMs**
  - adaptive vs nonadaptive training of a reduced-order basis (ROB)
  - finite sampling during training of a ROB
  - projection error due to truncation
  - modeling error due to adaption of a PROM

- **In the case of regression of QoIs (response surfaces, GPs, or ANNs)**
  - passive vs active training
  - Gaussian kernel (GP), network architecture (ANN)
  - amount of training data
  - local optimum of the loss function (ANN)

UQ and Model Updating (and thus Digital Twinning) – KPIs

- **For a given probability P_c, compute a confidence region with the following property**



UQ and Model Updating (and thus Digital Twinning) – KPIs

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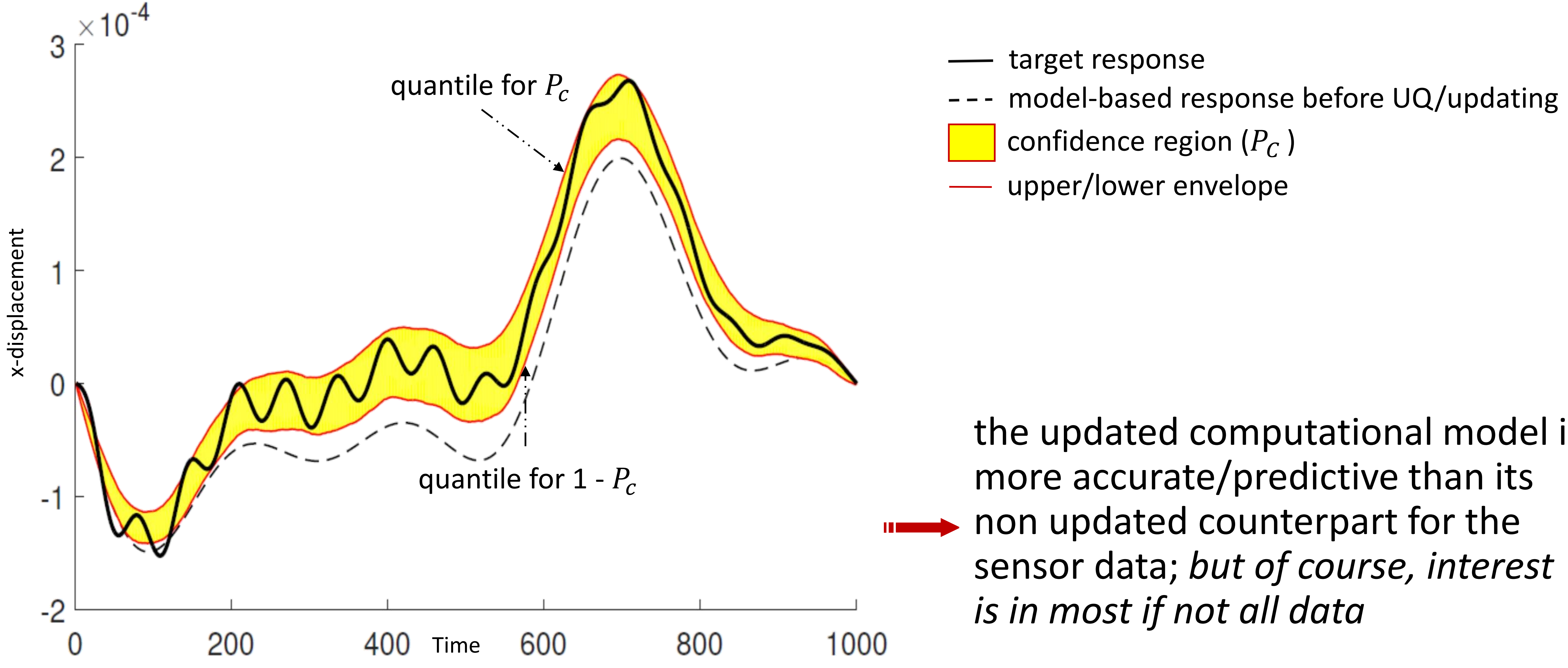
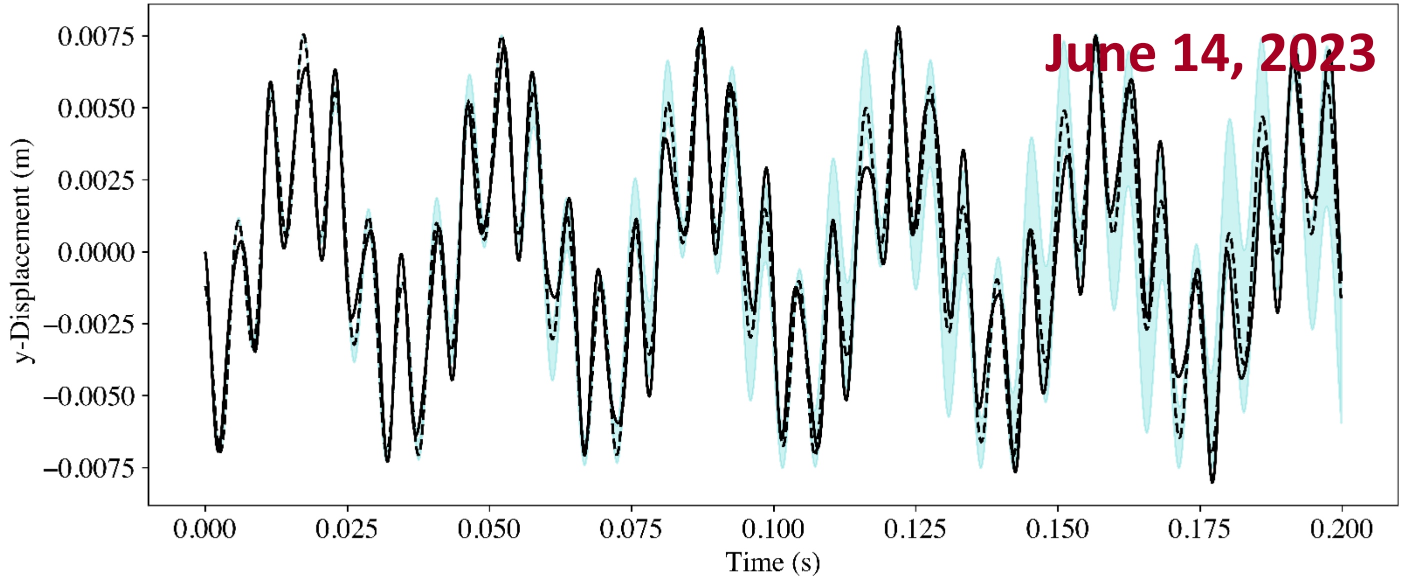
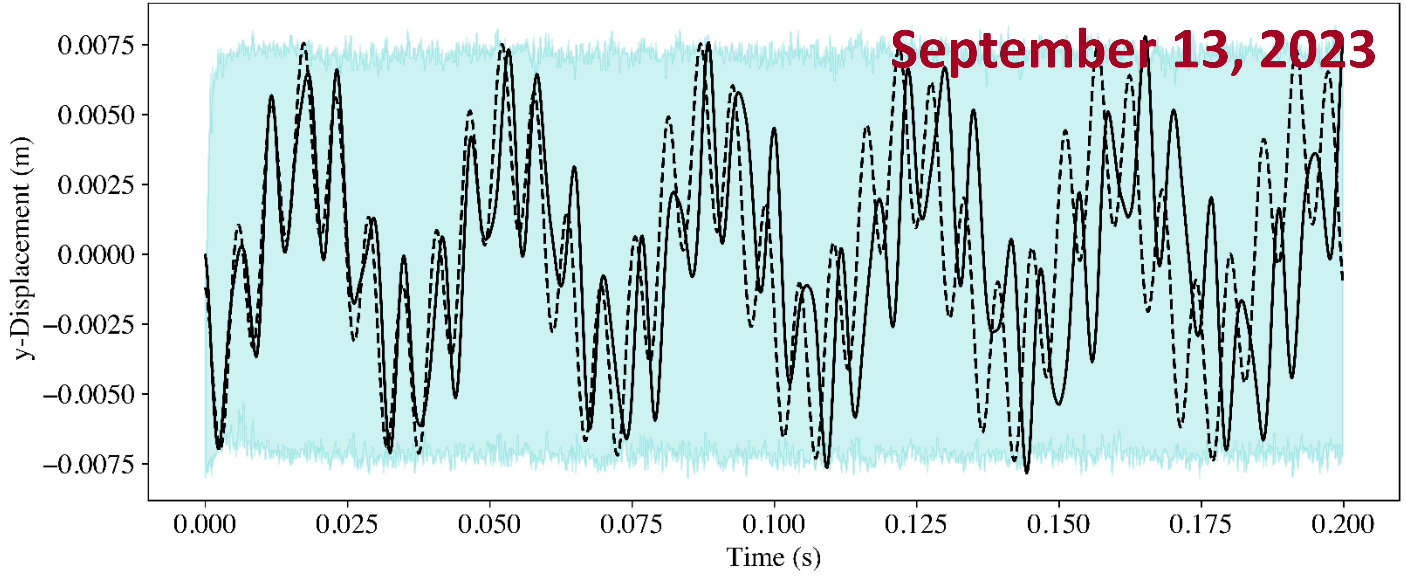
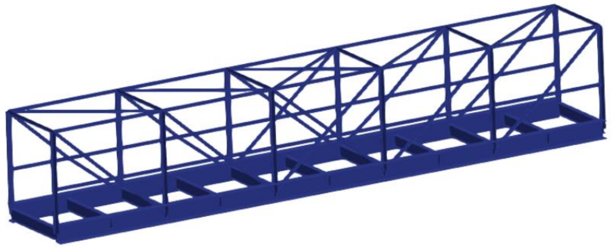


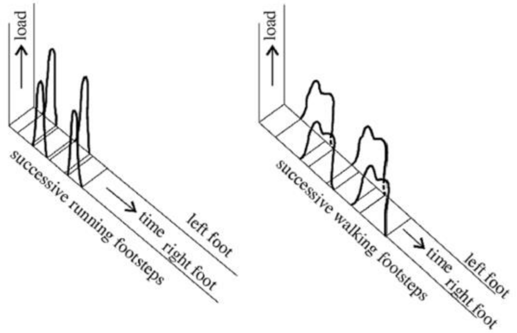
the updated computational model is more accurate/predictive than its non updated counterpart for the sensor data; *but of course, interest is in most if not all data*

DT Concept for Structural Health Monitoring (with Autodesk)







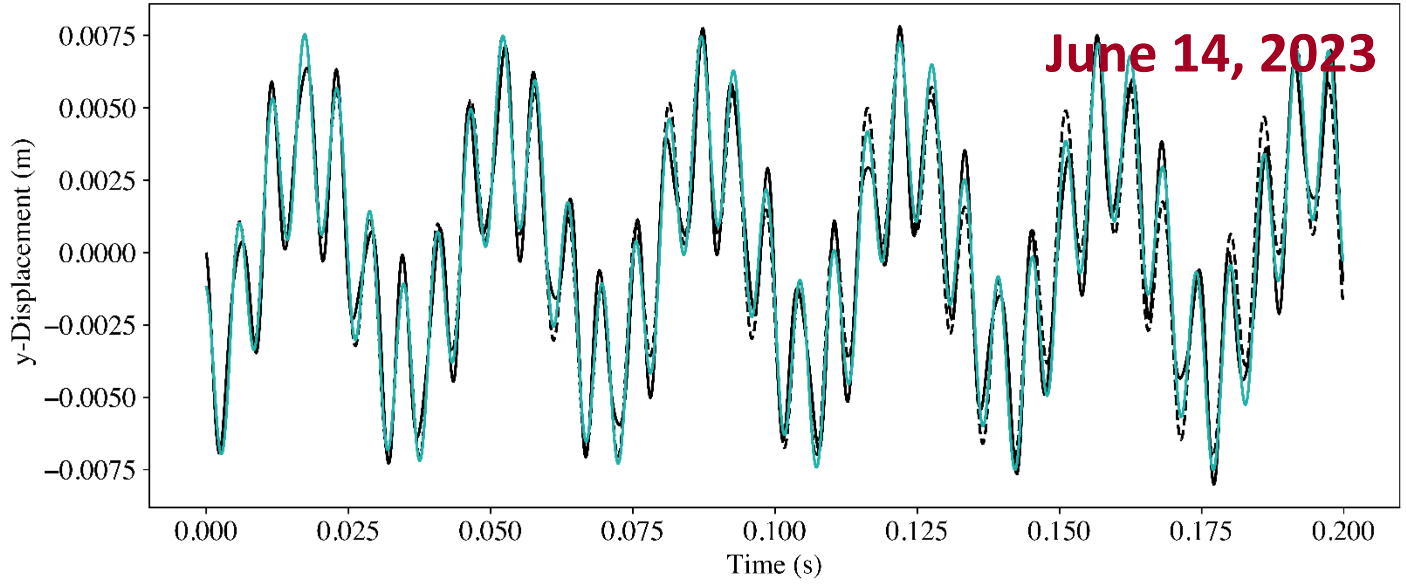


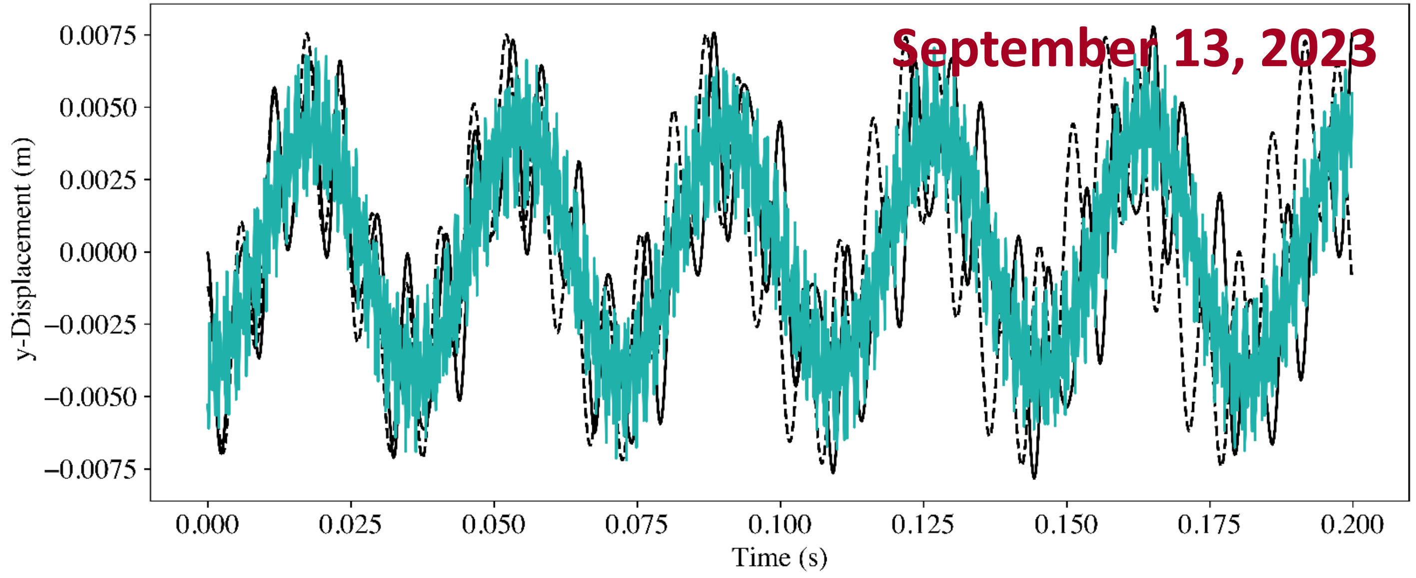
HPROM

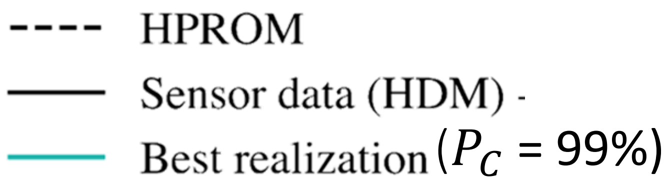
Sensor data (HDM)

SHRPOM realizations (P_C = 99%)

DT Concept for Structural Health Monitoring (with Autodesk)







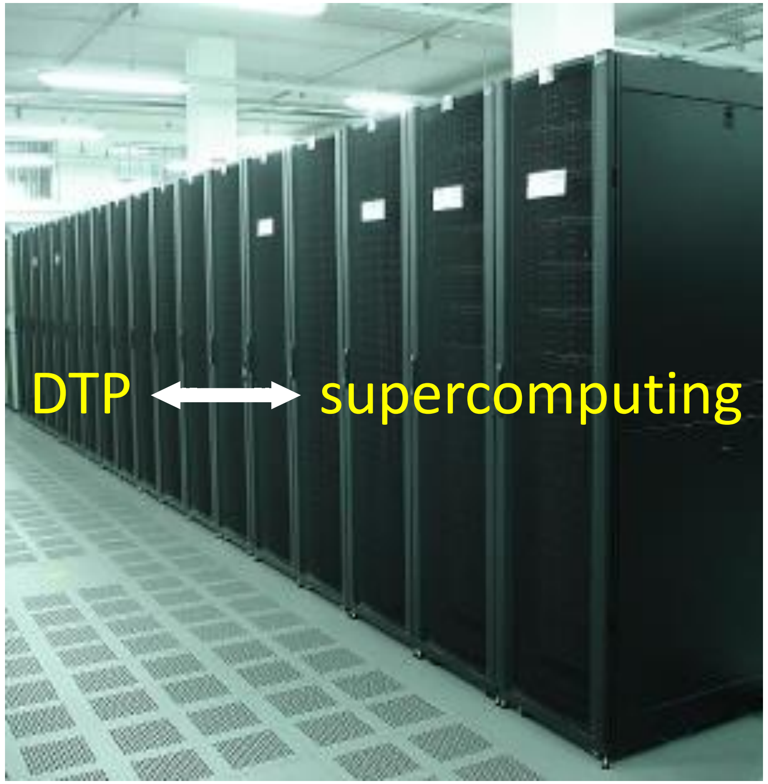
- **Preventive maintenance (more economical than scheduled maintenance)**
- **Early warning system for damage detection**

Backdrop Computational Models – DTP

- **Parametric, nonlinear, high-dimensional finite element (FE) model (HDM) of dimension N**

$$M(\mu)\ddot{u}(t;\mu) - f^{\text{int}}(u(t;\mu), \Xi(t);\mu) = f^{\text{ext}}(t;\mu)$$
$$u(0;\mu) = u_0(\mu), \quad \dot{u}(0;\mu) = \dot{u}_0(\mu), \quad \Xi(0;\mu) = \Xi_0(\mu)$$

- **Nomenclature**
  - $\mu \in \mathbb{D}$: vector of design parameters in a design parameter space of moderate dimension
  - $u \in \mathbb{R}^N$: semi-discrete high-dimensional solution
  - a dot : designates a time derivative
  - $f^{\text{int}} \in \mathbb{R}^N$: semi-discrete vector internal forces
  - $f^{\text{ext}} \in \mathbb{R}^N$: semi-discrete vector of source terms
  - $\Xi \in \mathbb{R}^{n_\Xi}$: vector of n_Ξ internal variables



Backdrop Computational Models – PROM (Entry-Level)

- **Corresponding parametric PROM of dimension $n \ll N$**

$$\text{ROB } V \in \mathbb{R}^{N\times n}:\ V^T Q V = I_n,\ Q \in \mathbb{R}^{N\times N},\ u(t;\mu) \approx V y(t;\mu) + u_{\text{ref}},\ y(t;\mu) \in \mathbb{R}^n,\ u_{\text{ref}} \in \mathbb{R}^N$$

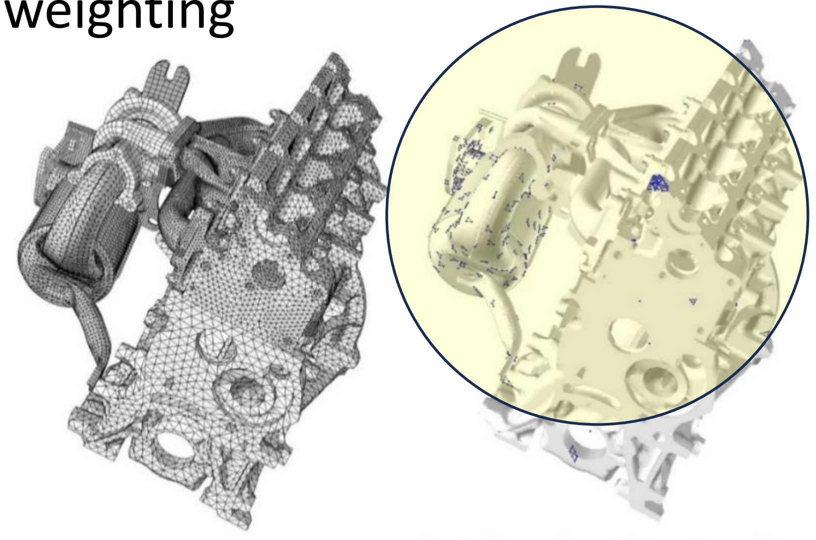
$$M_r(\mu)\ddot{y}(t;\mu) - f_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) = f_r^{\text{ext}}(t;\mu)$$

$$M_r(\mu) = V^T M(\mu) V,\ f_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) = V^T f^{\text{int}}(u(t;\mu),\Xi(t);\mu),\ f_r^{\text{ext}}(t;\mu) = V^T f^{\text{ext}}(t;\mu)$$

- **Nomenclature**
  - $y \in \mathbb{R}^n$: reduced-order vector of generalized coordinates
- **Observation/drawback**
  - complexity of the reduced-order (projected) quantity $V^T f^{\text{int}}(Vy + u_{\text{ref}})$ scales not only with the reduced dimension n, but also with the large dimension $N \gg n$

Backdrop Computational Models – HPROM/RT-DTP

- **Corresponding parametric hyperreduced PROM (HPROM) of dimension $n \ll N$**
  - ECSW (C. Farhat et. al., 2014): energy-conserving sampling and weighting



$$f_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) \approx \tilde{f}_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) = \sum_{e\in\tilde{\mathcal{E}}\subset\mathcal{E}} \xi^e (L^e V)^T f^{\text{int}^e}(L^e V y(t;\mu),\Xi(t);\mu)$$

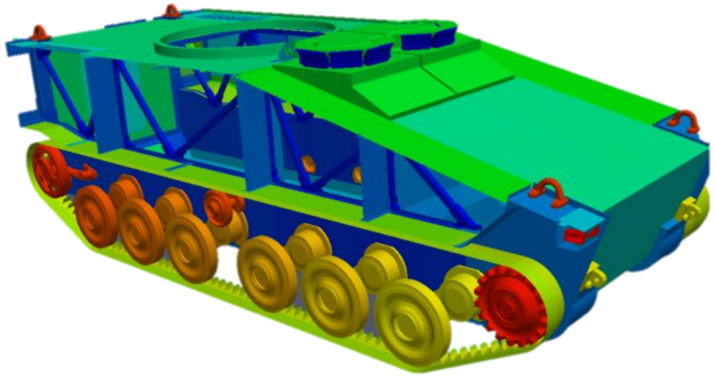
$$f_r^{\text{ext}}(t;\mu) \approx \tilde{f}_r^{\text{ext}}(t;\mu) = \sum_{e\in\tilde{\mathcal{E}}\subset\mathcal{E}} \xi^e (L^e V)^T f^{\text{ext}^e}(t;\mu)$$

$$M_r(\mu)\ddot{y}(t;\mu) - \tilde{f}_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) = \tilde{f}_r^{\text{ext}}(t;\mu)$$

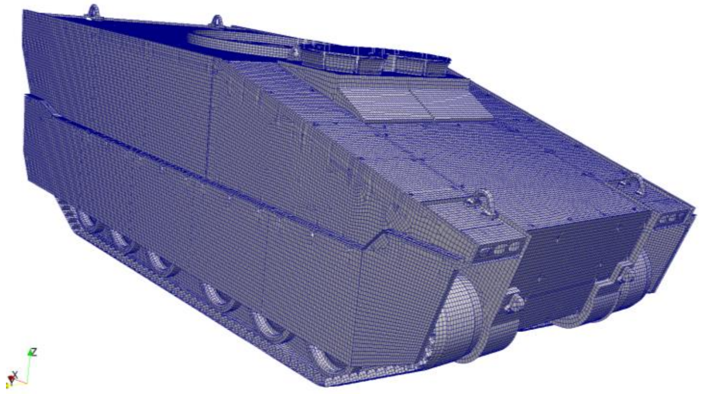
- ECSW computes the cubature parameters $\tilde{\mathcal{E}}\subset\mathcal{E}$ and $\{\xi^e\}_{e\in\tilde{\mathcal{E}}}$ by minimizing a ***loss function*** based on the solution snapshots computed for constructing the ROB V
- the complexity of the ECSW approximation is independent of the large dimension N
- ***ECSW preserves the Lagrangian structure*** of second-order dynamical systems
- ***ECSW preserves the numerical stability*** properties of the preferred time-integrator

Sample Performance of a Nonlinear HPROM/RT-DTP

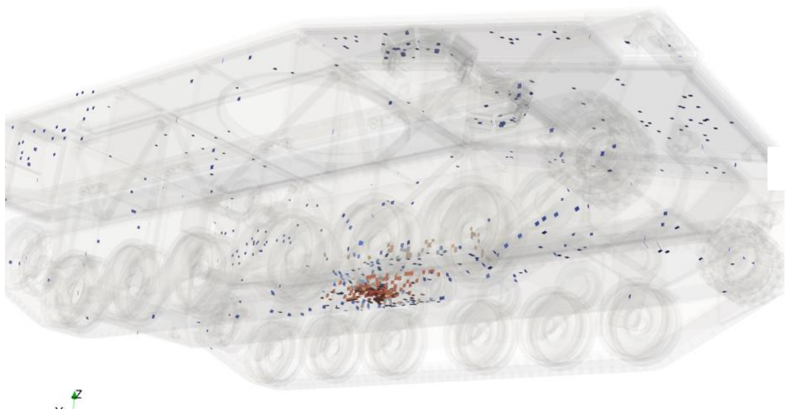
- **Simulation of the underbody blast of an ARES tank**
  - HDM: J2 plasticity; nonlinear kinematics, large deformation, and contact; 336,844 elements (bricks, shells, rigid beams); 346,896 nodes; and $\boldsymbol{N}$ **= 2,043,672** degrees of freedom (dofs)
  - 20 kg TNT (passenger side, wheel assembly) modeled using CONWEP module
  - explicit transient dynamic analysis
  - $\boldsymbol{n}$ **= 31** $\ll$ **2,043,673**; $|\widetilde{\mathcal{E}}|$ **= 697** $\ll$ **336,844**



CAD



Mesh (HDM)



Reduced mesh (HPROM)

Sample Performance of a Nonlinear HPROM/RT-DTP

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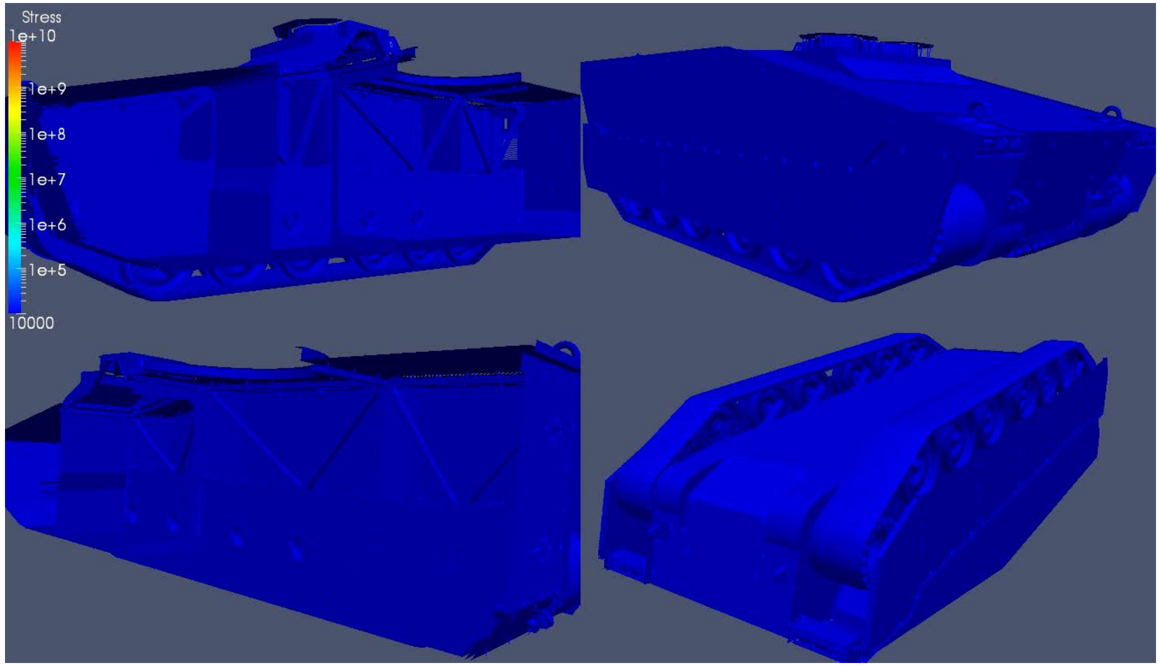
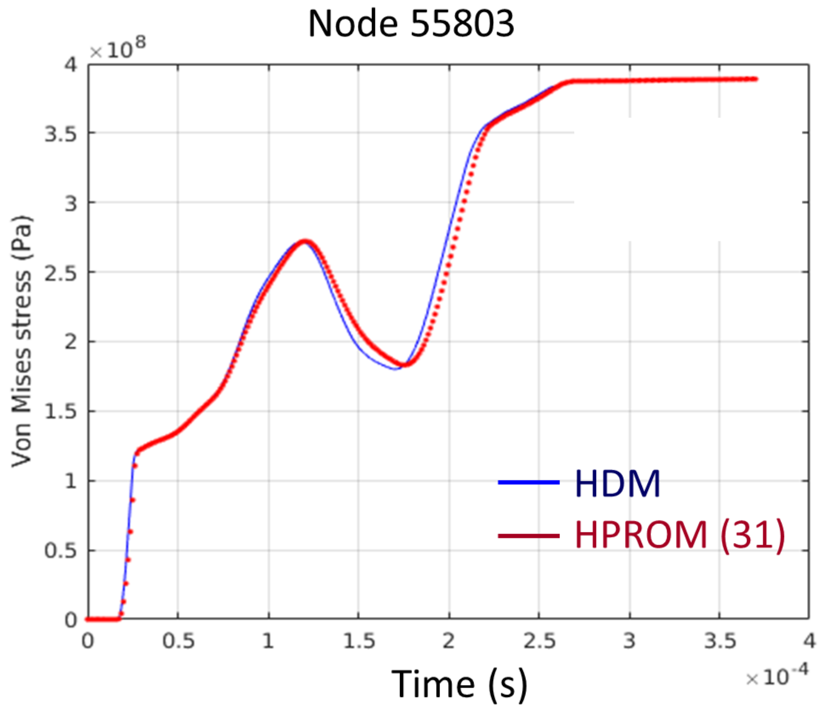




Model	Wall clock time	Speedup
HDM (2,043,673) – 250 cores	1.728×10^5 secs (48 hrs)	wall clock time: 8,228
HPROM (31) – 1 core	21 secs	CPU time: 2,057,142

→ ***a HPROM is a good candidate for constructing a RT-DTP***

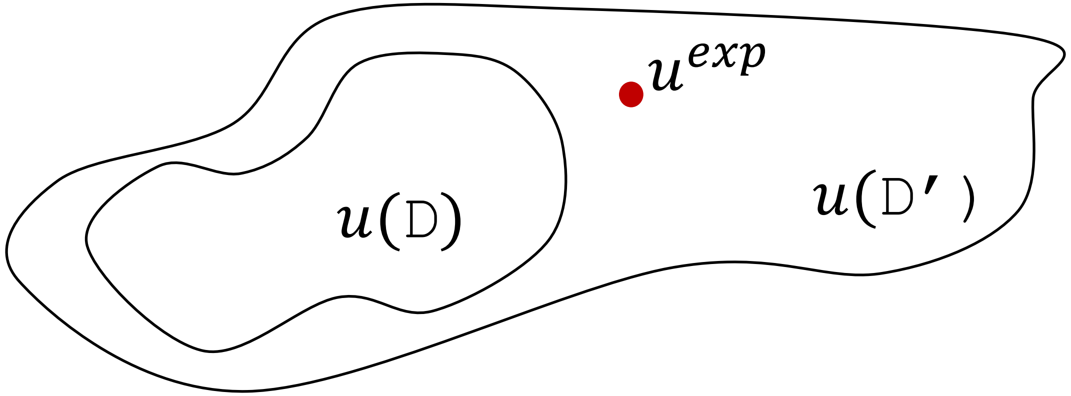
Nonparametric Probabilistic Method (NPM) for MFU

$$M(\mu)\ddot{u}(t;\mu) - f^{\text{int}}(u(t;\mu), \Xi(t);\mu) = f^{\text{ext}}(t;\mu)$$

$$u(0;\mu) = u_0(\mu), \quad \dot{u}(0;\mu) = \dot{u}_0(\mu), \quad \Xi(0;\mu) = \Xi_0(\mu)$$

- **Typical approach for performing UQ and last-generation approach for model updating**
  - randomize/vary the coefficients of the PDE – i.e. the parameter $\mu = (\mu_1, \mu_2, \dots, \mu_{n_\mu})$

  → ***performing model updating is difficult***



- **NPM (Soize and Farhat, 2017): randomizes the subspace in which u is approximated**
  - expands the scope of the approximation subspace without increasing its dimension

C. Soize and C. Farhat, "A Nonparametric Probabilistic Approach for Quantifying Uncertainties in Low- and High-Dimensional Nonlinear Models," IJNME, Vol. 109, pp. 837-888 (2017)

NPM for Modeling and Quantifying MFU – Randomization of the ROB

- **NPM randomizes the subspace in which the solution is approximated**
  - ***operates at the level of the HPROM*** instead of that of the HDM, in order to achieve ***computational tractability***
  - substitutes the deterministic ROB V with a stochastic counterpart $\mathbf{V}(\alpha)$, where $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_{n_\alpha})$ is a vector-valued hyperparameter → hyperparameterized stochastic ROB and HPROM

- **Desired properties of the stochastic ROB**
  - $\mathbf{V}(\alpha)$ is global and therefore independent of μ
  - $\mathbf{V}(\alpha)$ is random with values in $\mathbb{M}_{Nn}$
  - its probability distribution is constructed using MaxEnt
  - the support of this probability distribution is the subset of $\mathbb{M}_{Nn}$ satisfying almost surely the constraint

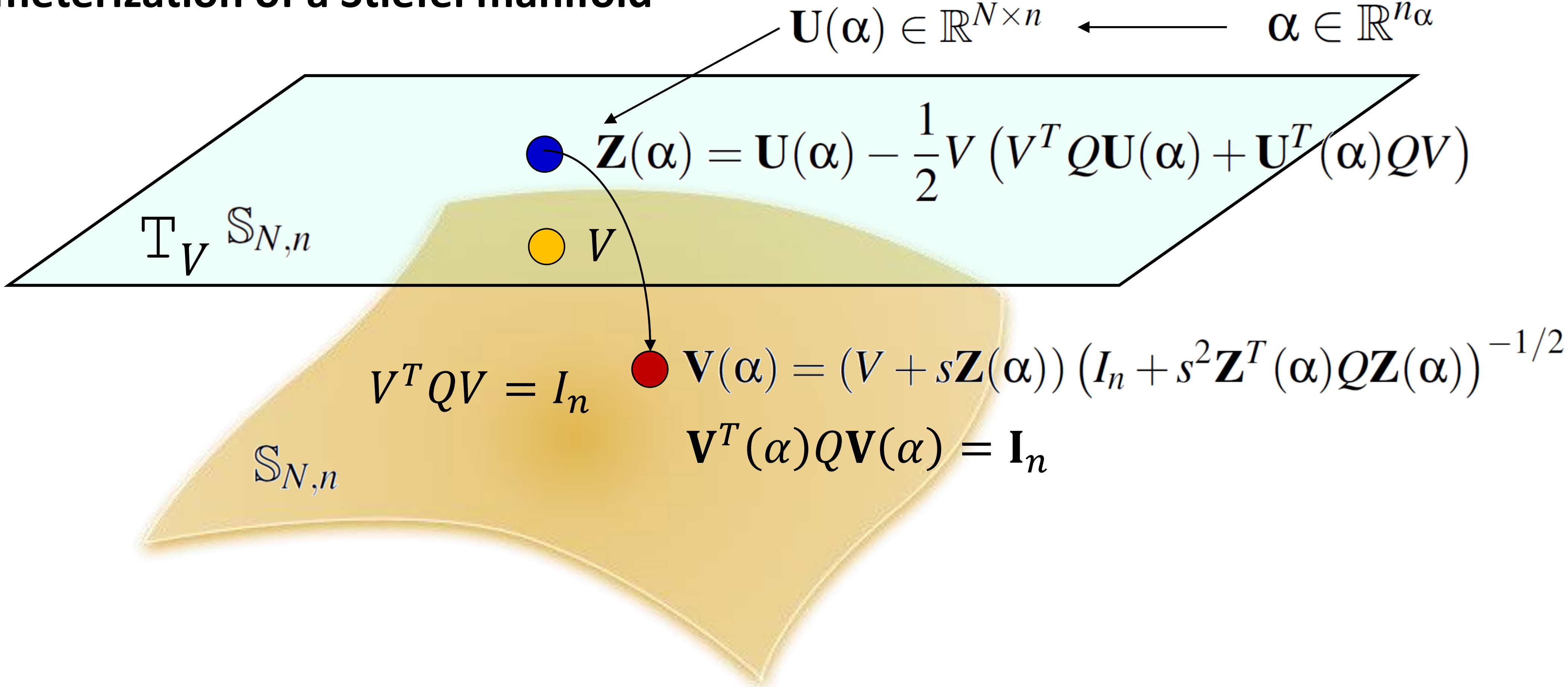
$$\mathbf{V}^T(\alpha) Q \mathbf{V}(\alpha) = \mathbf{I}_n$$

→ ***NPM constructs the probability measure of $\mathbf{V}(\alpha)$ on a compact Stiefel manifold***

C. Soize and C. Farhat, "A Nonparametric Probabilistic Approach for Quantifying Uncertainties in Low- and High-Dimensional Nonlinear Models," IJNME, Vol. 109, pp. 837-888 (2017)

NPM for Modeling and Quantifying MFU – Randomization of the ROB

- **Parameterization of a Stiefel manifold**

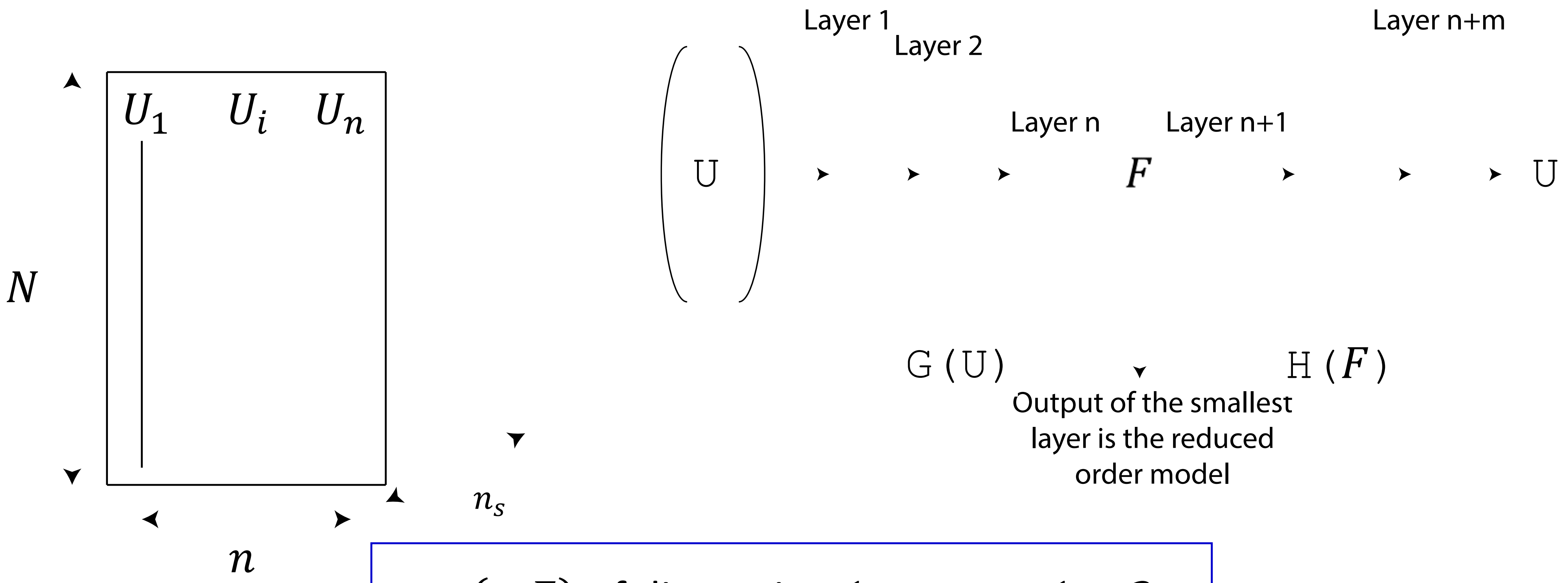


where $\varepsilon_o \leq s \leq 1$, $0 \leq \varepsilon_o \leq 1$, and s is an element of the hyperparameter set α

- **How to construct α with $n_\alpha \ll Nn$ and how to build $\mathbf{U}(\alpha)$?**

NPM – Dimensionality Reduction of the Hyperparameter Space

- **Convolution autoencoders with n_s filters in the input layer**



$$\alpha = (s, F) \text{ of dimension } 1 + n_F \approx 1 + 2n$$

$$\mathbf{U} = \mathrm{H}(F)$$

NPM for Modeling and Quantifying MFU – Model Hierarchy

- **Construction of the corresponding stochastic HPROM (SHPROM)**
  - HDM $$M(\mu)\ddot{u}(t;\mu) - f^{\text{int}}(u(t;\mu),\Xi(t);\mu) = f^{\text{ext}}(t;\mu)$$
  - PROM $$M_r(\mu)\ddot{y}(t;\mu) - f_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) = f_r^{\text{ext}}(t;\mu)$$
  - HPROM: deterministic **RT-DTP**
  $$M_r(\mu)\ddot{y}(t;\mu) - \tilde{f}_r^{\text{int}}(y(t;\mu),\Xi(t);\mu) = \tilde{f}_r^{\text{ext}}(t;\mu)$$
  - SHPROM: stochastic, **RT-DTI** as $\mathbf{V} = \mathbf{V}(\alpha)$

$$\mathbf{M}_r(\alpha;\mu)\ddot{\mathbf{y}}(t,\alpha;\mu) - \tilde{\mathbf{f}}_r^{\text{int}}(\mathbf{y}(t,\alpha;\mu),\Xi(t),\alpha;\mu) = \tilde{\mathbf{f}}_r^{\text{ext}}(t,\alpha;\mu)$$
$$\mathbf{M}_r(\alpha;\mu) = \mathbf{V}^T(\alpha)M(\mu)\mathbf{V}(\alpha)$$
$$\tilde{\mathbf{f}}_r^{\text{int}}(\mathbf{y}(t,\alpha;\mu),\Xi(t);\mu) = \sum_{e\in\widetilde{\mathcal{E}}\subset\mathcal{E}} \xi^e (L^e\mathbf{V}(\alpha))^T f^{\text{int}^e}(L^e\mathbf{V}\mathbf{y}(t,\alpha;\mu),\Xi(t);\mu)$$
$$\tilde{\mathbf{f}}_r^{\text{ext}}(t,\alpha;\mu) = \sum_{e\in\widetilde{\mathcal{E}}\subset\mathcal{E}} \xi^e (L^e\mathbf{V}(\alpha))^T f^{\text{ext}^e}(t;\mu)$$

Sampling snapshots

SVD

ECSW

NPM for Modeling and Quantifying MFU – Enrichment with Data

- **Observables (vector-valued QoI):** $o(t;\mu) = (o_1(t;\mu),\ o_2(t;\mu),\ \cdots,\ o_{n_o}(t;\mu))$
- **Real-time stochastic predictions using the parametric SHPROM:** $\mathbf{o}(t;\mu)$
- **Loss function:** $J(\alpha) = w_J J_{\text{mean}}(\alpha) + (1 - w_J) J_{\text{std}}(\alpha) \qquad 0 \le w_J \le 1$

$$J_{\text{mean}}(\alpha) = \frac{1}{c_{\text{mean}}(\mu)} \sum_{i=1}^{n_\mu^s} \int_{t_0}^{T} \left\| o^{\text{ref}}\left(t;\mu^i\right) - E\left(\mathbf{o}\left(t,\alpha;\mu^i\right)\right) \right\|^2 dt$$

$$c_{\text{mean}}\left(\mu^1,\ \cdots,\ \mu^{n_\mu^s}\right) = \sum_{i=1}^{n_\mu^s} \int_{t_0}^{T} \left\| o^{\text{ref}}\left(t;\mu^i\right) \right\|^2 dt$$

$$J_{\text{std}}(\alpha) = \frac{1}{c_{\text{std}}(\mu)} \sum_{i=1}^{n_\mu^s} \int_{t_0}^{T} \left\| v^{\text{ref}}\left(t;\mu^i\right) - \mathbf{v}\left(t,\alpha;\mu^i\right) \right\|^2 dt$$

$$c_{\text{std}}\left(\mu^1,\ \cdots,\ \mu^{n_\mu^s}\right) = \sum_{i=1}^{n_\mu^s} \int_{t_0}^{T} \left\| v^{\text{ref}}\left(t;\mu^i\right) \right\|^2 dt$$

- Norm: ***Wasserstein distance*** due to its convexity w.r.t translation and dilation of signals

NPM for Modeling and Quantifying MFU – Enrichment with Data

- **Data types**
  - if only high-dimensional data is generated
    - o^{ref} corresponds to the QoIs predicted using the μ-parametric HDM

      → ***NPM models and quantifies MFU due to projection-based model order reduction (PMOR)***
  - if experimental data is available
    - if this data is nonstatistical, $o^{\text{ref}} = o^{\text{exp}}$
    - if this data is statistical, $o^{\text{ref}} = E\left(\mathbf{o}^{\text{exp}}\right)$

      → ***NPM models and quantities MFU inherited by the HDM <u>and</u> MFU due to nonlinear PMOR***
    - multi-modal data assimilation and regularization (see next slide)
- **Identification of NPM's vector-valued hyperparameter α $(\alpha_1, \ldots, \alpha_{n_\alpha})$ and *model update***

$$\alpha^{\text{opt}} = \arg\min_{\alpha} J(\alpha)$$

→

$$\mathbf{M}_r(\alpha^{\text{opt}})\ddot{\mathbf{y}} - \tilde{\mathbf{f}}_r^{\text{int}}(\mathbf{y}; \alpha^{\text{opt}}) = \tilde{\mathbf{f}}_r^{\text{ext}}(\alpha^{\text{opt}})$$

→ **RT-DTI**

NPM for Modeling and Quantifying MFU – Enrichment with Data

- **Multi-modal data assimilation and regularization**
  - in the presence of statistical or nonstatistical experimental data, $o^{\text{ref}} = \{\mathbf{o}^{\text{exp}}, u^{\text{HDM}}\}$
  - in this case, the following composite loss function is appropriate

$$J(\alpha) = w_m J_{\text{mean}}(\alpha) + w_s J_{\text{std}}(\alpha) + (1 - w_m - w_s) J_{\text{orth}}(\alpha), \quad w_m \geq 0, w_s \geq 0, (w_m + w_s) \leq 1$$

where

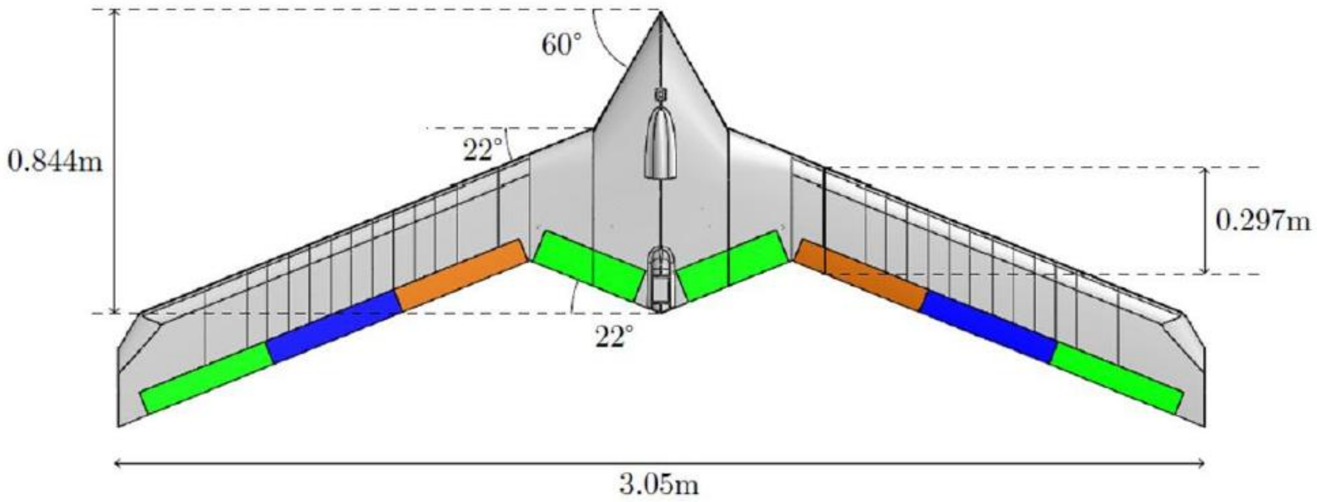
$$J_{\text{orth}}(\alpha) = E\left(\left\| \left(I - \mathbf{V}(\alpha)\mathbf{V}^T(\alpha)\right) u^{\text{HDM}} \right\|^2 \right)$$

- can be generalized to data of different modalities, including pictures, texts, etc.

→ ***NPM extracts knowledge and/or information from multi-modal data*** *via the solution of the reduced-order inverse problem* $\alpha^{\text{opt}} = \arg\min_{\alpha} J(\alpha)$ ***and infuses it into a stochastic reduced-order model*** *– namely, the SHPROM – via the randomized and hyperparameterized ROB* $\mathrm{V}(\alpha)$: *continuous and transfer learnings*

Ground Vibration Analysis of the Flying Wing mAEWing1

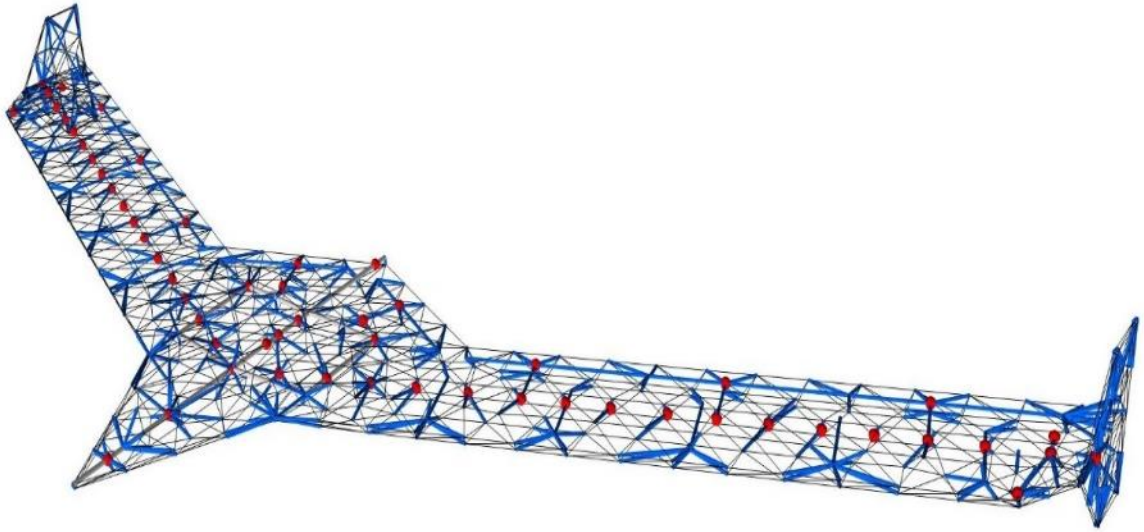
- **Eigenvalue analysis of the mAEWing1 (replica of an X56 type of aircraft made of a composite material and fabricated at the University of Minnesota)**
  - ground vibration tests



Aircraft	f_1 (Hz)		f_2 (Hz)		f_3 (Hz)		f_4 (Hz)		f_5 (Hz)		f_6 (Hz)	
	IDM-1	IDM-2	IDM-1	IDM-2	IDM-1	IDM-2	IDM-1	IDM-2	IDM-1	IDM-2	IDM-1	IDM-2
Sköll	7.23	7.23	8.17	8.14	–	–	15.58	15.58	–	–	26.10	26.02
Hati	7.95	7.96	–	–	–	13.83	15.96	15.97	–	–	32.0	31.9

Ground Vibration Analysis of the Flying Wing mAEWing1

- **Sample application: eigenvalue analysis of the mAEWing1 (replica of an X56 type of aircraft made of a composite material and fabricated at the University of Minnesota)**
  - simplified finite element (FE) model (NASTRAN) of dimension N = **4,146**
  - sources of modeling error (MFU)
    - stick model
    - lumped masses
    - homogenized composite materials
    - undamped model

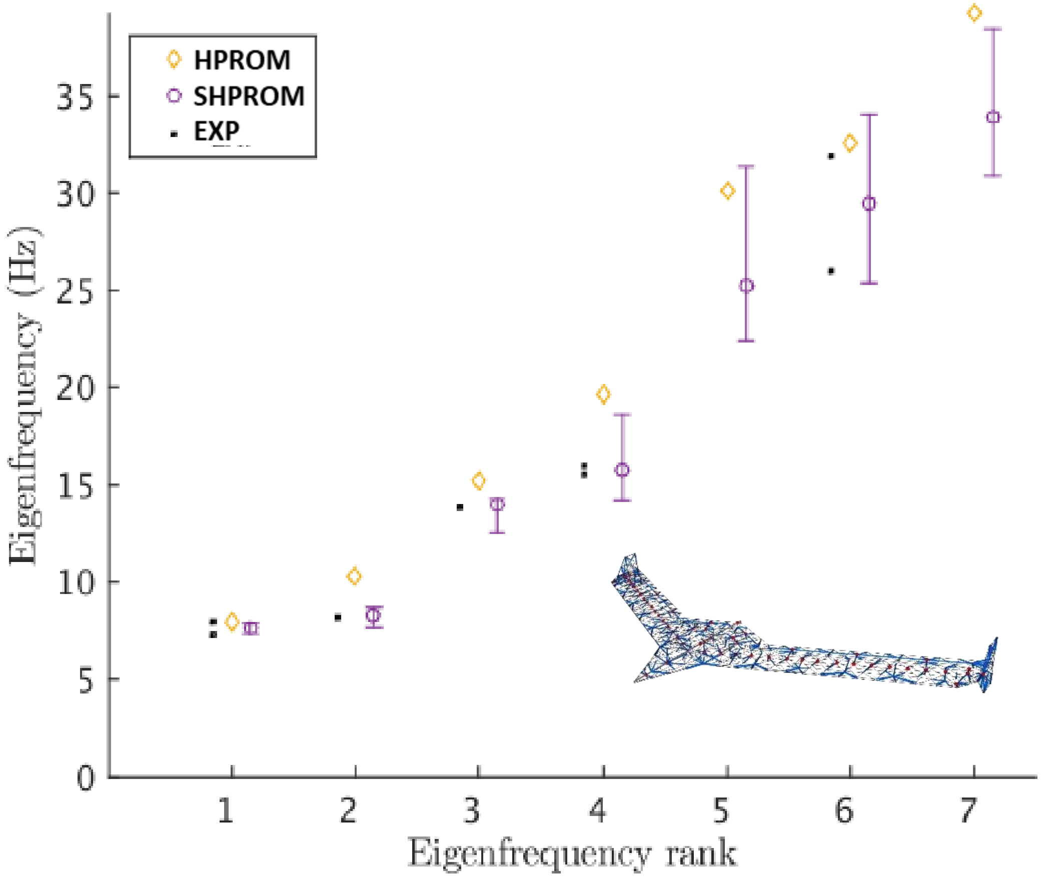


Flexible mode	1	2	3	4	5	6	7
Frequency f (Hz)	7.94	10.29	15.21	19.71	30.16	32.54	39.21

- **SHPROM of dimension n = 10**

Ground Vibration Analysis of the Flying Wing mAEWing1

- **Sample application: eigenvalue analysis of the mAEWing1**
  - confidence intervals constructed with 100 samples corresponding to the quantiles 0.98 and 0.02 – that is, for P_C = 98%



- deterministic HPROM (RT-DTP) captures well the mean values
- SHPROM (RT-DTI) captures well the statistical fluctuations

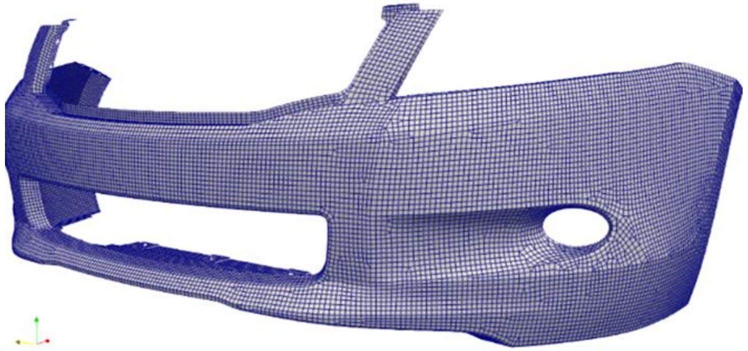
Early DTI at Stanford for Paving the Way to Autonomy

- Quadrotor as a fencing opponent

Crash Analysis of the Front Bumper of the 2013 Honda Accord EX-L

- **HDM, HPROM, and NPM settings**
  - nonlinear kinematics and nonlinear material laws
  - 36,819 shell elements; 37,750 nodes; 37,750 multi-point constraints; and $\boldsymbol{N}$ **= 226,500** dofs
  - explicit transient dynamic analysis
  - $\boldsymbol{n}$ **= 20** $\ll$ **226,500**; $|\widetilde{\mathcal{E}}|$ **= 314** $\ll$ **36,819**
  - HDM on **48 cores: 2,704 secs**
  - HPROM on **1 core: *4.6 secs***

    → wall-clock **speedup factor = 588**
    cpu-time **speedup factor = 28,216**

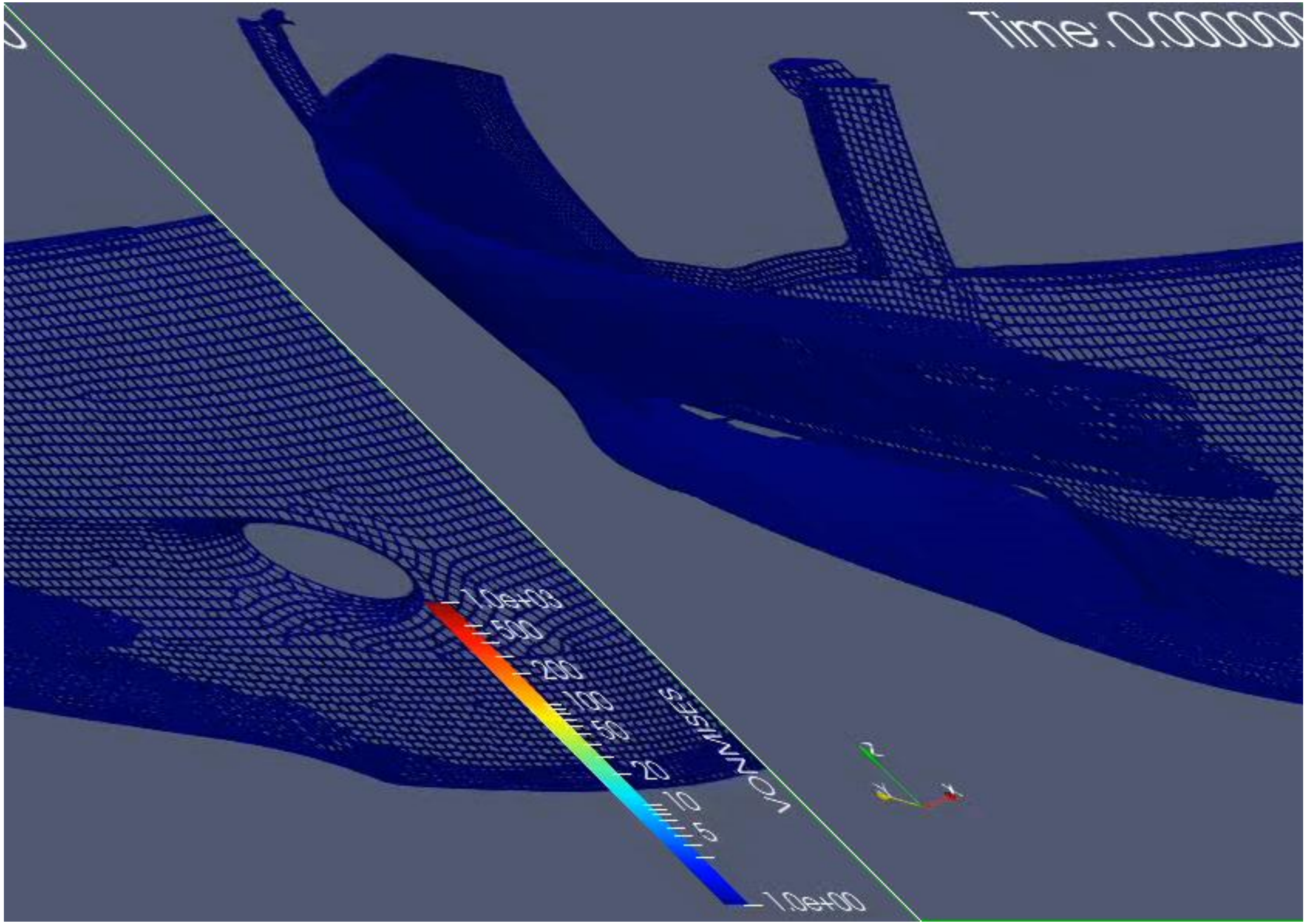


Mesh (HDM)

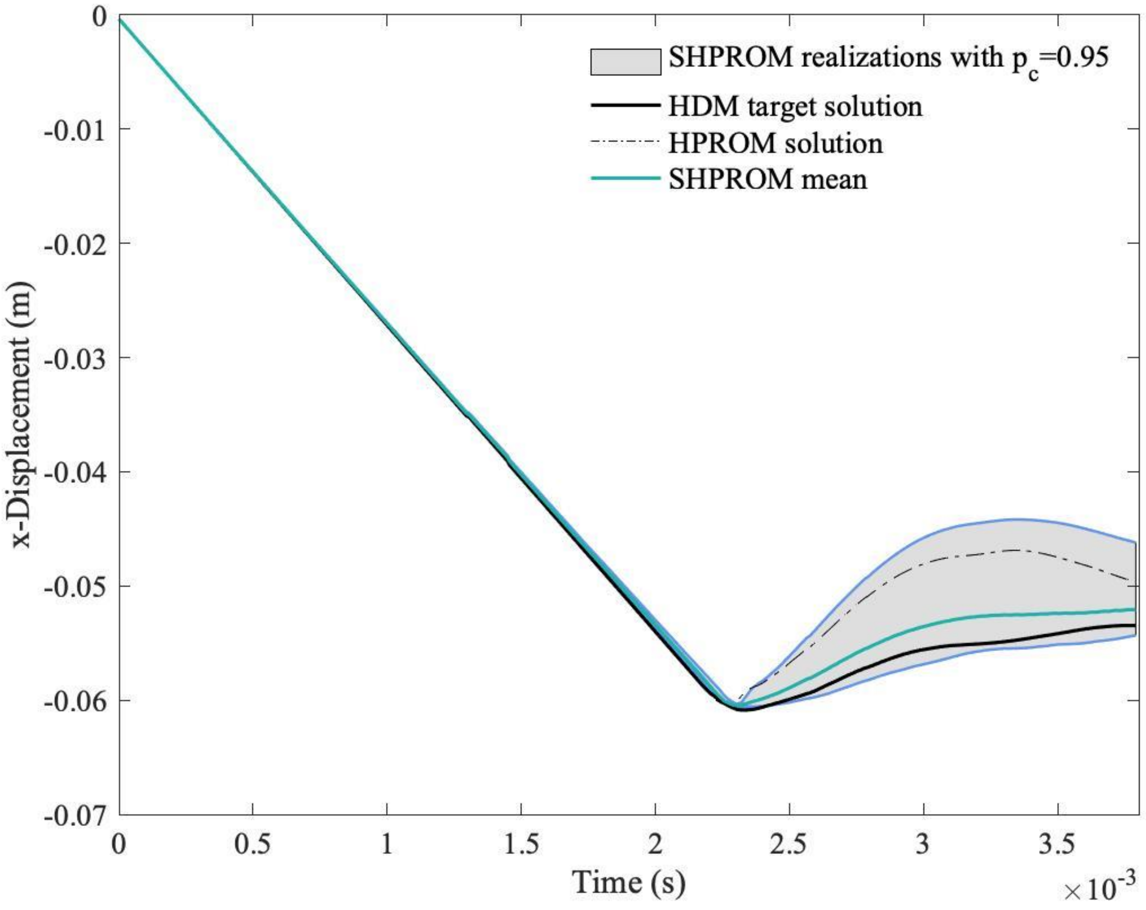
  - w_J = 0.9; $Q = M$
  - $\boldsymbol{n_\alpha}$ **= 212;** $\boldsymbol{n_F}$ **= *61***
  - n_s = 30; P_C = 95%
  - optimizer: MATLAB's fmincon

Reduced mesh (HPROM)

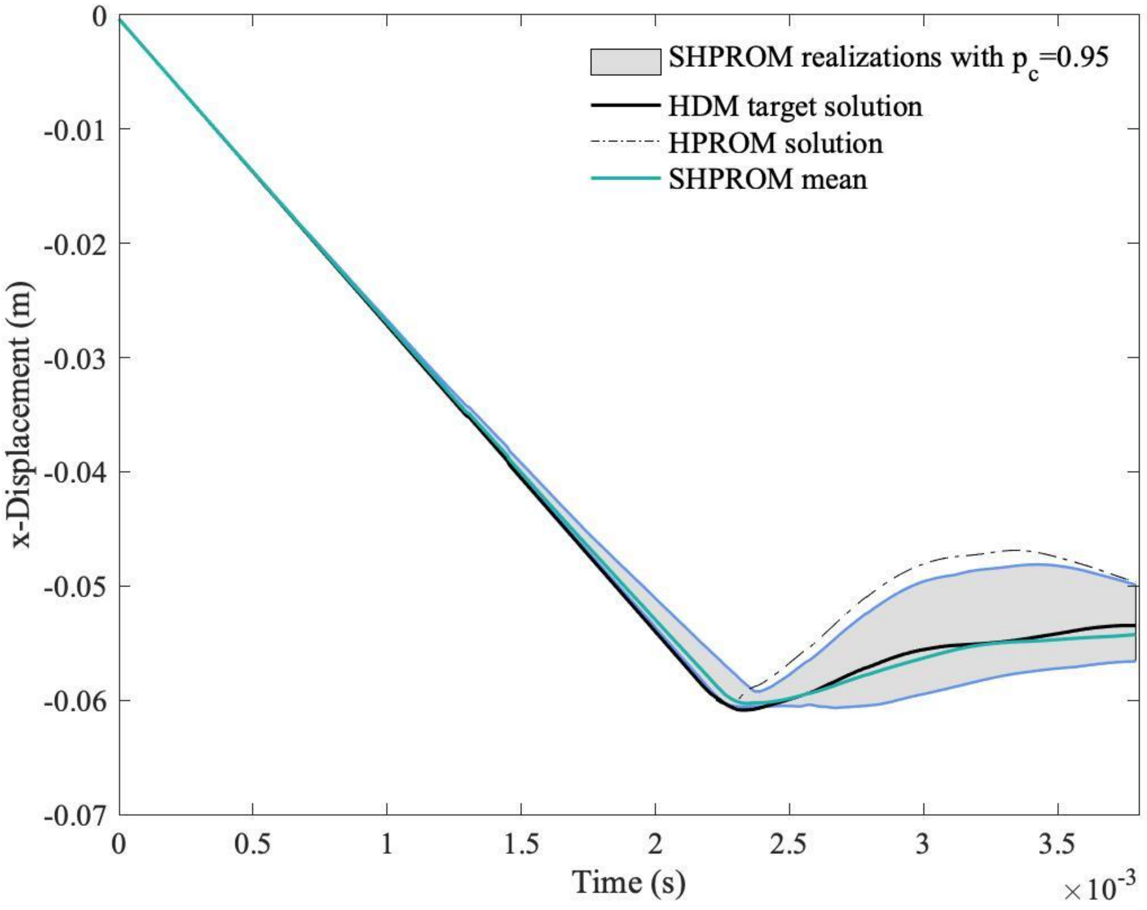
Crash Analysis of the Front Bumper of the 2013 Honda Accord EX-L



Crash Analysis of the Front Bumper of the 2013 Honda Accord EX-L



n_α = 212; 76 hrs on 48 cores



n_F = 61; 3 hrs on 48 cores

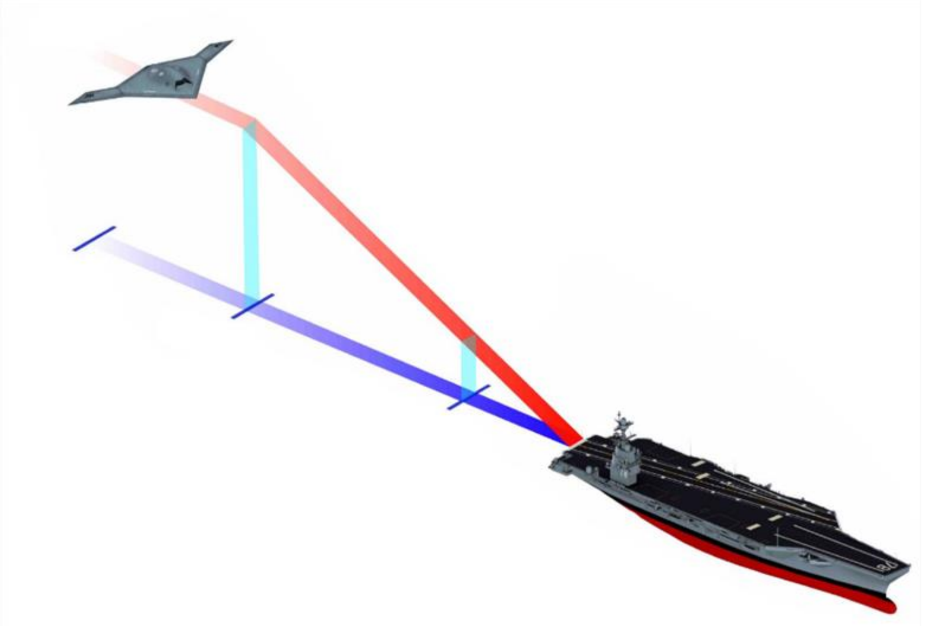
Autonomous Carrier Landing (ACL) Systems

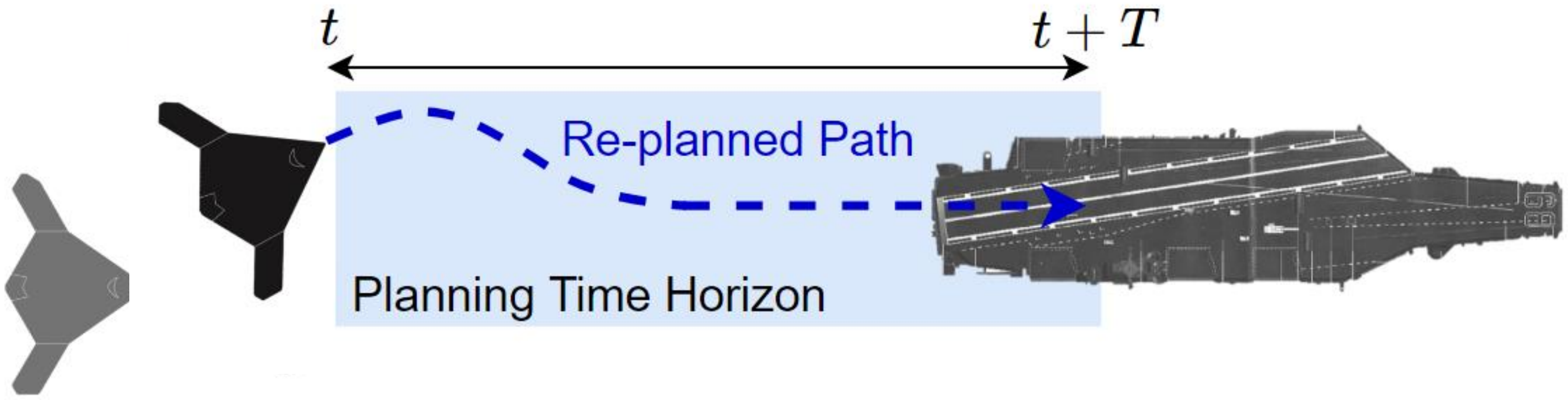
Adapted from "X-47B UCAS Aviation History Under Way" by Northrop Grumman,
Retrieved from https://www.youtube.com/watch?v=WC8U5_4lo2c

Adapted from "Lynx Helicopter Operating Limit Development" by Prism Defence,
Retrieved from https://www.youtube.com/watch?v=bC2XIGMI2kM&t=78s

Model Predictive Control (MPC, with M. Pavone)

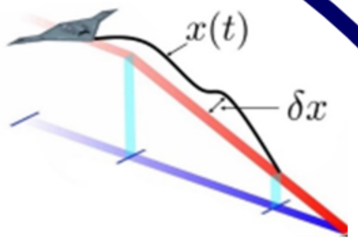
- **Principled method in optimal control theory**
- **Utilizes a *computational model* to optimize a system and predict its future behavior (*OCP*)**
- **Leverages state measurements to incorporate feedback into the system**
- **Accounts for state and control constraints and therefore may enable autonomous abort, and operation at performance limits**



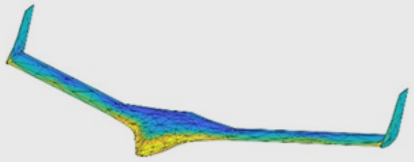


Two-Level Digital Twin

RT-DTI
for MPC of ACL



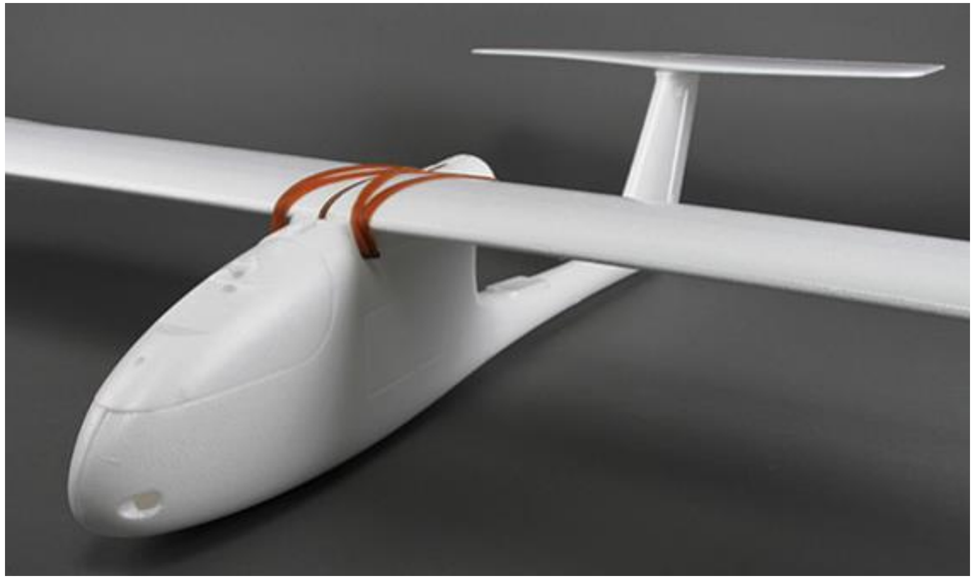
RT-DTP
for aerodynamic state and loads predictions

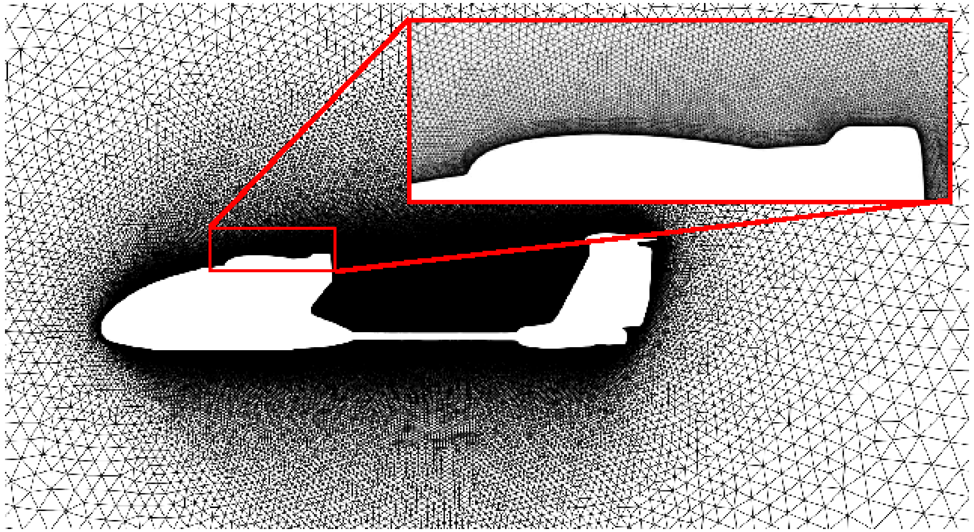


Skywalker 1720 – First CFD-Based HDM and Associated PROM

- **Hobby UAV for a first-person view (FPV) payload**
- **FE structure model**
  - 6-DOF rigid body
  - 4 control surfaces and 4 joint elements
- **CFD-based fluid model for verification simulations**
  - RANS; Spalart-Allmaras turbulence model
  - 2,930,804 grid points → N_{CFD} **= 17,584,824**
  - free-stream: V_∞ = 15 m/s, α = 1.789°, H = 304.8 m
- **Linearized PROM for fluid-structure-control (RT-DTP)**
  - frequency domain

    $\mathcal{B}_\omega = \begin{bmatrix} 0 & 10\pi \end{bmatrix}\ \mathrm{rad\,s^{-1}}$; training at 10 equally-spaced frequencies → 189 solution snapshots
  - PROM dimension: n_{CFD} **= 88**



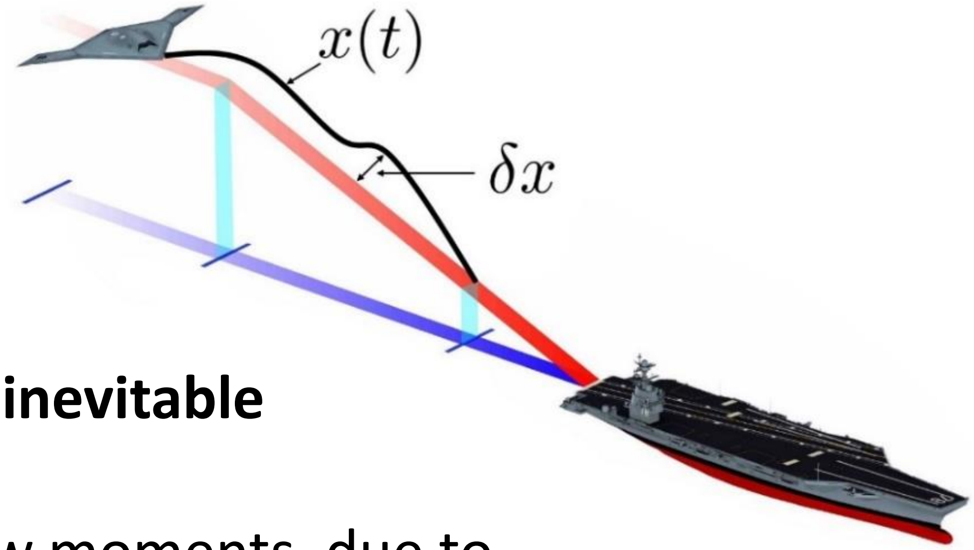


Skywalker 1720 – Simulation of Flight Dynamics and Control

- **Planned aircraft descent simulated using a couped fluid-structure-control HDM**
- **Objective: correct the following initial line-up error using the two-level DT**

$$\delta u_R(0) = \begin{bmatrix} \mathbb{I} & 0 \end{bmatrix} \delta y_R(0) = \begin{bmatrix} 1.0 & -1.0 & 1.0 \end{bmatrix} \mathrm{m},$$

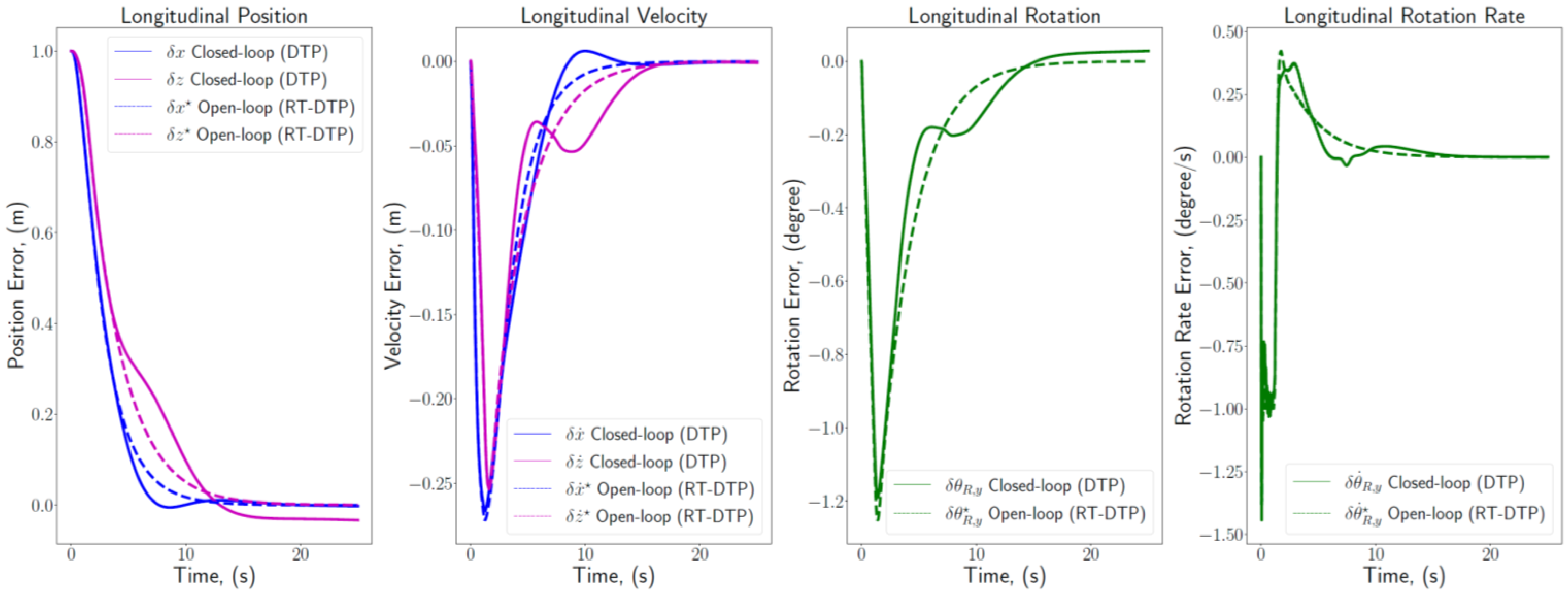
$$\delta \dot{\theta}_{R,y}(0) = 1.24 \times 10^{-3}\,{}^{\circ}\,\mathrm{s}^{-1}, \quad \delta\theta_{\mathrm{CS},e}(0) = -0.307\,{}^{\circ}$$



- **In addition to the initial line-up error, the following is inevitable**
  - disturbances from linearization and PMOR errors
  - disturbance from nonzero lateral force, roll, and yaw moments, due to round-off errors (despite CFD mesh symmetry)
- **Verification of two-level DT**
  - ***closed-loop***: nonlinear DTP for flight dynamics; two-level DT for MPC
  - ***open-loop***: RT-DTP for flight dynamics; two-level DT with RT-DTP for states and loads predictions

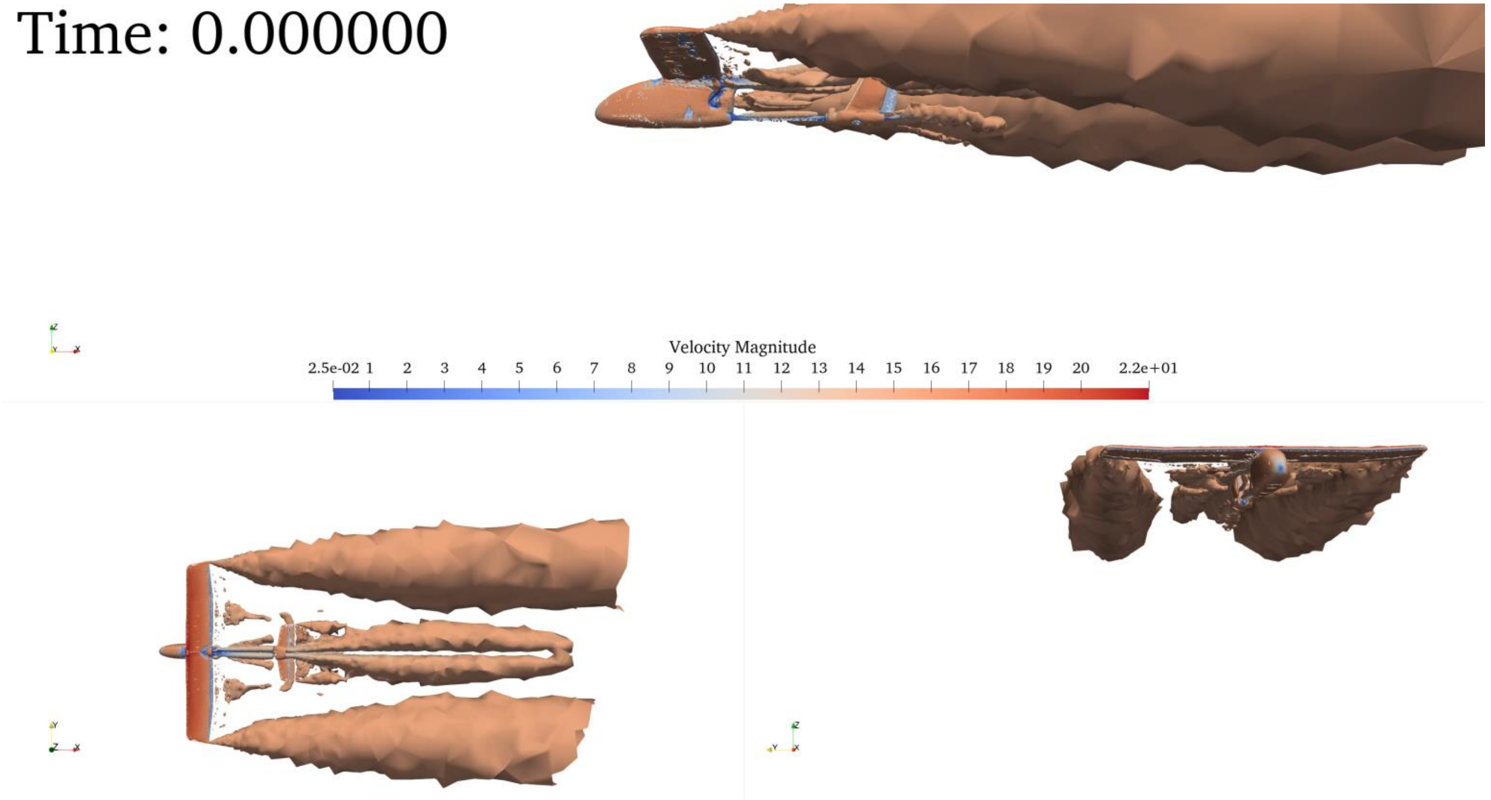
Skywalker 1720 – Simulation of Flight Dynamics and Control: Results

- **Longitudinal components of the dynamic state of the UAV**



Skywalker 1720 – Simulation of Flight Dynamics and Control: Results

- **Line-up error corrections and disturbance eliminations: Q-Criterion contours colored by $||v||$**



RT-DTI component	Wall clock time (msecs)	Number of calls
PROM, state-estimator	6.7×10^{-2}	2,490
OCP	8.4	250

Embedded RT-DTI

intel inside

IDIOT OUTSIDE

DTinside

Conclusions

- Digital twins (DTs) of the instance (DTI) and aggregate (DTA) types are the *real thing*: depending on the physical asset/application, their construction can be challenging and may require starting from a digital twin prototype (DTP)
- Pure DTPs are *marketing ploys*: they may be digital, but are rarely the real McCoy
- The proposed NPM-based approach for building DTIs and DTAs starts from a DTP: through a number of learning steps, it then transforms the DTP into a RT-DTP; then into a DTI; and eventually into a DTA