Component-Based Reduced Order Modeling for Large-Scale Industrial Digital Twins

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Principal Scientist

AKSELOS

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Protecting infrastructure across the energy industry with Akselos Structural Performance Management

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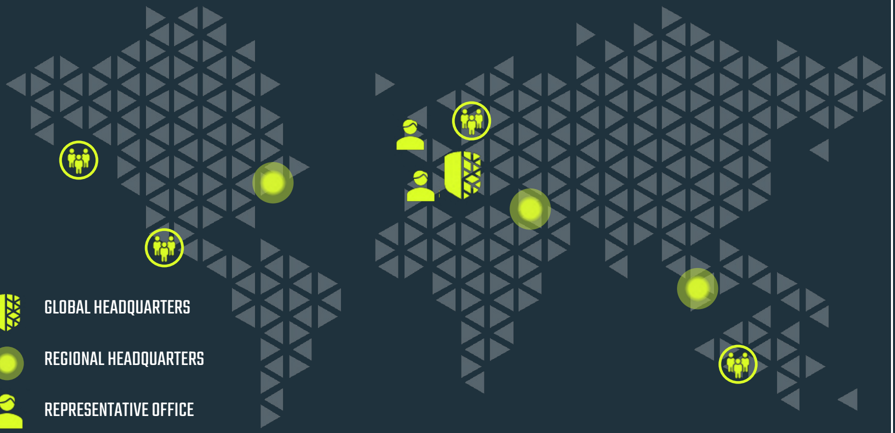

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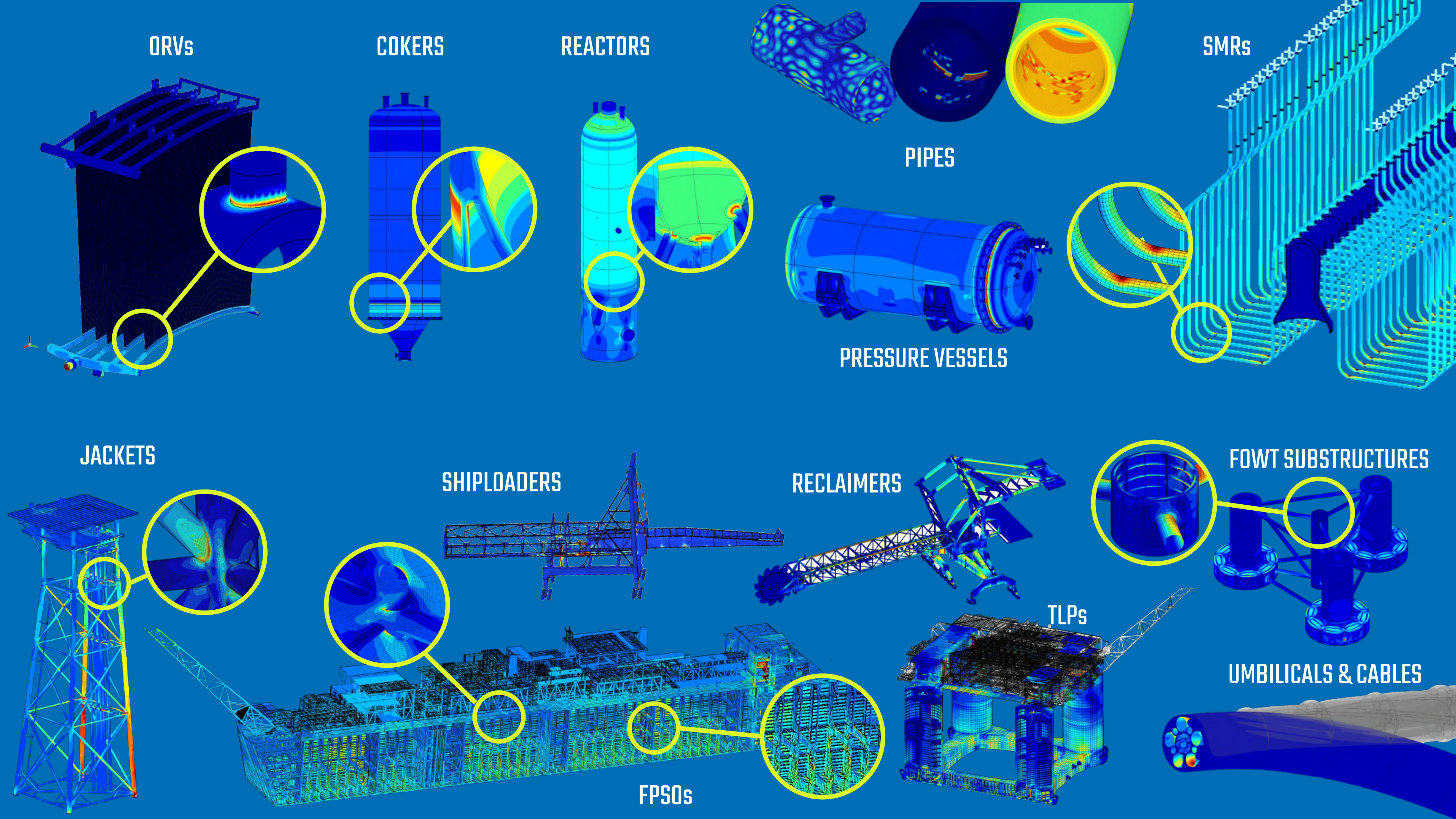
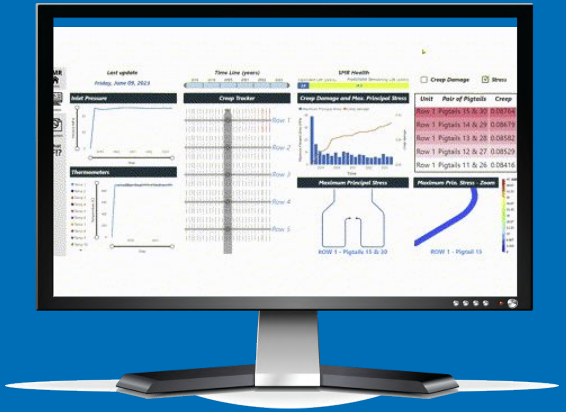
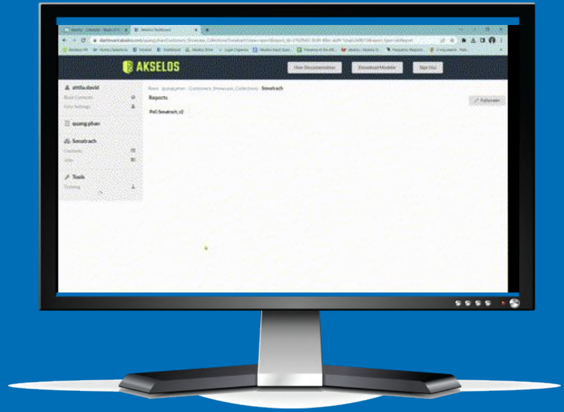
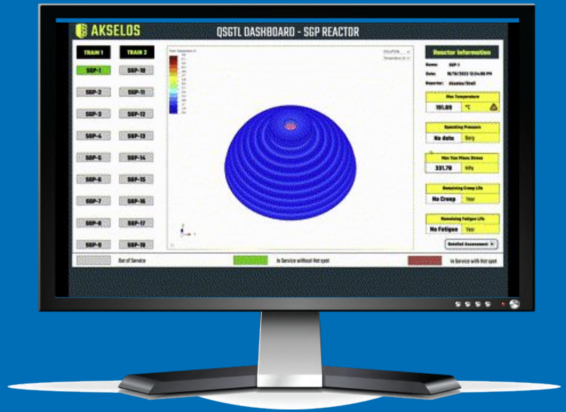

ORVs
COKERS
REACTORS
PIPES
SMRs
PRESSURE VESSELS
JACKETS
SHIPLOADERS
RECLAIMERS
FOWT SUBSTRUCTURES
TLPs
UMBILICALS & CABLES
FPSOs

DASHBOARD EXAMPLES







A Digital Twin Definition

A digital twin is a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value. The bidirectional interaction between the virtual and the physical is central to the digital twin.

US National Academies Report on Digital Twins, Dec 2023

Focus of Akselos Digital Twins

- Structural analysis
- Used in operations, incorporates all data available (design data, sensor feeds, inspection reports, etc.), deliver value to operators!
- Model entire asset in full 3D including “as is” condition data
- Must be fast enough to “keep up” with cadence of operations
- Must be compliant with industry standards (e.g. ASME, API, DNV, ABS, LR, ...)

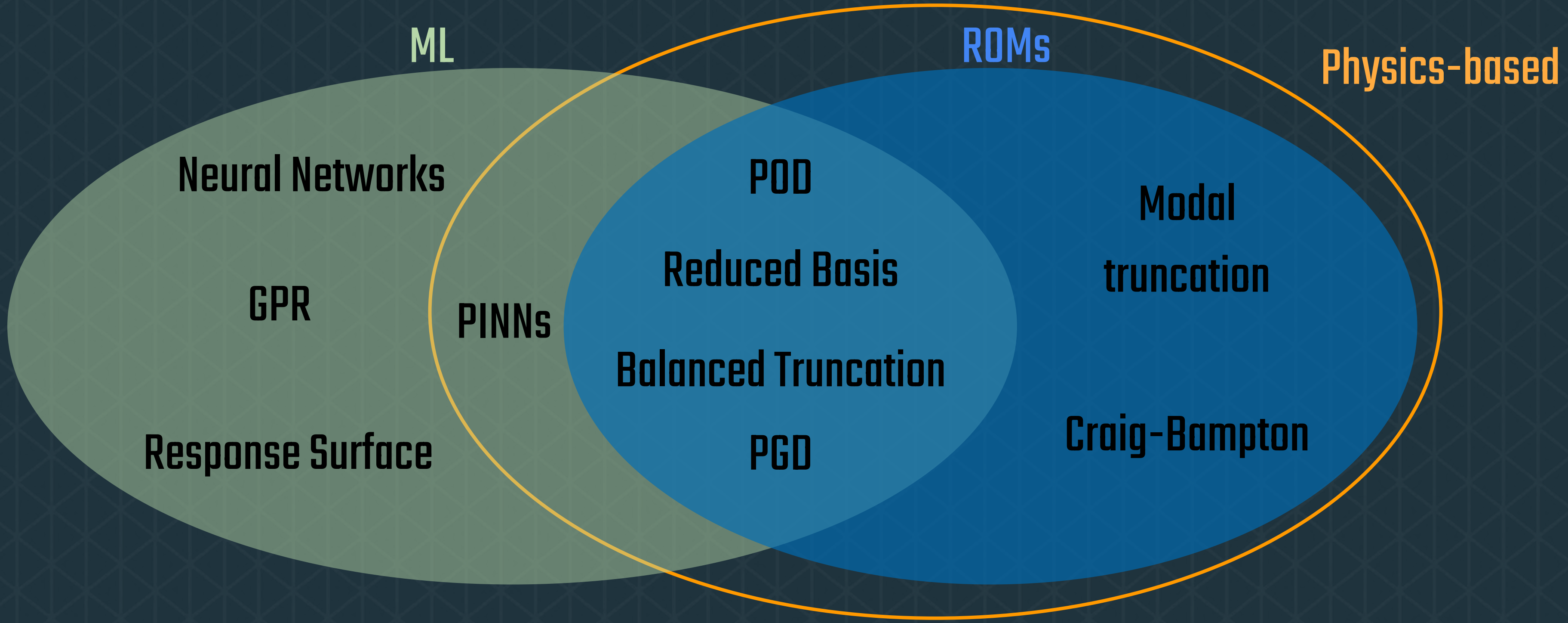
Reduced Order Modeling (ROM) for Digital Twins

To achieve these goals, Akselos uses physics-based ROMs:

- Reduced Basis (RB): ROM for fast response to “keep up” with operations
- Component-based: Large-scale, detailed models of entire assets
- Parametric: Incorporate new data based on sensor or inspections (temperatures, strains, loads, defects, etc.), or run “what if” scenarios
- Based on FEA, with a posteriori error estimators: Compliant with industry standards

ROMs and ML

RB can be considered Physics-based ML: Training phase based on physics to "learn" the response, and fast Online evaluation phase



Reduced Basis Method

FEA: Given the parameter vector μ find solution that satisfies PDE weak form for all "test functions":

$$a(u^N(\mu), v; \mu) = f(v; \mu) \quad \forall v \in X^N$$

RB: Same as FEA, but "trial" and "test" spaces are span of a Reduced Basis ($n \ll N$):

$$a(u_n(\mu), v; \mu) = f(v; \mu) \quad \forall v \in X_n$$

(See review article: Rozza, Huynh, Patera, Arch. Comput. Methods Eng., 2007)

Reduced Basis Method: Linear Algebra Version

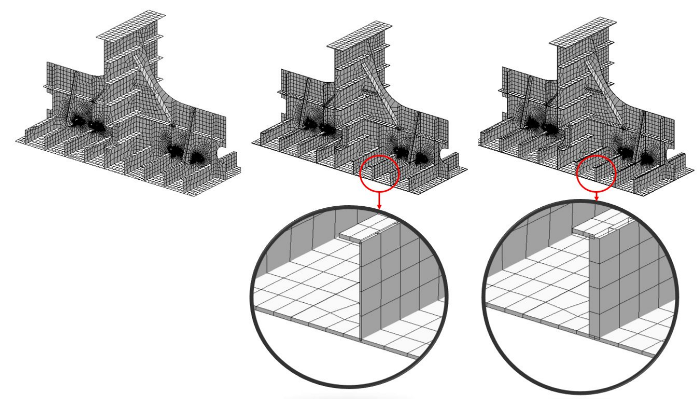
FEA matrices/vectors: $A(\mu) \in \mathbb{R}^{N \times N}$, $U(\mu), F(\mu) \in \mathbb{R}^N$

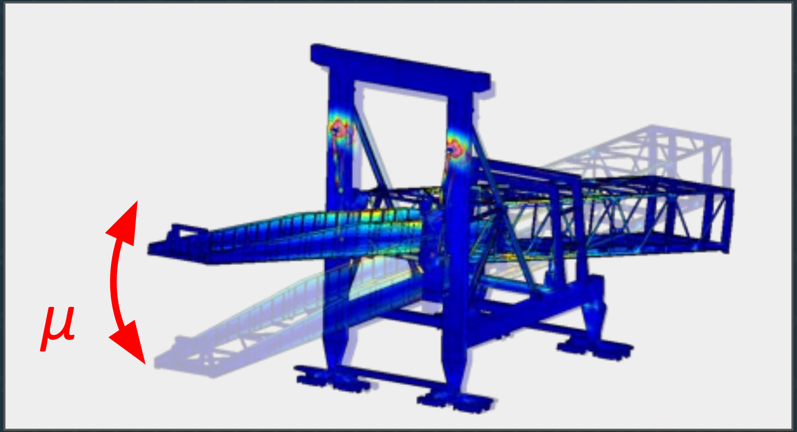
$$A(\mu)U(\mu) = F(\mu)$$

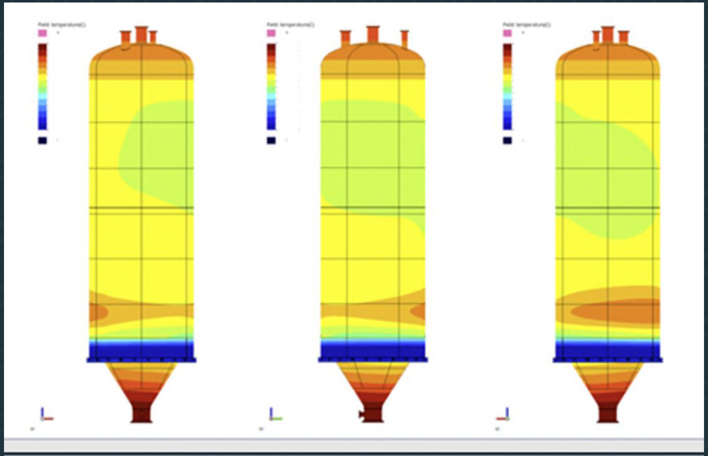
Reduced Basis: $Z \in \mathbb{R}^{N \times n}$, $U_{RB} \in \mathbb{R}^n$

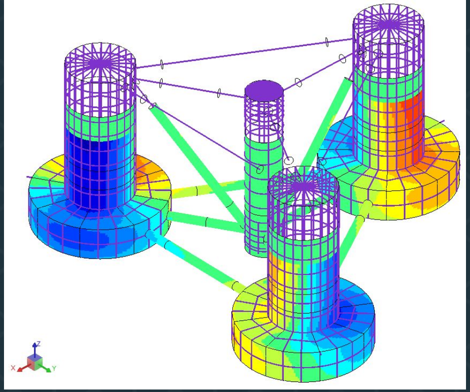
$$Z^T A(\mu) Z U_{RB}(\mu) = Z^T F(\mu)$$

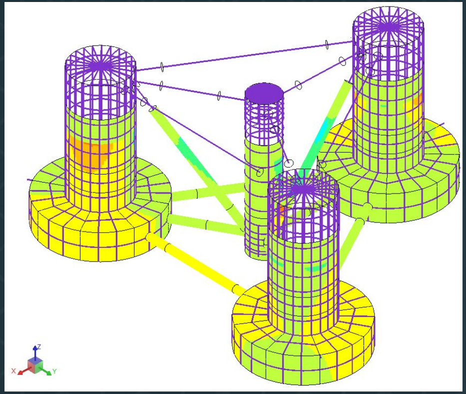
Reduced Basis Method: Parameters



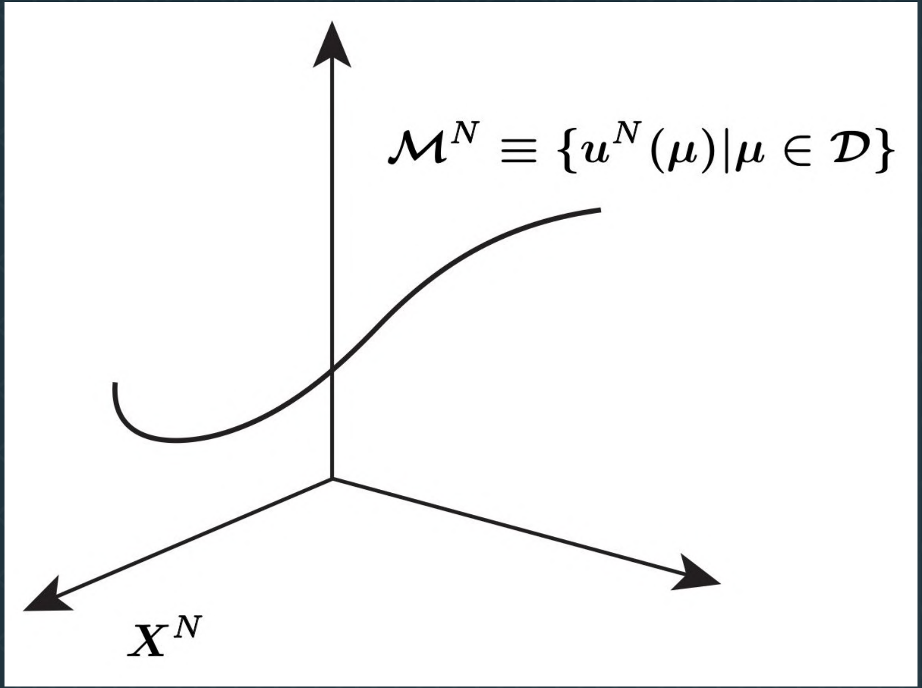






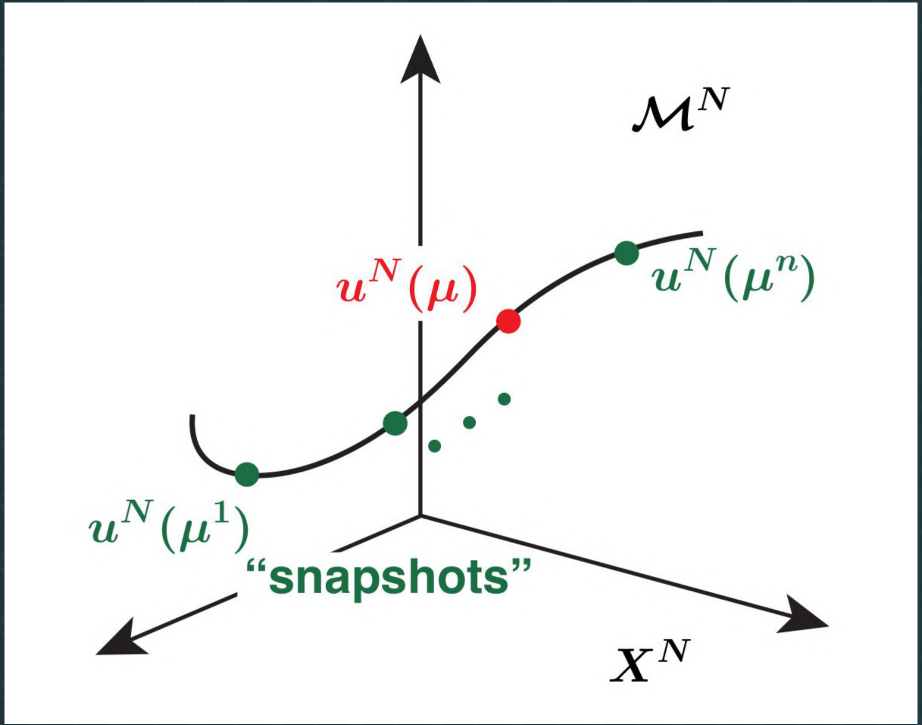


Reduced Basis Method: Solution Manifold



Parametrized "solution manifold" in a high-dimensional space, this is what we want to "learn"

Reduced Basis Method: Solution Manifold



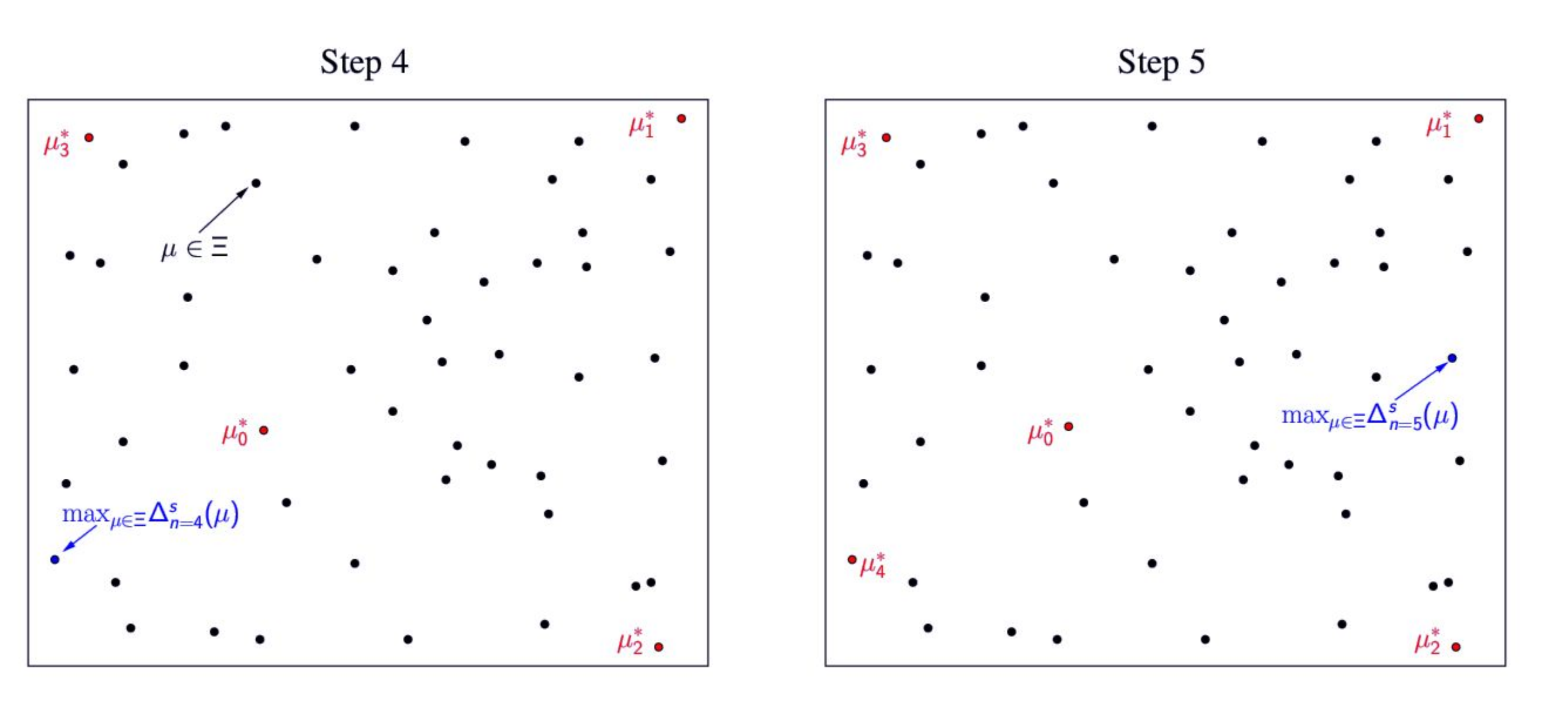
- RB: Generate a subspace highly targeted to the solution manifold via "snapshots"
- Other ML methods aim to learn the nonlinear manifold directly rather than building a subspace

Reduced Basis Method

Two paths to a Reduced Basis:

- POD: Compute snapshots, apply SVD to get “compressed” Reduced Basis (full order solve for each parameter sample, can be expensive!)
- Greedy algorithm: Compute “most beneficial” snapshot at each iteration guided by error estimator (full order solve for each RB basis function only)

Reduced Basis Method: Greedy Algorithm



Greedy algorithm converges rapidly (exponential convergence under reasonable assumptions, see Binev et al., 2010) hence typically reach tolerance with small RB space

Reduced Basis Method: Extensions & Limitations

- RB has been applied to a wide range of PDE types (time-dependent, frequency domain, nonlinear, etc.) following the framework described above

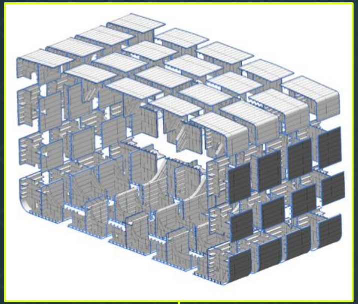
- Key requirement for nonlinear: “hyper-reduction” (e.g. EIM, DEIM, gappy POD) to ensure fast Online response

- Main limitation of RB: Solution manifold must be “smooth” (low Kolmogorov n-width) to permit an accurate low-dimensional Reduced Basis

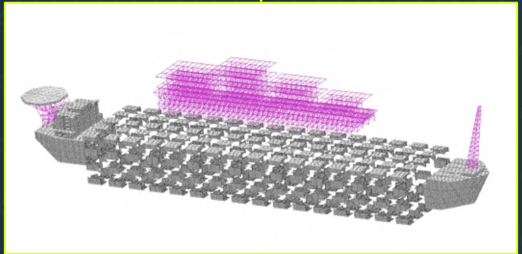
- “Single domain” RB: Limited in model size and number of parameters

Component-Based RB

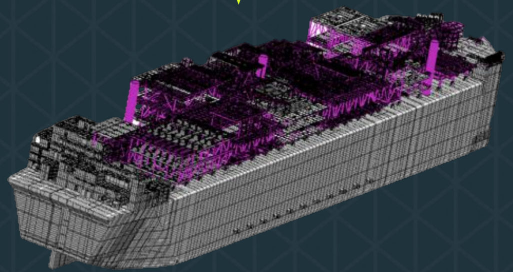
Huynh, Knezevic, Patera, “A Static condensation Reduced Basis Element method: approximation and a posteriori error estimation”, M2AN 2012.



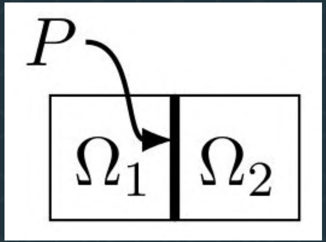
- Component interior and interface ROMs for efficient system modeling with many parameters



- Automated training based on system-level error indicators
- Training based on individual components and component groups, no “global Full Order” solves required in training!



Component-Based: linear case = static condensation



$$\begin{bmatrix} A_{\mathsf{P}} & A^{\mathsf{T}}_{\mathsf{P},\Omega_1} & A^{\mathsf{T}}_{\mathsf{P},\Omega_2} \\ A_{\mathsf{P},\Omega_1} & A_{\Omega_1} & 0 \\ A_{\mathsf{P},\Omega_2} & 0 & A_{\Omega_2} \end{bmatrix} \begin{bmatrix} \mathbb{U} \\ \mathbf{u}_{\Omega_1} \\ \mathbf{u}_{\Omega_2} \end{bmatrix} = \begin{bmatrix} \mathbf{f}_{\mathsf{P}} \\ \mathbf{f}_{\Omega_1} \\ \mathbf{f}_{\Omega_2} \end{bmatrix}$$

$$\mathcal{O}(\mathcal{N}^{1+\alpha})$$

- Schur complement

$$\mathbb{A} = A_{\mathsf{P}} - A^{\mathsf{T}}_{\mathsf{P},\Omega_1} A^{-1}_{\Omega_1} A_{\mathsf{P},\Omega_1} - A^{\mathsf{T}}_{\mathsf{P},\Omega_2} A^{-1}_{\Omega_2} A_{\mathsf{P},\Omega_2}$$

$$\mathbb{F} = \mathbf{f}_{\mathsf{P}} - A^{\mathsf{T}}_{\mathsf{P},\Omega_1} A^{-1}_{\Omega_1} \mathbf{f}_{\Omega_1} - A^{\mathsf{T}}_{\mathsf{P},\Omega_2} A^{-1}_{\Omega_2} \mathbf{f}_{\Omega_2}$$

$$\underbrace{[\mathbb{A}]}_{\mathcal{N}_p \times \mathcal{N}_p} \underbrace{[\mathbb{U}]}_{\mathcal{N}_p \times 1} = \underbrace{[\mathbb{F}]}_{\mathcal{N}_p \times 1}$$

$$\mathcal{O}(\mathcal{N}_p(\mathcal{N}_1^{1+\alpha} + \mathcal{N}_2^{1+\alpha}) + \mathcal{N}_p^3)$$

Component-Based: reduction

- Solve $A_{\Omega_1}^{-1} A_{\mathsf{P},\Omega_1}$ and $A_{\Omega_1}^{-1}\mathbf{f}_{\Omega_1}$ with reduced basis

  $\mathcal{O}(\mathcal{N}_p N^3)$ instead of $\mathcal{O}(\mathcal{N}_p \mathcal{N}_1^{1+\alpha})$

  In total

  $\mathcal{O}(\mathcal{N}_p N^3 + \mathcal{N}_p^3)$ instead of $\mathcal{O}(\mathcal{N}_p(\mathcal{N}_1^{1+\alpha} + \mathcal{N}_2^{1+\alpha}) + \mathcal{N}_p^3)$

- Use a reduced basis for P to make $\mathcal{N}_p$ as small as possible

  Eftang, Patera, "Port reduction in parametrized component static condensation: approximation and a posteriori error estimation.", IJNME 2013.

Component-Based: system-level error indicator

- Based on residual calculation (similar to traditional FEA)

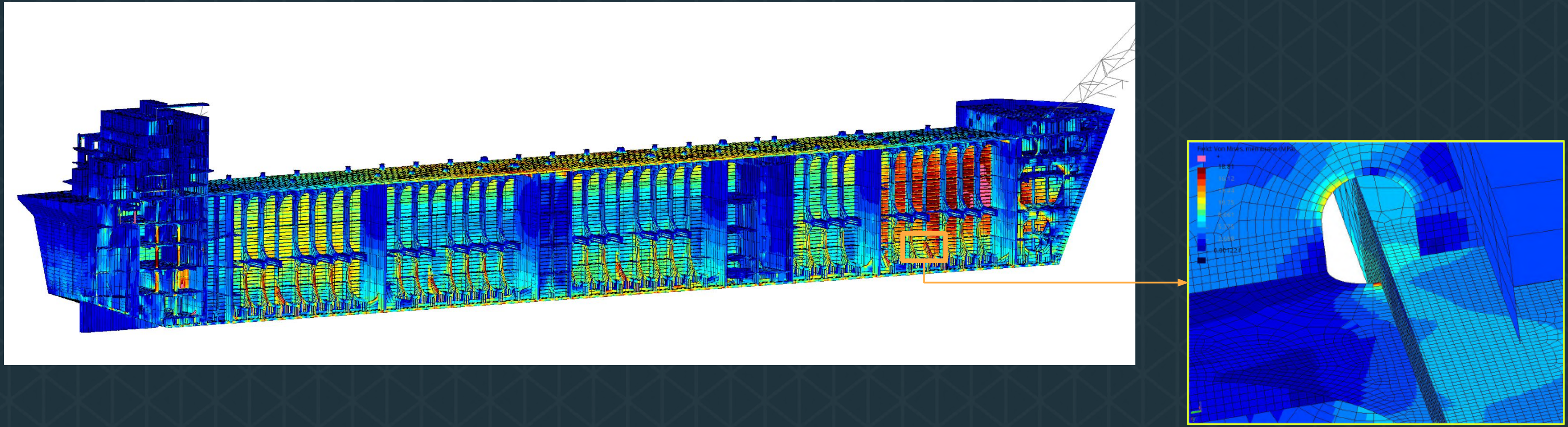
  Smetana, "A new certification framework for the port reduced static condensation Reduced Basis Element method", CMAME 2015.

- Cost is negligible compared to system-level online solve

- Critical to ensure trust from customers: all the industry standards refer to FEA accuracy.

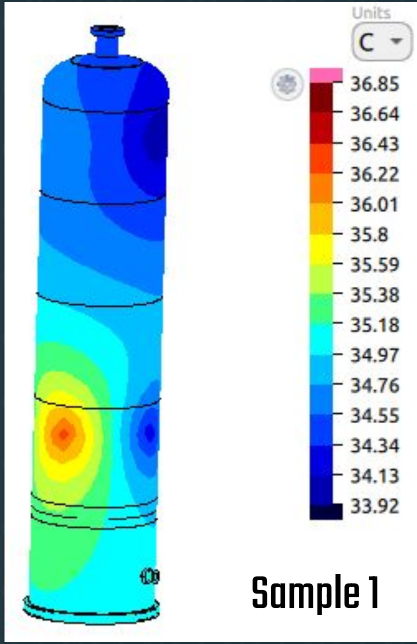
Component-Based RB

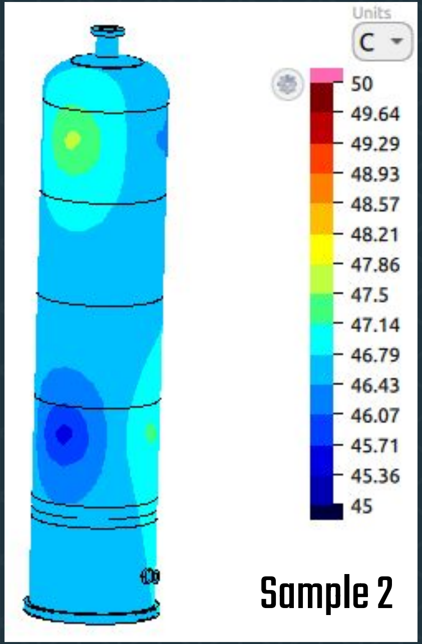
- Orders of magnitude speedup and "scale up" compared to FEA, e.g. >100 million DOF hull model solved in < 10 seconds with error indicator to ensure accuracy

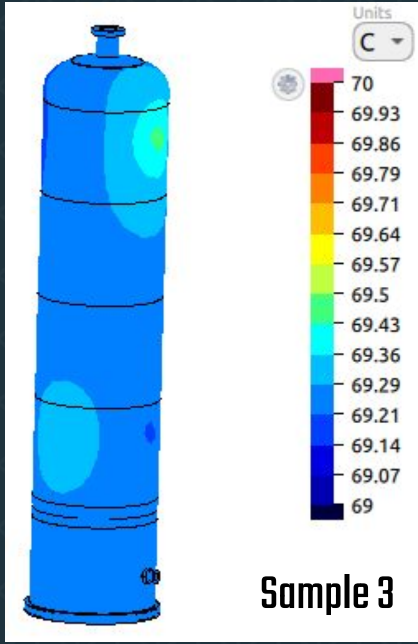


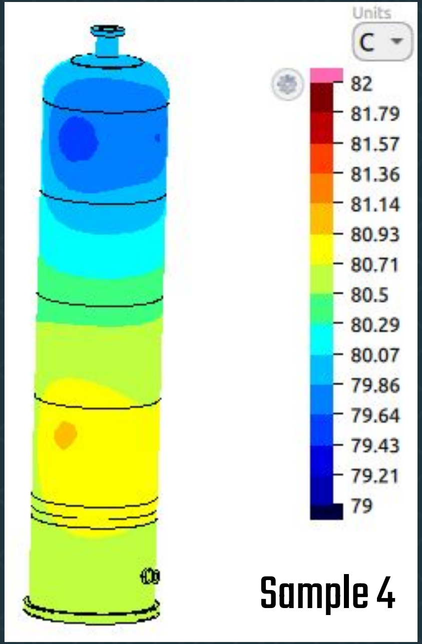
Error Indicators + Automated Enrichment

Initial training based on a sample set of relevant data, training runs automatically on cloud-based HPC (components trained in parallel)









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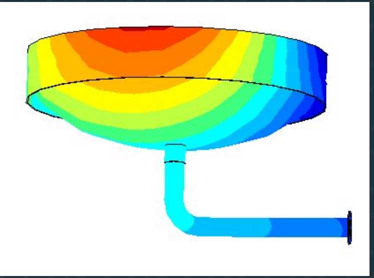
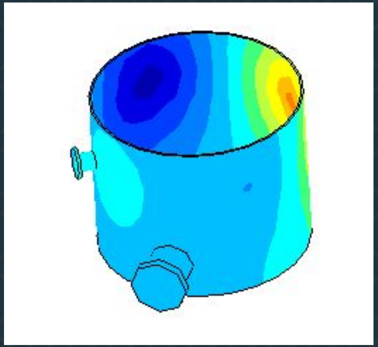
Error Indicators + Automated Enrichment

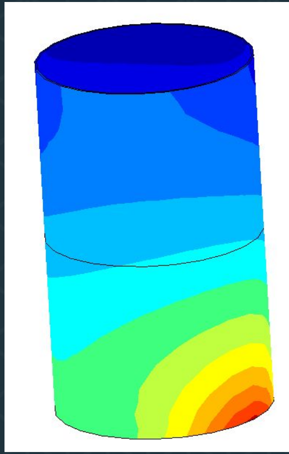
Training via individual components and groups, “global Full Order” solves not required!

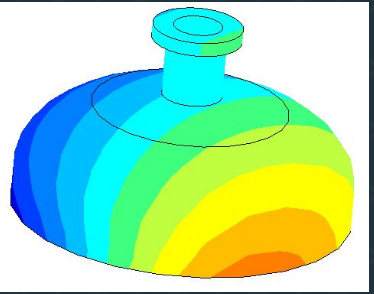
Individual components





Groups





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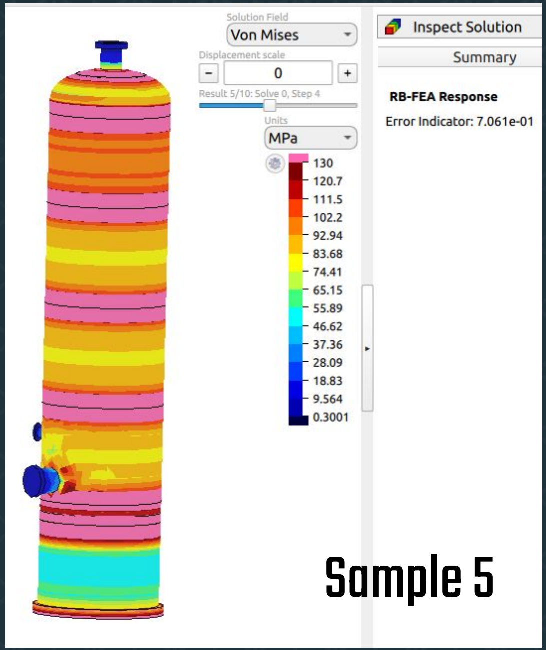
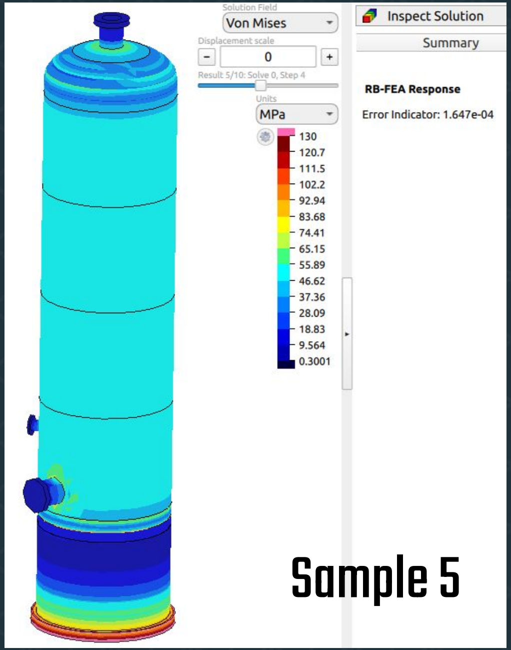
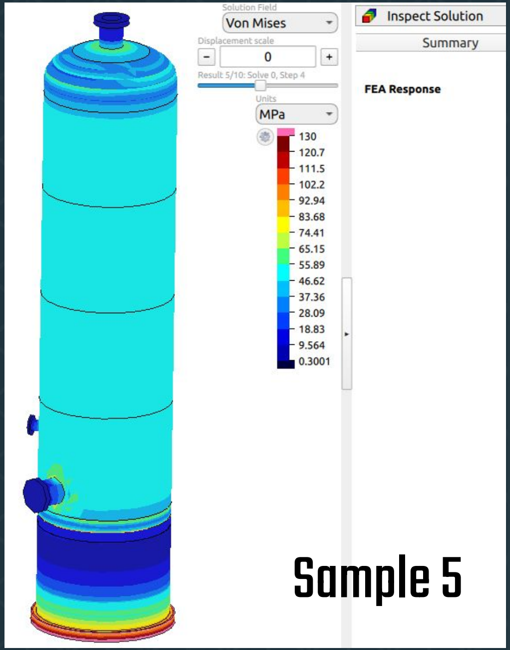
Error Indicators + Automated Enrichment

Training ensures error indicator < tolerance for all samples, typical tolerance: 0.01







before training,

error indicator 0.7061

after training,

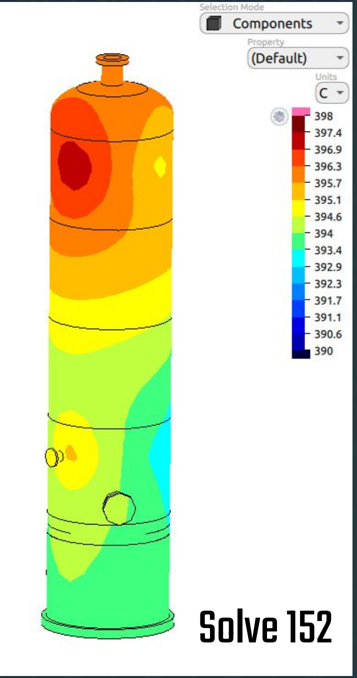
error indicator 1.647e-4

Check: Compare to FEA

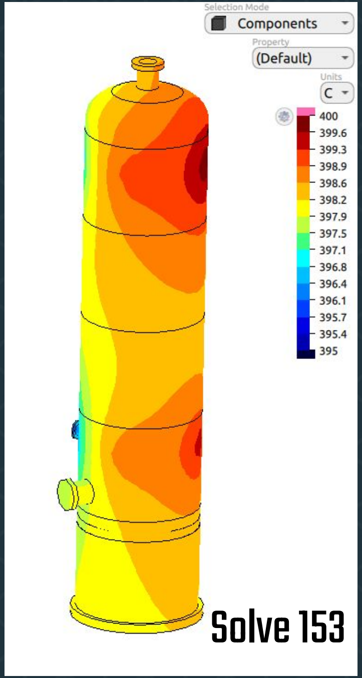
Error Indicators + Automated Enrichment

Deploy in operations, connected to data from asset (e.g. temperature, pressure, load monitoring, inspection data), will encounter new parameter values!

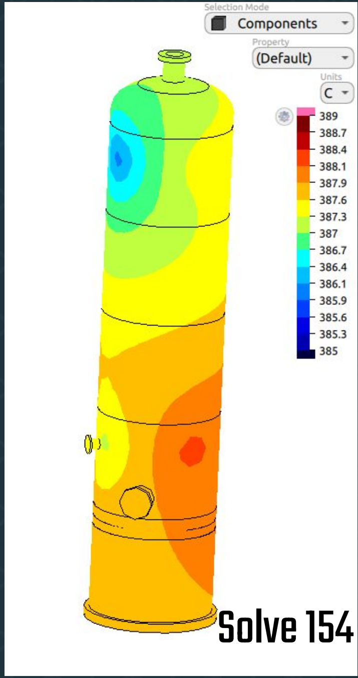
…



Solve 152



Solve 153



Solve 154

…

Error Indicators + Automated Enrichment

Error indicator is computed for every Online solve, if we exceed specified tolerance auto-enrichment is triggered, hence model continues to “learn” based on operational data

Solve	Error Indicator
…	…
152	2.872e-3
153	5.603e-3
154	1.203e-2
155	5.253e-3
156	5.112e-3
157	2.041e-3

→ enrichment using parameters from Solve 154

→ Automated re-solve, error indicator 9.863e-4

Hybrid Solver for “Non-Smooth” Nonlinearities

Ballani et al., “A component-based hybrid reduced basis/finite element method for solid mechanics with local nonlinearities”, CMAME 2018.

We use Full Order modeling for “non-smooth” nonlinearities (e.g. plasticity, contact), can be included as localized regions in a “Hybrid” RB/FEA model

Couple RB and FEA regions using coupling matrix C:

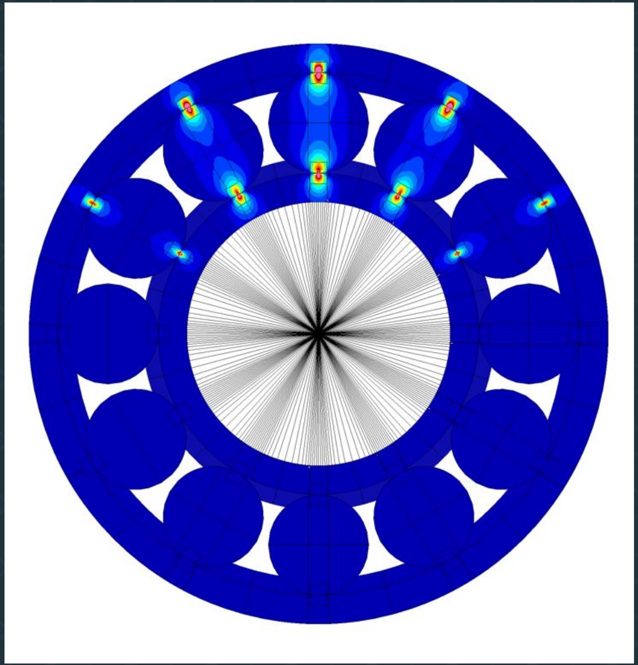
$$G(U) = C^T \begin{bmatrix} \mathbb{F}(\mu) - \mathbb{A}(\mu)\mathbb{U}(\mu) \\ G_{\mathrm{FE}}(U) \end{bmatrix}$$

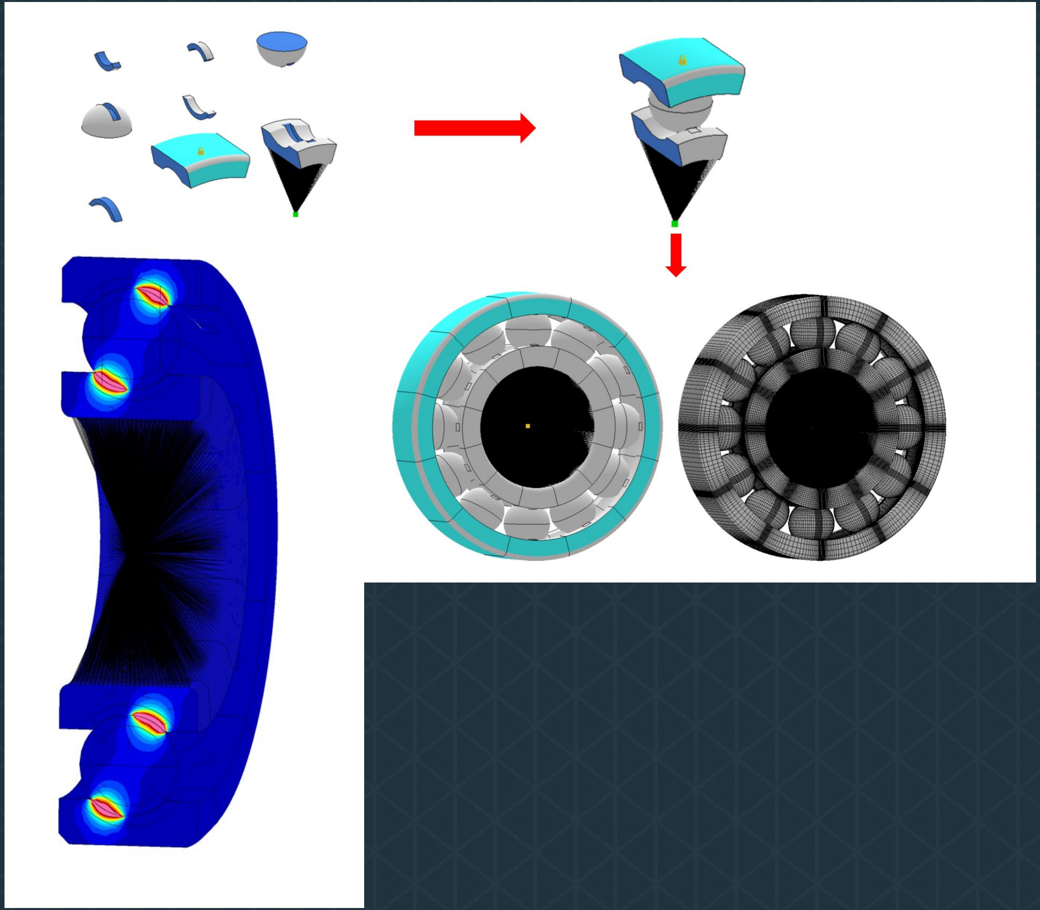
$$J_G(U) = C^T \begin{bmatrix} -\mathbb{A}(\mu) & 0 \\ 0 & J_{G_{\mathrm{FE}}}(U) \end{bmatrix} C$$

Apply Newton’s method to coupled system:

$$\begin{aligned} J_G(U^k)\Delta U^k &= -G(U^k) \\ U^{k+1} &= U^k + \Delta U^k \end{aligned}$$

Hybrid Solver for “Non-Smooth” Nonlinearities





Digital Twin Examples

FPSO

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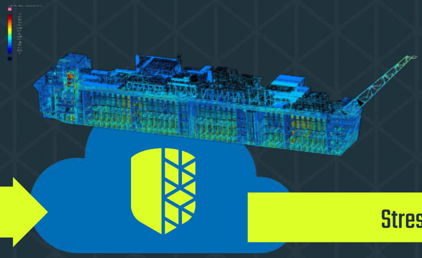
REAL ASSET

Data

PHYSICS-BASED MODEL



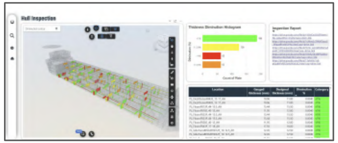
Stress/Damage

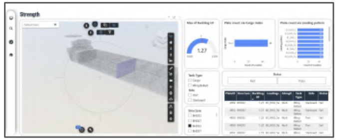
Data

>100 million DOF FEA model

REAL-TIME VISUALIZATION, REPORTING & INTEGRATIONS

DATA VISUALIZATION





DASHBOARD

+

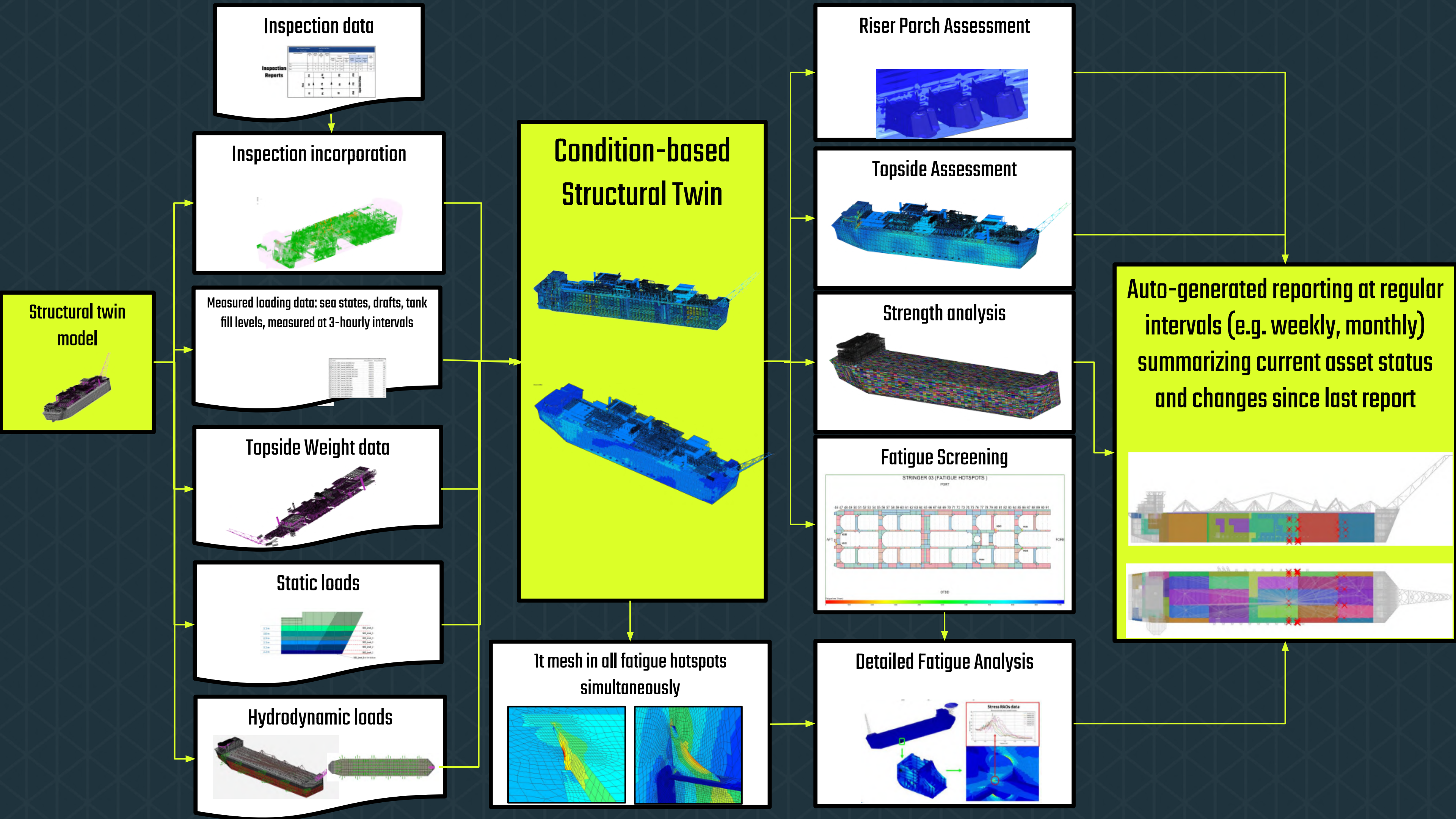
REPORTING CAPABILTIES

INTEGRATIONS

DATA ACQUISITION

CALCULATION

RESULTS

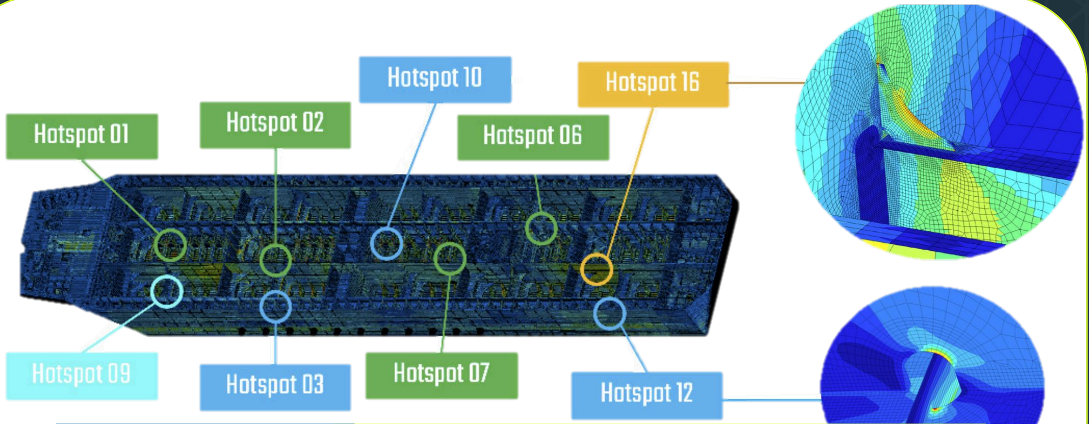

Inspection data
Inspection Reports
Inspection incorporation
Measured loading data: sea states, drafts, tank fill levels, measured at 3-hourly intervals
Topside Weight data
Static loads
Hydrodynamic loads
Structural twin model
Condition-based Structural Twin
1t mesh in all fatigue hotspots simultaneously
Riser Porch Assessment
Topside Assessment
Strength analysis
Fatigue Screening
STRINGER 03 (FATIGUE HOTSPOTS)
PORT
AFT
FORE
STBD
Detailed Fatigue Analysis
Stress RAOs data
Auto-generated reporting at regular intervals (e.g. weekly, monthly) summarizing current asset status and changes since last report

Reduce OPEX– Inspect where it is critical

LOWER RISK

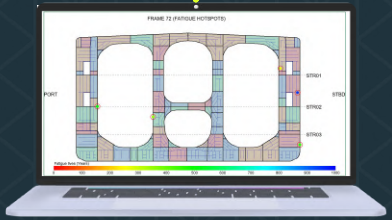
MORE ASSET LIFE

REDUCED OPEX

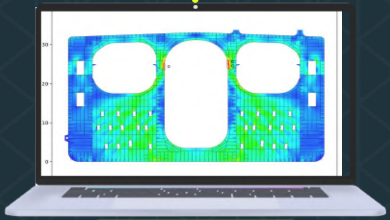


15,000 top tier fatigue locations

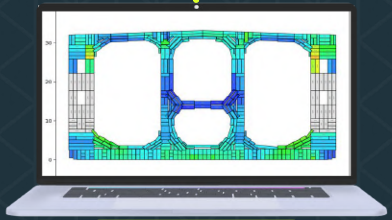
Reclassified and efficiently streamlined down to 230 hotspots in the most **critical inspection points**



Fatigue Hot Spot



Strength Check



Buckling Check

More Asset Life –As-is assessment with actual metocean data

MORE ASSET LIFE

LOWER RISK

REDUCED OPEX

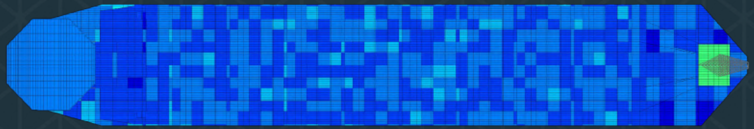
Inspection

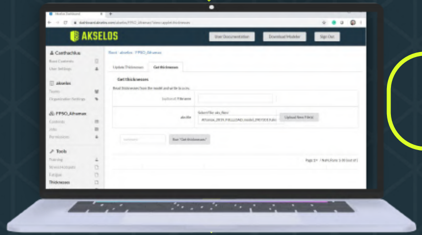
Inspection plan generated by AKSELOS

	A	B	C
1	name	new_thickness	max_diminution
2	CO_02_STBD_PrimSW_FR78_WP_No48	0.0127	20
3	CO_02_STBD_PrimSW_FR78_WP_No49	0.0127	20
4	CO_02_STBD_PrimSW_FR78_WP_No50	0.0128	20
5	CO_02_STBD_PrimSW_FR78_WP_No51	0.0128	20
6	CO_02_STBD_PrimSW_FR78_WP_No52	0.0128	20
7	CO_02_STBD_PrimSW_FR78_WP_No53	0.0197	20
8	CO_02_STBD_PrimSW_FR78_WP_No54	0.0178	20
9	CO_02_STBD_PrimSW_FR78_WP_No55	0.0163	20
10	CO_02_STBD_PrimSW_FR78_WP_No56	0.0162	20
11	CO_02_STBD_PrimSW_FR78_WP_No57	0.0179	20
12	CO_02_STBD_PrimSW_FR78_WP_No58	0.0217	20

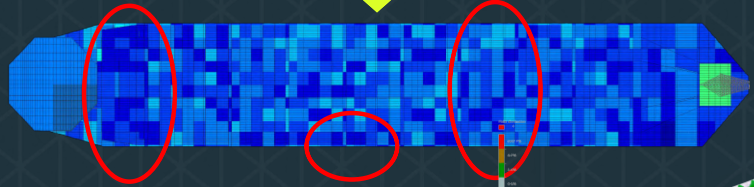
Inspection data (csv format)

Before updating thicknesses

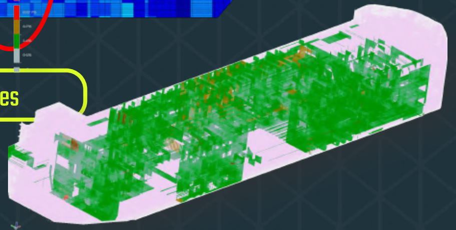




Thickness Update Tool (web browser)



After updating thicknesses

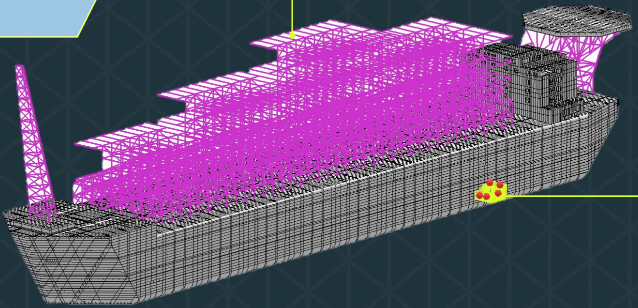


Lower Risk – Assess defects quickly

MORE ASSET LIFE

LOWER RISK

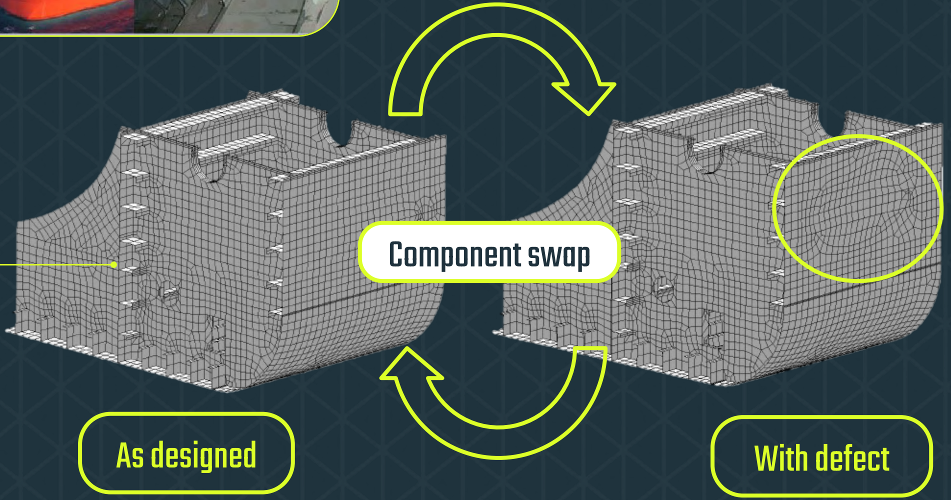
REDUCED OPEX

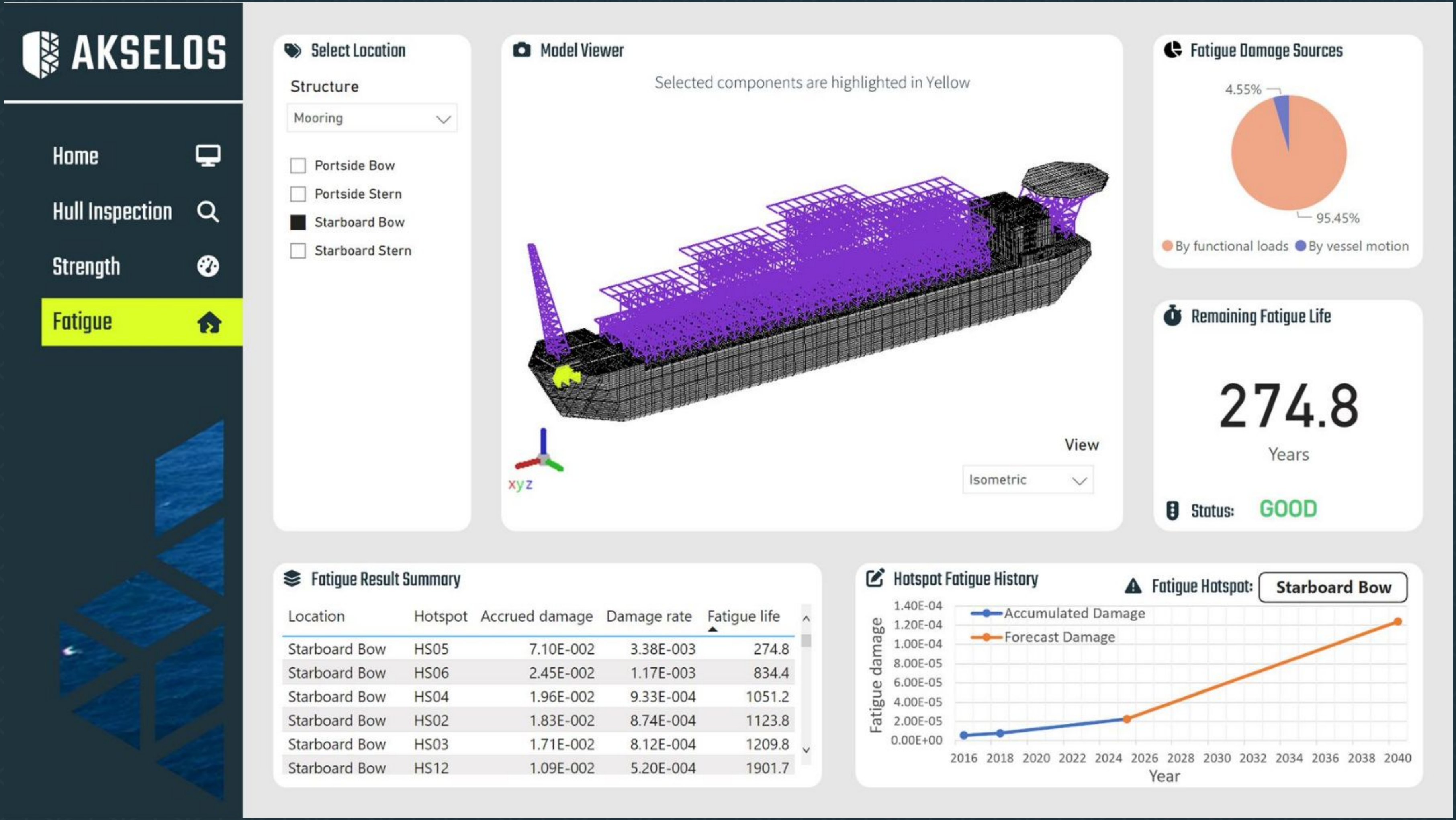


Component based approach

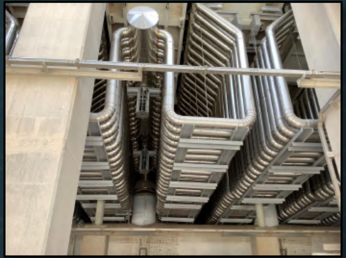
Dent assessment

Quick response
- Model already exists
- Only the effected region needs to be modelled
- Fast assessment of the defect on the entire structure




AKSELOS
Home
Hull Inspection
Strength
Fatigue
Select Location
Structure
Mooring
Portside Bow
Portside Stern
Starboard Bow
Starboard Stern
Model Viewer
Selected components are highlighted in Yellow
xyz
View
Isometric
Fatigue Damage Sources
4.55%
95.45%
By functional loads
By vessel motion
Remaining Fatigue Life
274.8
Years
Status:
GOOD
Fatigue Result Summary
Location Hotspot Accrued damage Damage rate Fatigue life
Starboard Bow HS05 7.10E-002 3.38E-003 274.8
Starboard Bow HS06 2.45E-002 1.17E-003 834.4
Starboard Bow HS04 1.96E-002 9.33E-004 1051.2
Starboard Bow HS02 1.83E-002 8.74E-004 1123.8
Starboard Bow HS03 1.71E-002 8.12E-004 1209.8
Starboard Bow HS12 1.09E-002 5.20E-004 1901.7
Hotspot Fatigue History
Fatigue Hotspot:
Starboard Bow
Accumulated Damage
Forecast Damage
Fatigue damage
1.40E-04
1.20E-04
1.00E-04
8.00E-05
6.00E-05
4.00E-05
2.00E-05
0.00E+00
2016 2018 2020 2022 2024 2026 2028 2030 2032 2034 2036 2038 2040
Year

CASE STUDY



Steam Methane Reformer

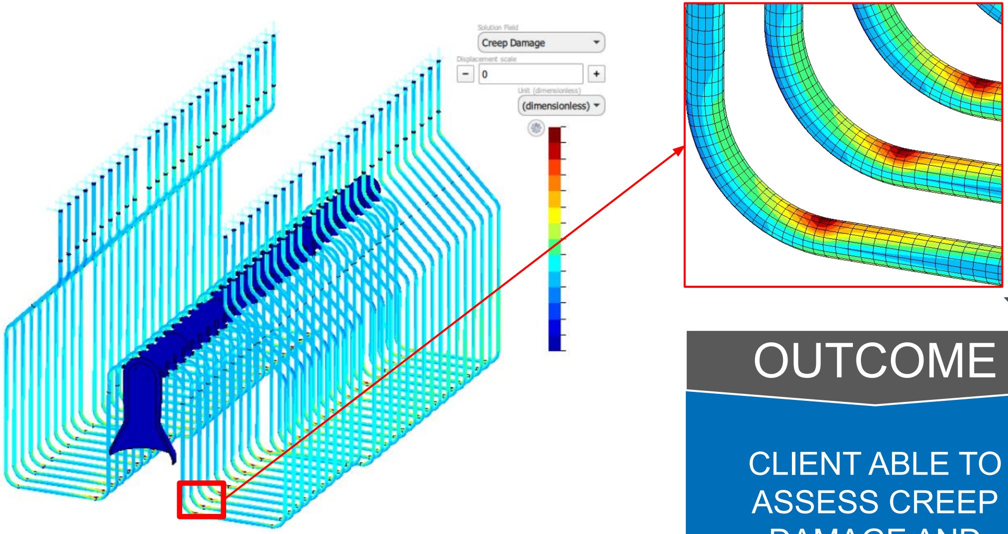
VALUE FRAMES

EXTEND ASSET LIFE

PREVENT DAMAGE & DOWNTIME

CHALLENGE

UNKNOWN IMPACT OF OPERATIONAL USE ON ASSET INTEGRITY

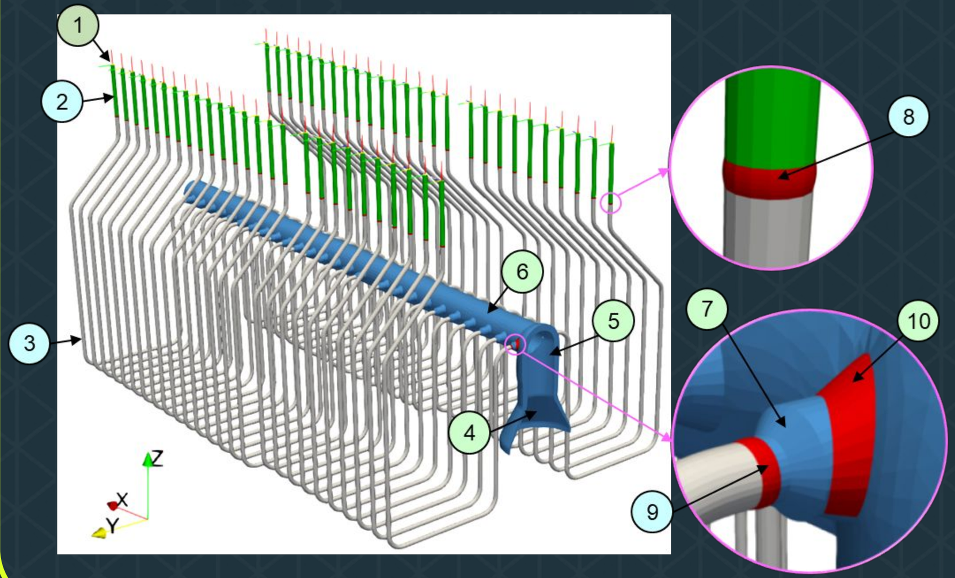


OUTCOME

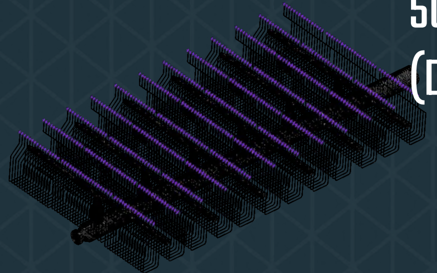
CLIENT ABLE TO ASSESS CREEP DAMAGE AND REMAINING LIFE

Geometry CAD, Material Properties

CAD

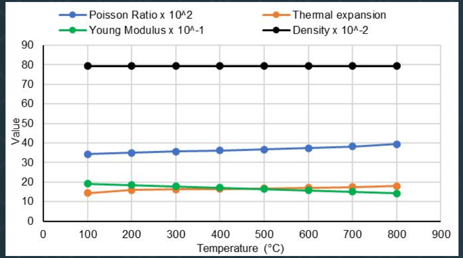


MODEL



50,316,666 (DoFs)

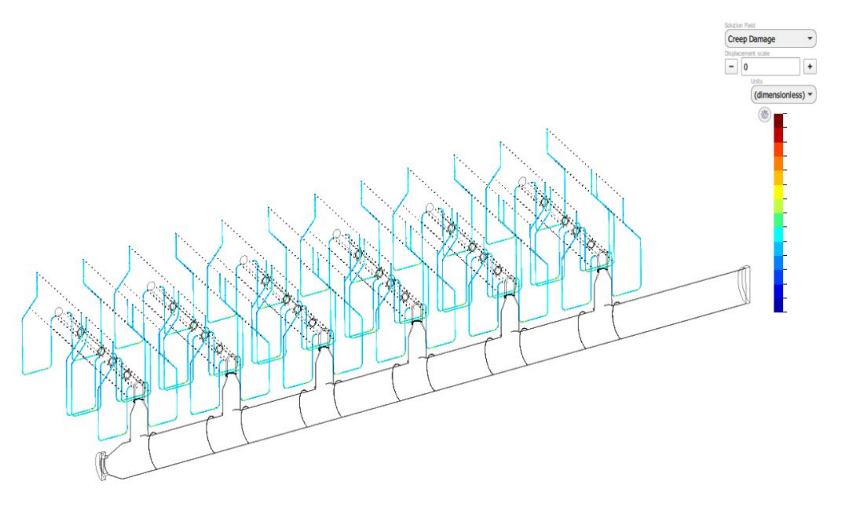
Temperature dependent material properties



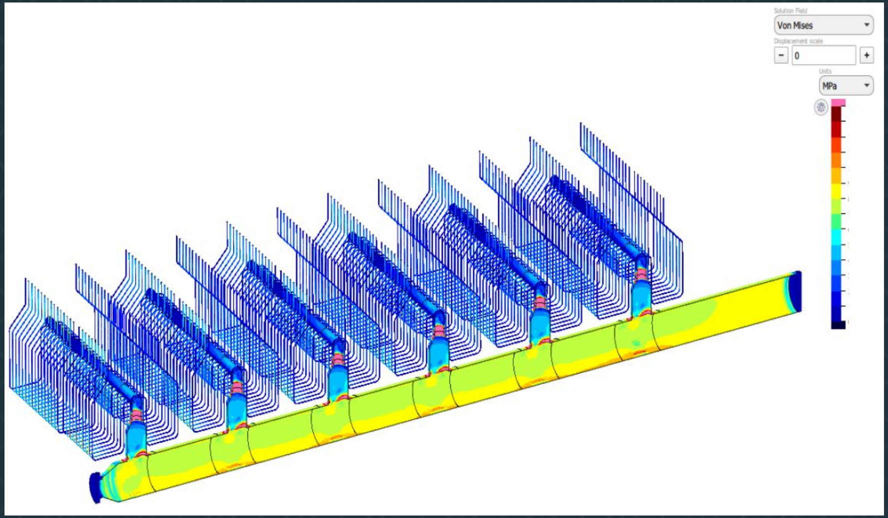
Analysis results

Track creep damage during operation to maximize operational life and enable maximum throughput

Creep Damage



Von Mises Stress



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SMR (Steam Methane Reformer)

Copenhagen Central Square, Rådhuspladsen

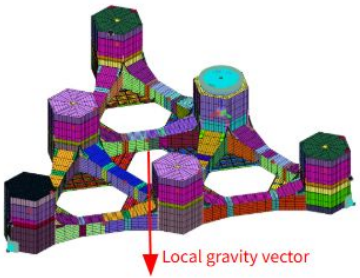
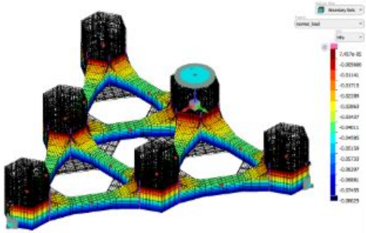
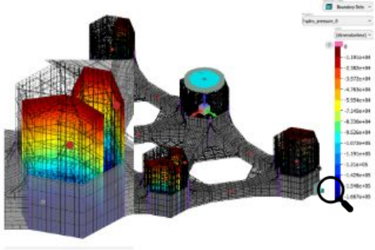
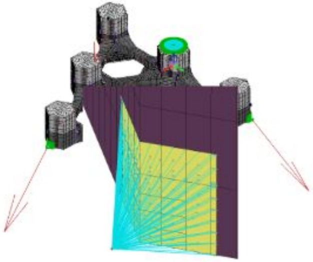
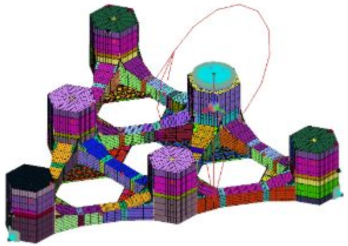
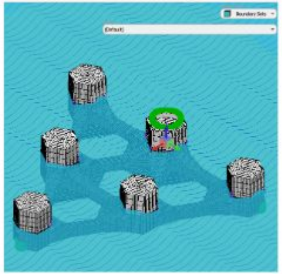
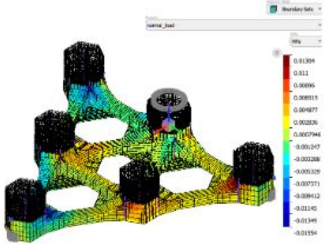
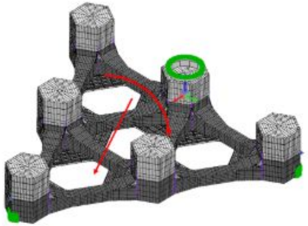
Funded by the European Union
Plan de Recuperación, Transformación y Resiliencia
GOBIERNO DE ESPAÑA
MINISTERIO DE INDUSTRIA Y TURISMO

Decimap Project

The Challenges:

- Validate the **detailed** structural design for Mediterranean conditions
- Analyse impacts of simultaneous **time domain** loads from WTG (Bladed) and Waves for > 20 000 DLCs
- Find potential design optimization paths to **reduce weight and increase competitiveness**

Applied Loads: Permanent load (G) & Environmental load (E)

Gravity load	Hydrostatic	Ballast load	Moorings load
			
Tower load	**Morison wave load**	**Radiation & Diffraction**	**Acceleration**
			

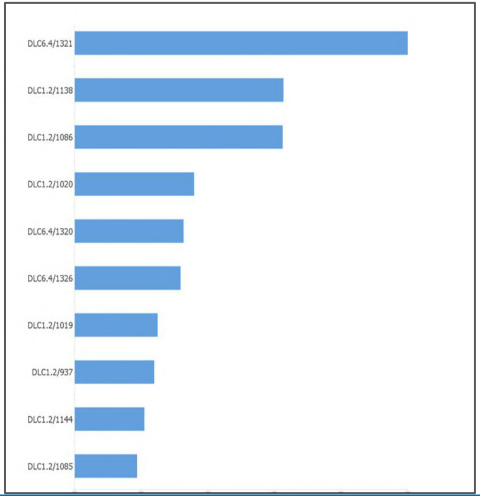
Detailed Fatigue Analysis

- Detailed fatigue analysis was performed on **1339 simulations**
- total probability of occurrence = **97.7%.**
- **1h** per simulation (18,000 timesteps – 5hz)
- => In total, **~ 24 millions of simulation time steps**
- **6M Degree of Freedom**
- **1000 hotspots**

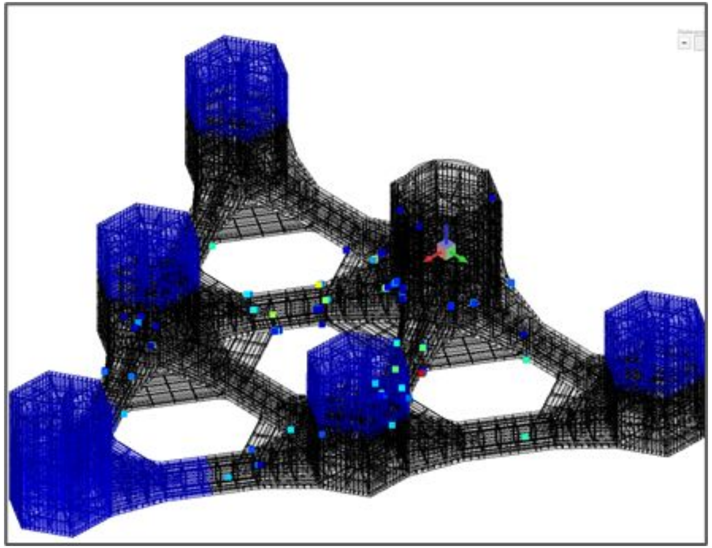
18 000 tsteps -> 2.5CPUh

Full analysis in less than a day on parallel cloud

10 most damaging simulations:



Detailed fatigue results in selected hotspots:



Value(s):

- Full derisking of Structural integrity
- Identification of Critical DLC

Conclusions:

Funded by the European Union
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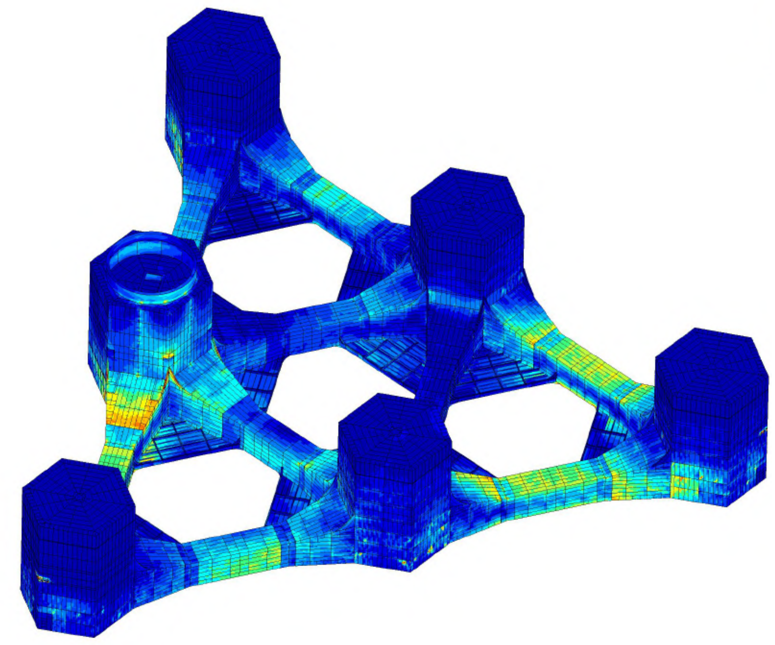
- The Software solution successfully **de-risked the DECIMAP** project using **detailed structural analysis**.
- The project enabled Sener to **adjust its design** to meet standard criteria and identify potential **material savings**.
- Future collaboration will target **the weight optimization** of the HiveWind substructure for commercial projects.

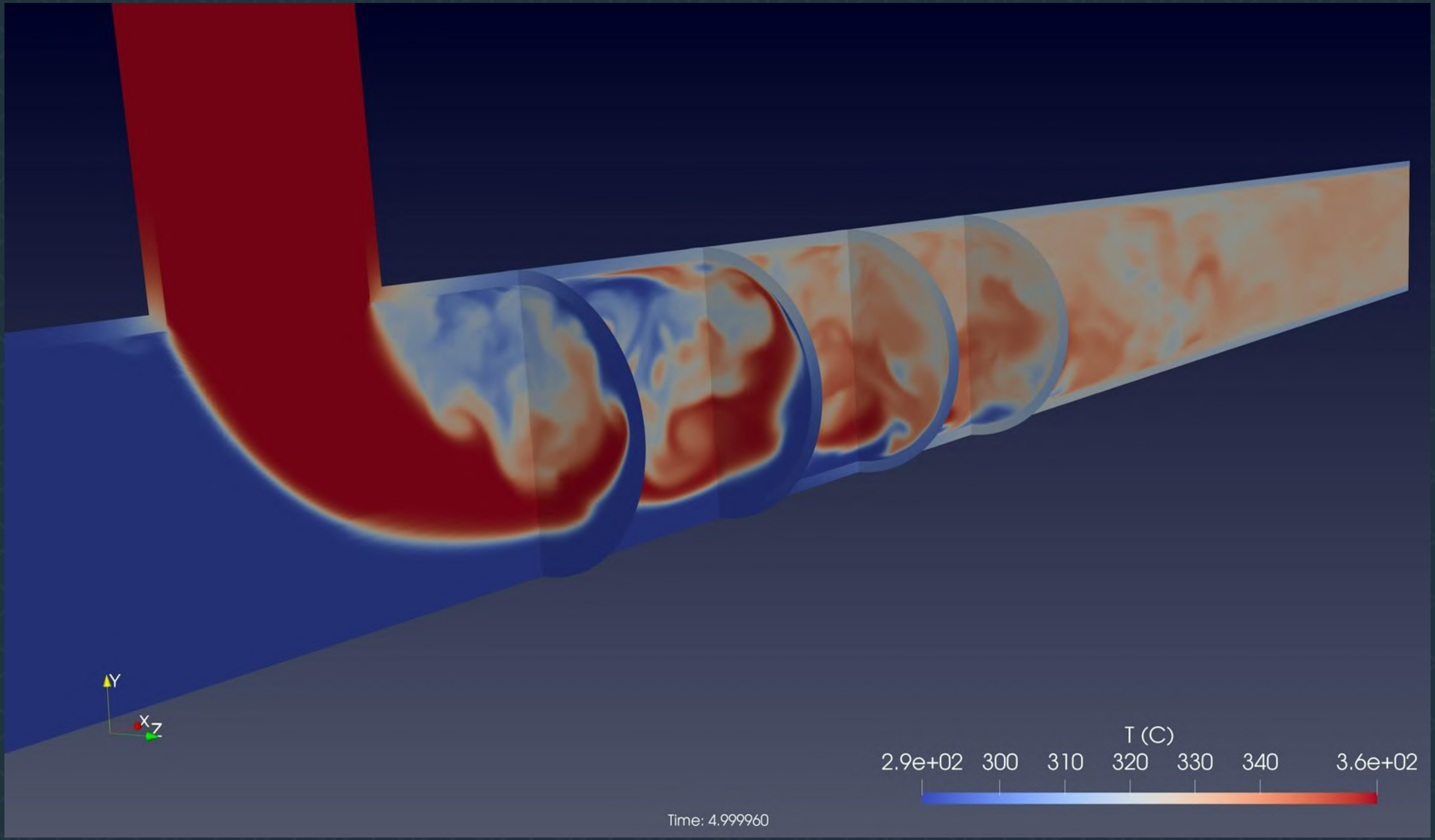


Challenges and opportunities for R&D

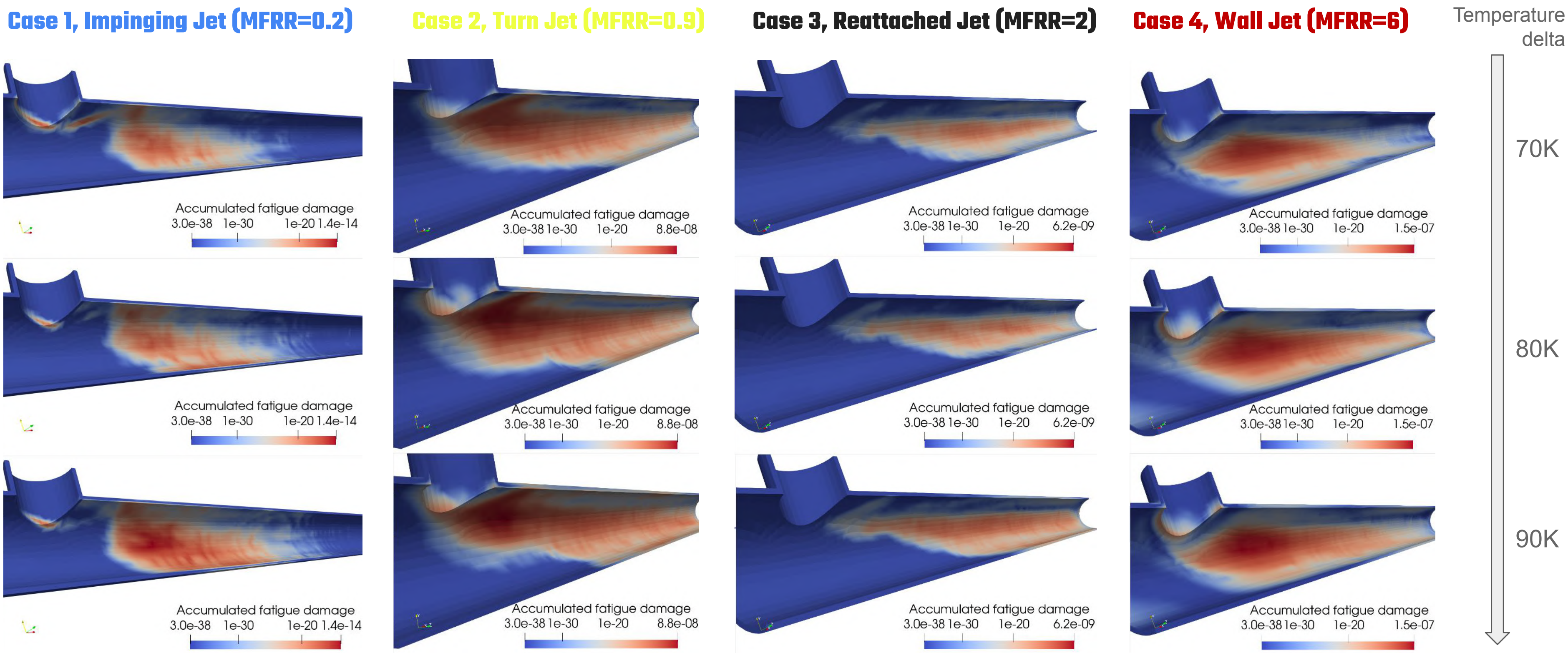
- Transport-dominated phenomena,
  example: CFD with high Reynolds number.

- Traveling waves,
  example: transient structural dynamics with abrupt load variation.

CFD example: thermal mixpoint



Example Fatigue Results for 12 Representative Cases



MFRR = Mass Flow Rate Ratio

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