Structural optimization of cruise ships with non-intrusive parameter and model order reduction

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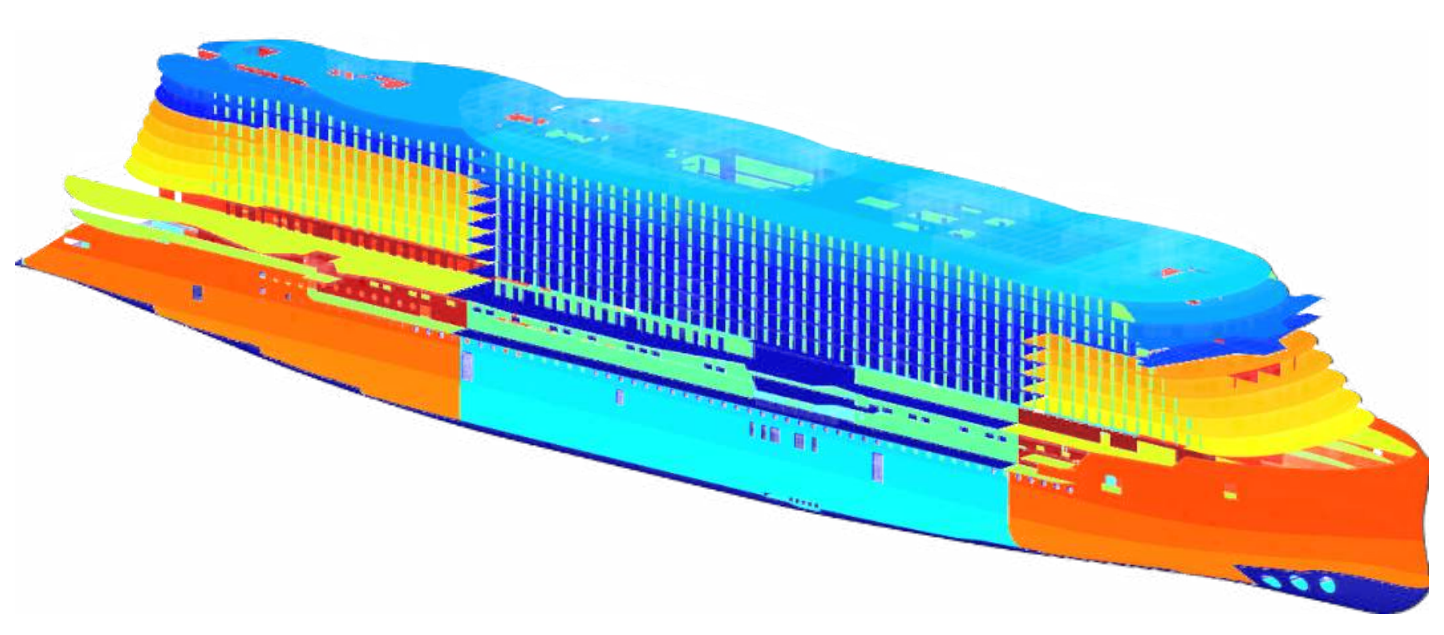
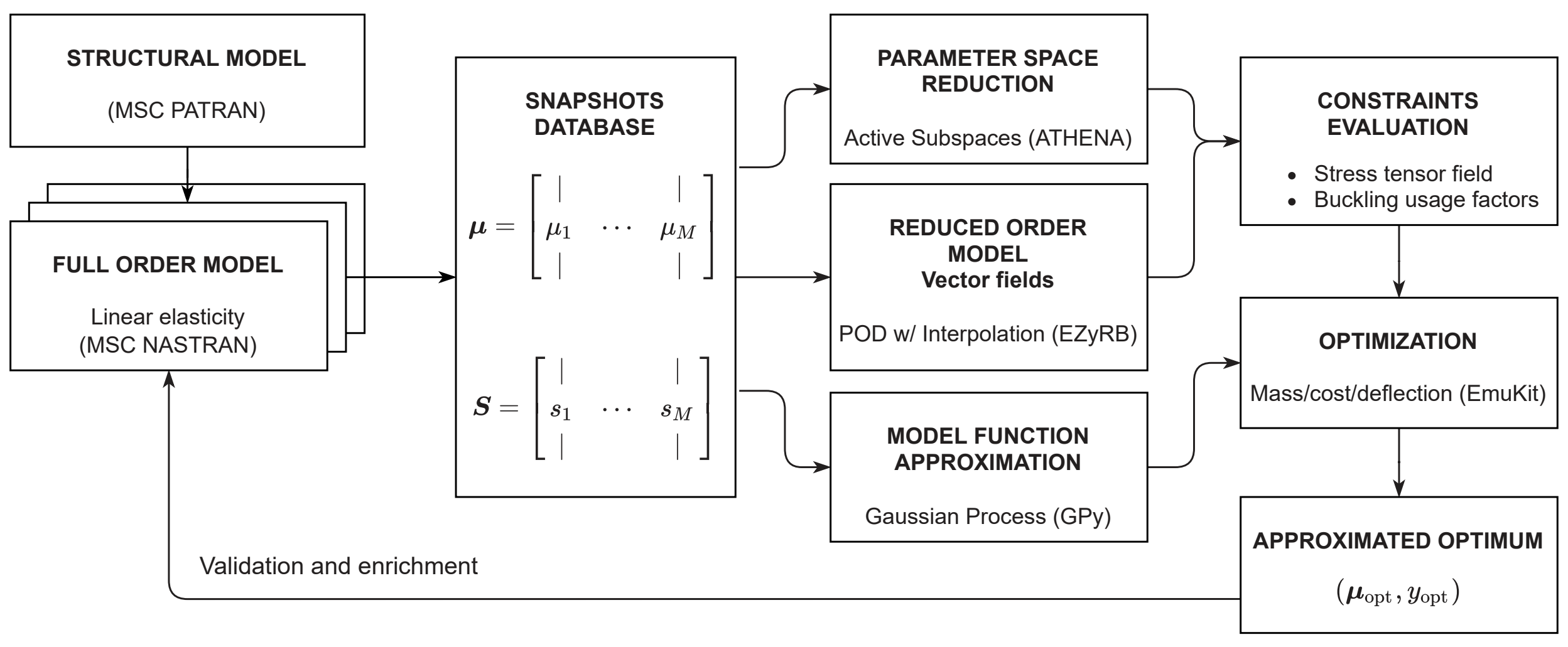
The call to reduce the environmental impact of cruise ship manufacturing

The cruise ship industry is facing a continuous evolution in the requirements for lower fuel consumption, building and operational costs, and increased alternative fuels adoption. These targets often act in contrast to the regulatory constraints imposed on the structural response of the ship, under a variety of wave and equipment loads.



In the initial design phase, the designers assign the thickness of steel plates that compose the ship, while ensuring that yielding and buckling events are limited.

To optimize the steel usage during the preliminary design phase, we developed an automated computational pipeline based on non-intrusive ROMs. The pipeline accounts for the structural stability of the hull under multiple loading conditions [1].



STRUCTURAL MODEL
(MSC PATRAN)

FULL ORDER MODEL
Linear elasticity
(MSC NASTRAN)

SNAPSHOTS DATABASE

$$\boldsymbol{\mu} = \begin{bmatrix} | & & | \\ \mu_1 & \cdots & \mu_M \\ | & & | \end{bmatrix}$$

$$\boldsymbol{S} = \begin{bmatrix} | & & | \\ s_1 & \cdots & s_M \\ | & & | \end{bmatrix}$$

PARAMETER SPACE REDUCTION
Active Subspaces (ATHENA)

REDUCED ORDER MODEL Vector fields
POD w/ Interpolation (EZyRB)

MODEL FUNCTION APPROXIMATION
Gaussian Process (GPy)

CONSTRAINTS EVALUATION
- Stress tensor field
- Buckling usage factors

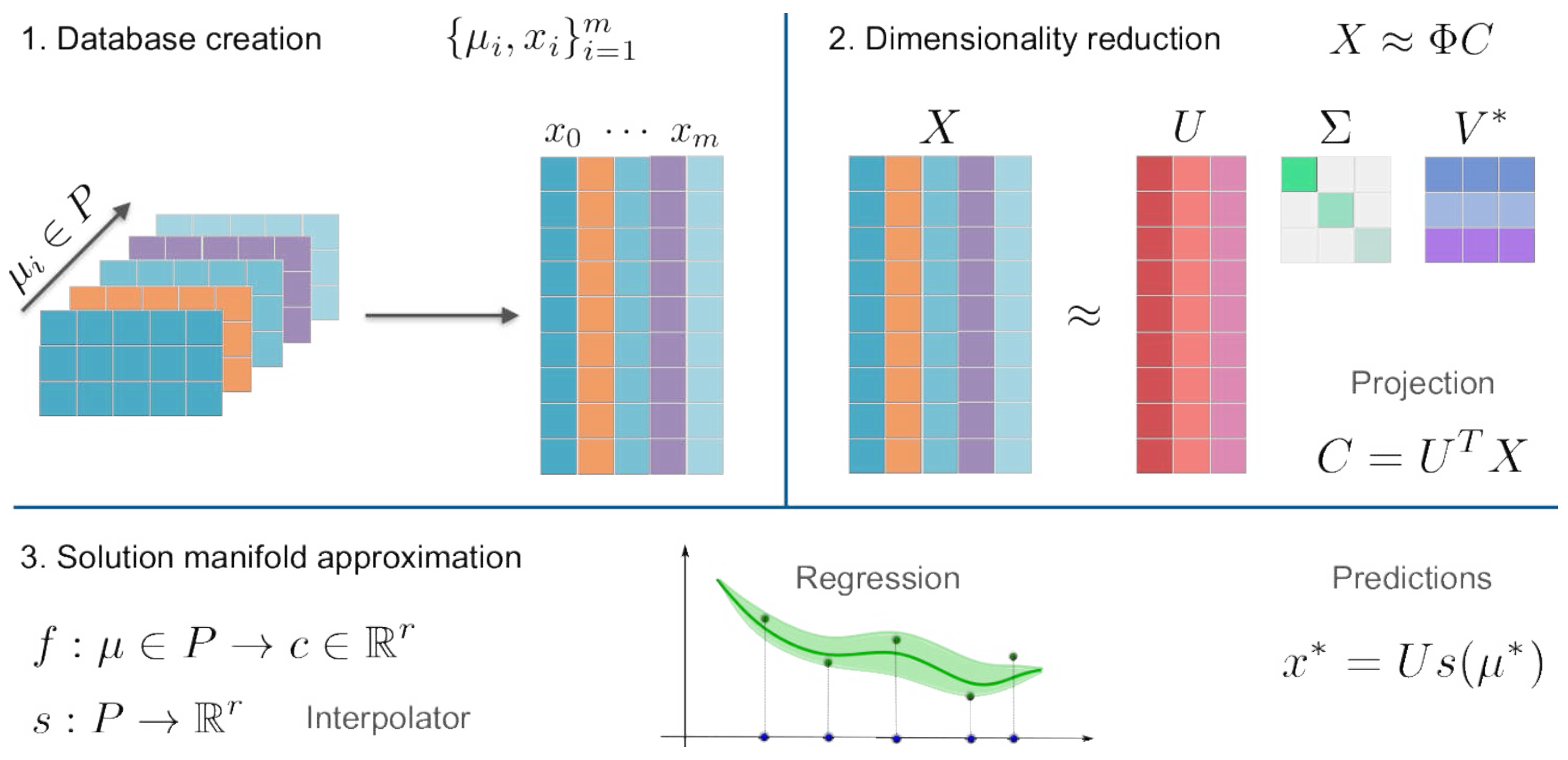
OPTIMIZATION
Mass/cost/deflection (EmuKit)

APPROXIMATED OPTIMUM
$(\boldsymbol{\mu}_{\text{opt}}, y_{\text{opt}})$

Validation and enrichment

Non-intrusive surrogate modeling for the stress tensor field prediction

Dimensionality reduction is achieved through singular value decomposition of a database of high fidelity simulations. The truncation of the U matrix gives a map between full and reduced solutions; the surrogate is completed by a Gaussian process regression (GPR) in the reduced space.



1. Database creation $\{\mu_i, x_i\}_{i=1}^{m}$

2. Dimensionality reduction $X \approx \Phi C$

Projection $C = U^T X$

3. Solution manifold approximation

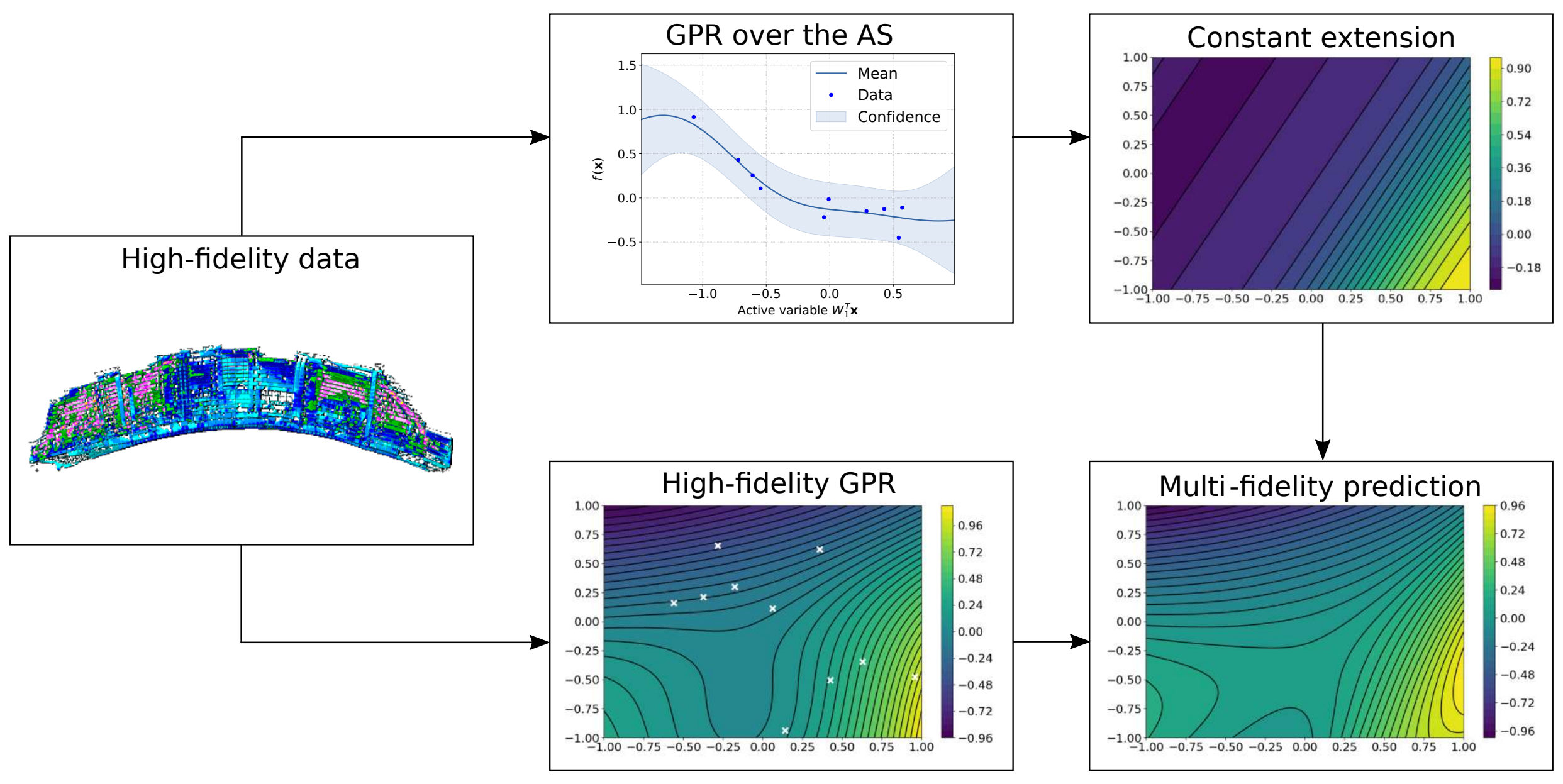
$f : \mu \in P \to c \in \mathbb{R}^r$

$s : P \to \mathbb{R}^r$ Interpolator

Regression

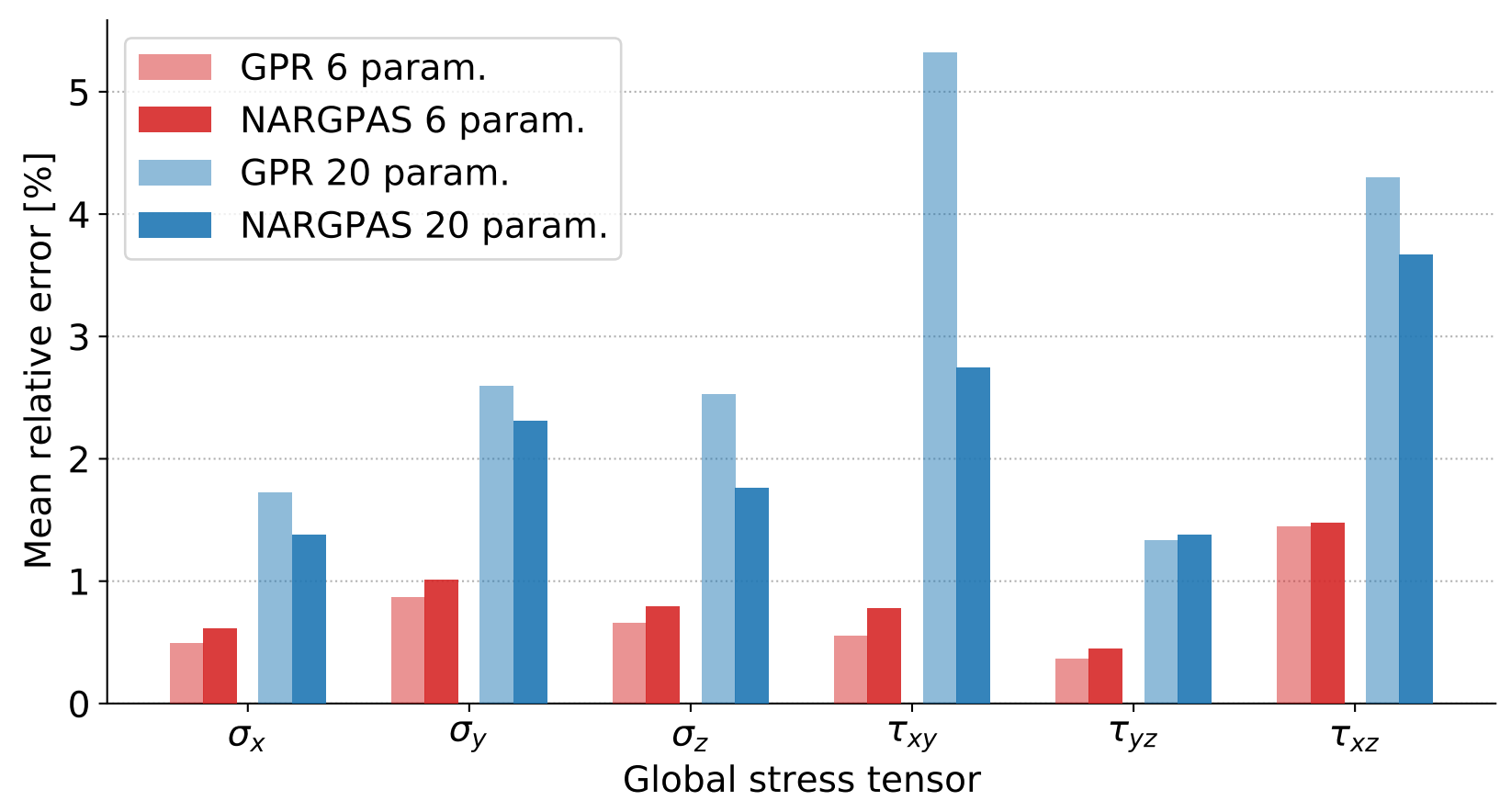
Predictions $x^* = U s(\mu^*)$

The construction of an active subspace in the reduced manifold enables a low-fidelity surrogate, which is then combined with the higher-fidelity GPR in a multi-fidelity fashion. The resulting predictor is a non-linear auto regressive GP with active subspaces (NARGPAS) [2].

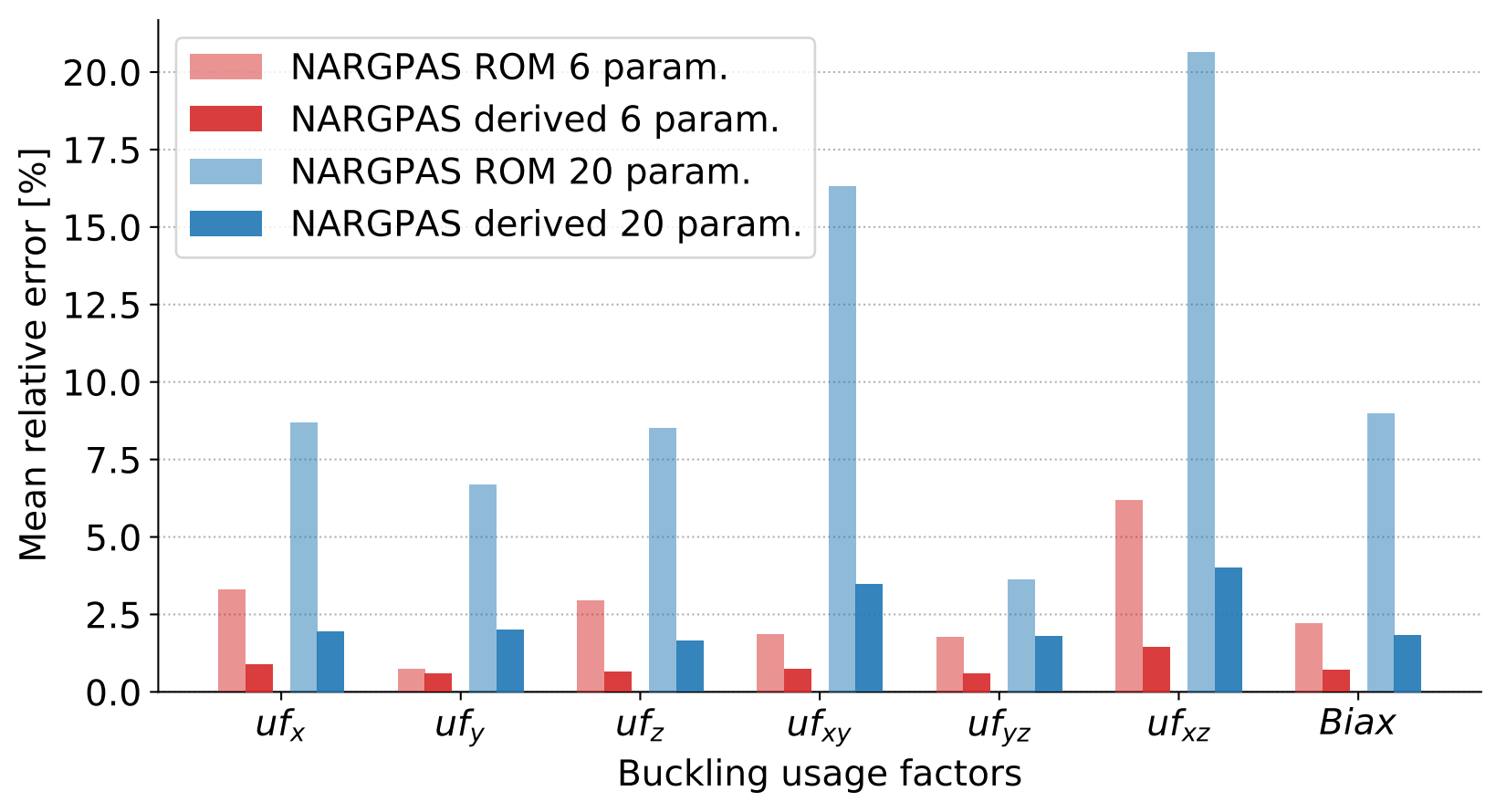


Error performance

We compare the GPR and NARGPAS in terms of the relative error of the full order stress field, using two parameterizations of a simplified mesh: one with 6 parameters and one with 20.



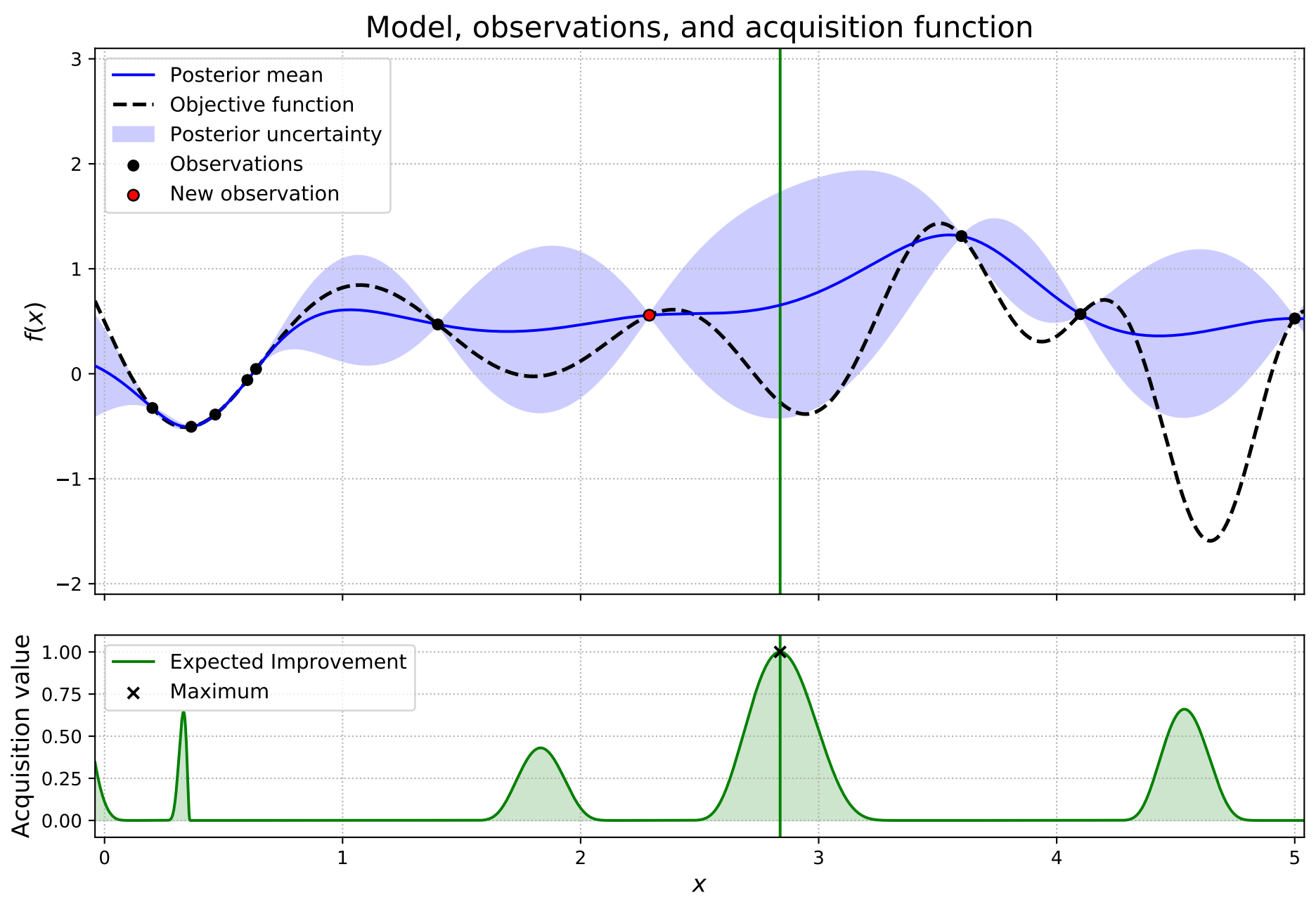
The buckling usage factors are the result of a highly non-linear computation of the stress state. We compare two approaches: building a surrogate of each usage factor (labeled "ROM"), and combining the stress state surrogate with a postprocessing step (labeled "derived").



Optimization

Bayesian optimization (BO) employs a GPR surrogate of the quantity of interest (mass, cost, or vertical deformation) to minimize an acquisition function of the objective and its uncertainty.

- (soft) constraints on the number of yielded and buckled elements are integrated as quadratic penalization of the objective
- the linear component of the objective (for mass and cost) is easily constrained and the upper bound tightened along the search
- plate thickness is restricted to commercially available sizing, making the domain discrete, while BO optimizes the continuous relaxation. Rounding is performed with a linear integer program preserving constraints



Work in progress: we aim to combine the uncertainty quantification provided by the BO GPR with the the uncertainty propagated from the GPRs of the surrogate model.

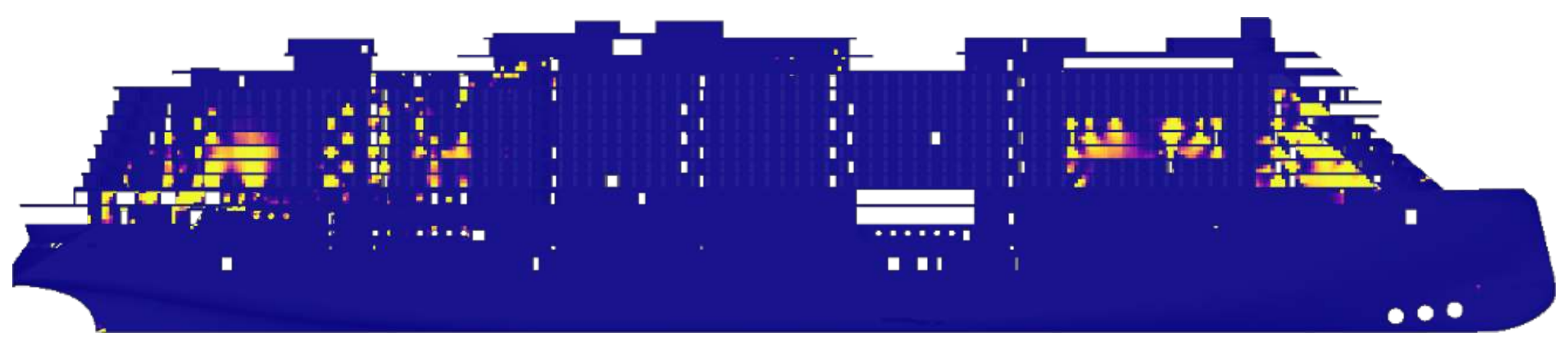
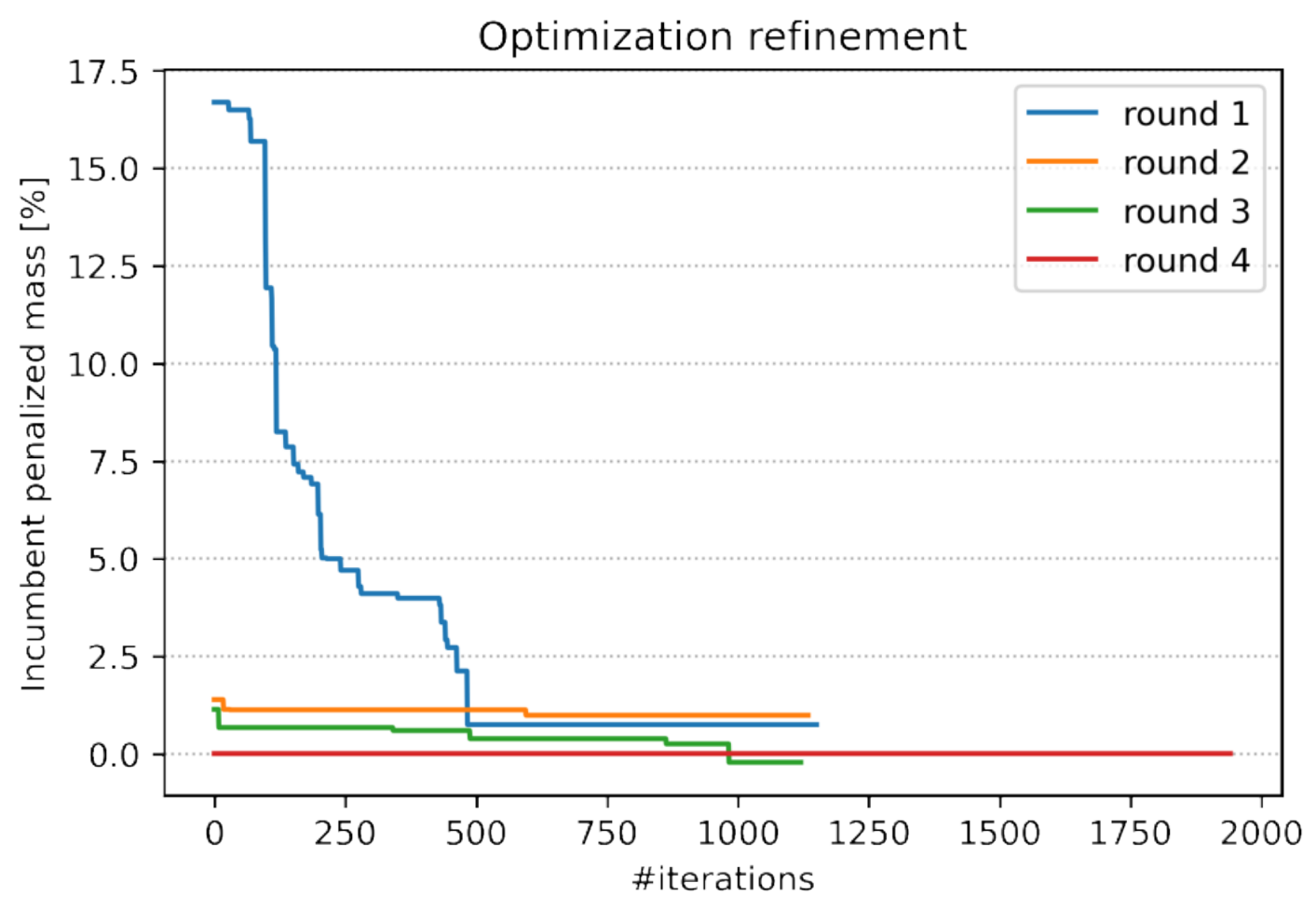


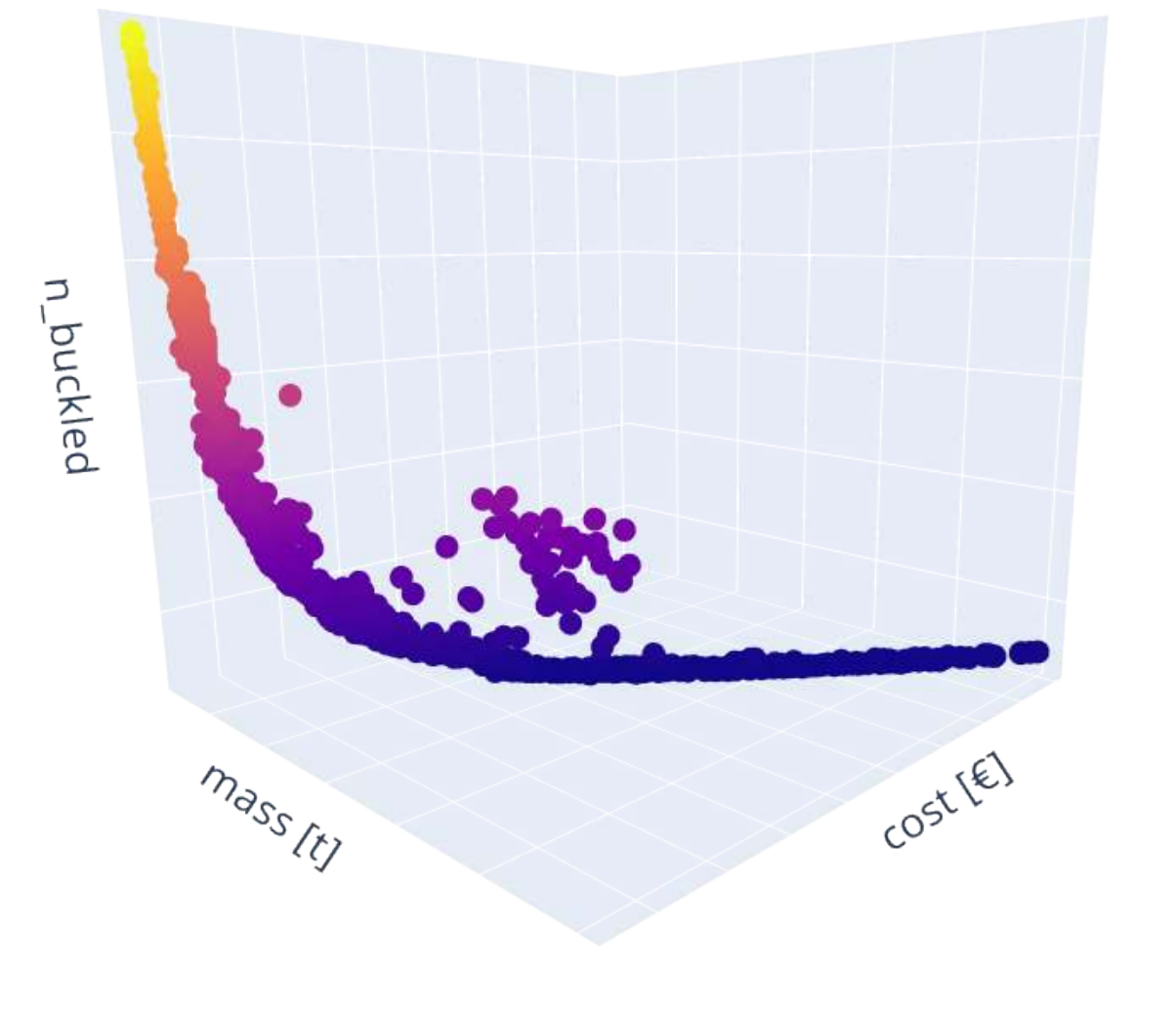
Figure 1: Marginalized probability of yielding

Numerical results on a full scale problem

The pipeline has been succesfully tested to optimize the total mass of a commercial cruise ship, sporting 670000 elements and parameterized with 76 parameters.
The BO was able to find good optimum candidates, which were then validated with high fidelity simulations. The final result decreased the parameterized mass of the initial design by 17%.



Work in progress: multi-objective optimization based on non-dominated sorting genetic algorithm (NSGAIII) for the approximation of the Pareto frontier in the objective and constraint function space.
The designer are able to inspect the most effective trade-offs between the different targets and refine the critical thresholds accordingly.



References and acknowledgements

[1] Marco Tezzele, Lorenzo Fabris, Matteo Sidari, Mauro Sicchiero, and Gianluigi Rozza. A multifidelity approach coupling parameter space reduction and nonintrusive POD with application to structural optimization of passenger ship hulls. *International Journal for Numerical Methods in Engineering*, 124:1193–1210, 2023.

[2] Francesco Romor, Marco Tezzele, Markus Mrosek, Carsten Othmer, and Gianluigi Rozza. Multi-fidelity data fusion through parameter space reduction with applications to automotive engineering. *International Journal for Numerical Methods in Engineering*, 124:5293–5311, 2023.

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