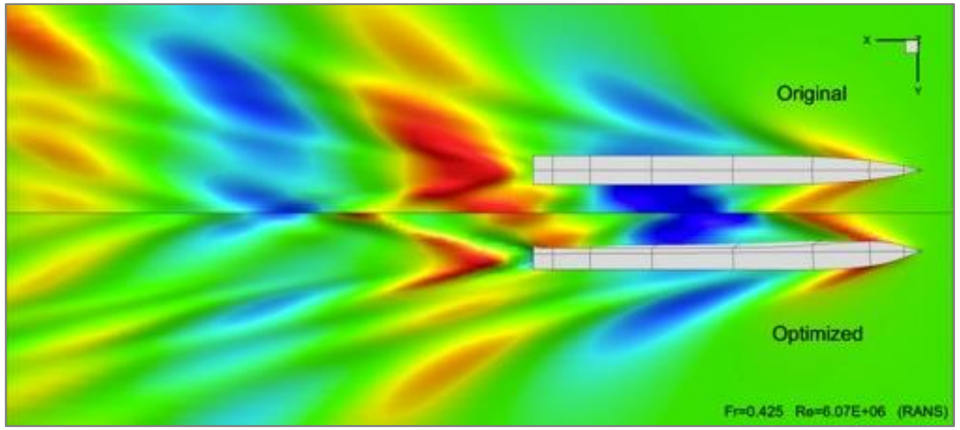
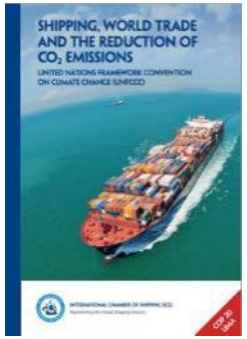
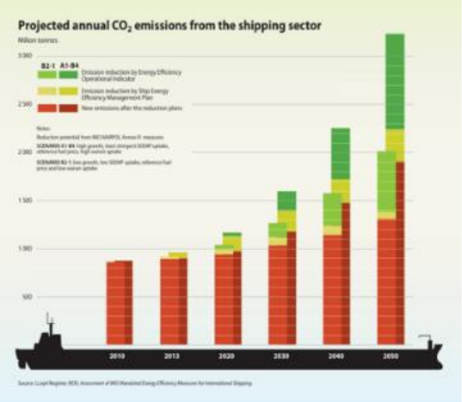
TM1.4 STRUMENTI DI SIMULAZIONE AD ALTA FEDELTÀ NELLA DIGITALIZZAZIONE DELLA PROGETTAZIONE NAVALE



Presentato da: Ing. Matteo Diez, Istituto di Ingegneria del Mare, Consiglio Nazionale delle Ricerche

Motivation





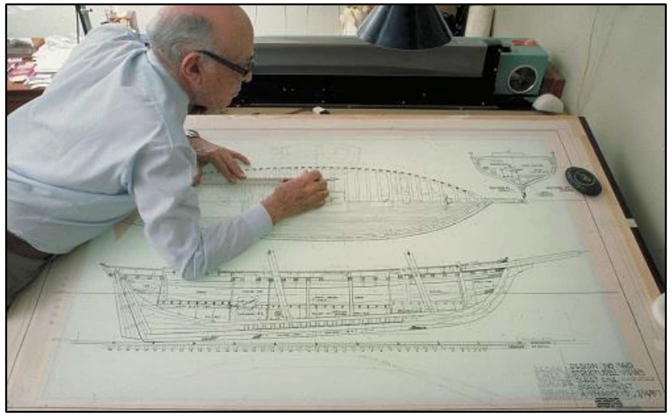
- Carbon dioxide emissions from shipping were equal to 2.7% of the global human-made emissions in 2007 (source: IMO) are expected to rise by as much as 2 to 3 times by 2050 if no action is taken
- IMO set mandatory measures to reduce emissions of greenhouse gases, with the Energy Efficiency Design Index (EEDI) for new ships, and the Ship Energy Efficiency Management Plan (SEEMP) for all ships (2013)
- Not only industries, but also Navies demand for more efficient and safer ships, with optimized performances with respect to range, cruise/flank speeds, payload, and operability in high sea-states
- Climate changes will likely induce high sea states with large environmental uncertainties involved

Context

https://www.youtube.com/watch?v=Sx57-LnuuFs

Build-and-Test Approach

Design



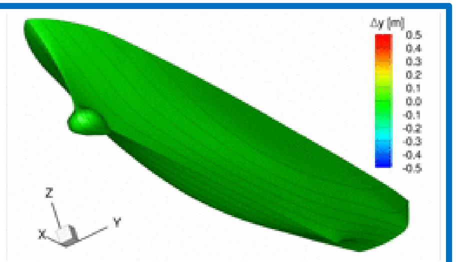
Build

Test

Simulation-Based Design Optimization (Process Digitalization)

$$
\begin{aligned}
&\text{Minimize} \quad f(\mathbf{x}) \\
&\text{subject to} \quad l_k \le x_k \le u_k, \quad k = 1, \ldots, n \\
&\text{and to} \quad g_j(\mathbf{x}) \le 0, \quad j = 1, \ldots, N_g
\end{aligned}
$$

Design/Shape modification and automatic meshing



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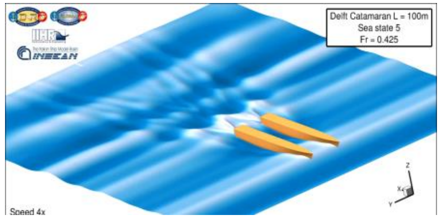
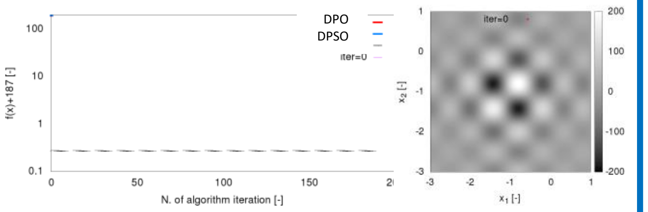
Single/multi-disciplinary analysis tools (CFD, FEM, UQ, etc.)



$f(\mathbf{u})$

Optimization algorithm



$$\min_{\mathbf{u} \in \mathcal{U}} \quad f(\mathbf{u})$$

$$\mathbf{u} = \operatorname{argmin}[f(\mathbf{u})]$$

Simulation-Based Design Optimization

$$
\begin{aligned}
\text{Minimize} \quad & f(\mathbf{x}) \\
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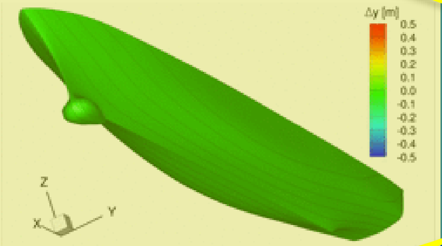
$$\min_{\mathbf{u} \in \mathcal{U}} \quad f(\mathbf{u})$$

Design/Shape modification and automatic meshing



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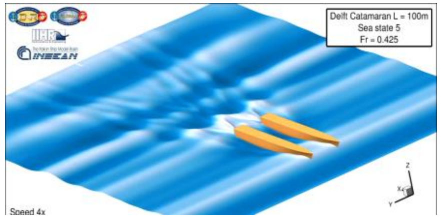
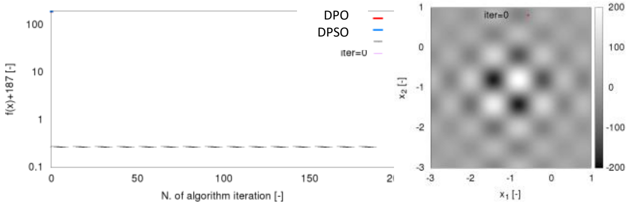


$f(\mathbf{u})$

Optimization algorithm



$\mathbf{u} = \mathrm{argmin}[f(\mathbf{u})]$

Design-space Dimensionality Reduction via Machine Learning

$$\mathbf{u} = \mathrm{argmin}[f(\mathbf{u})]$$

Design-space dimensionality

Potential design improvements

Difficulty of exploration and computational cost

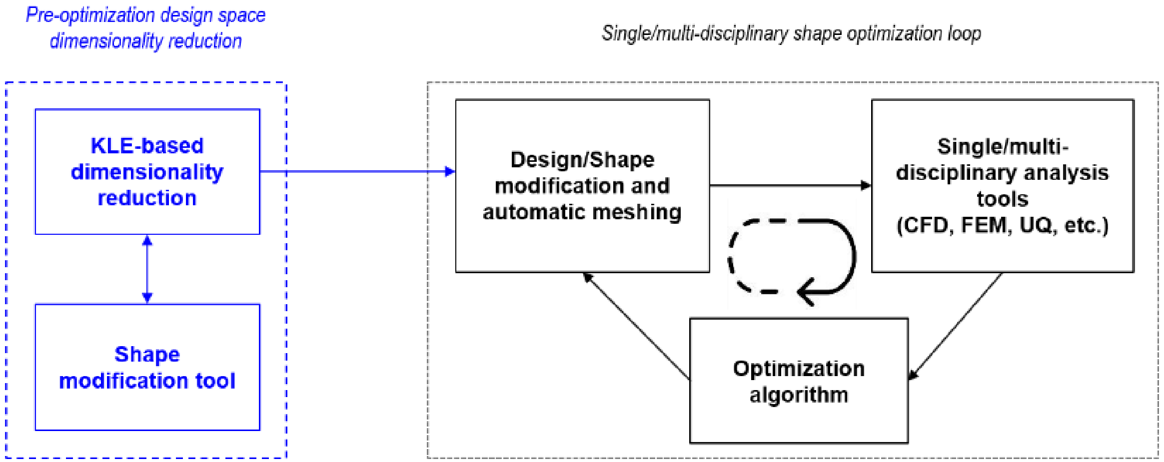
“Curse of dimensionality”

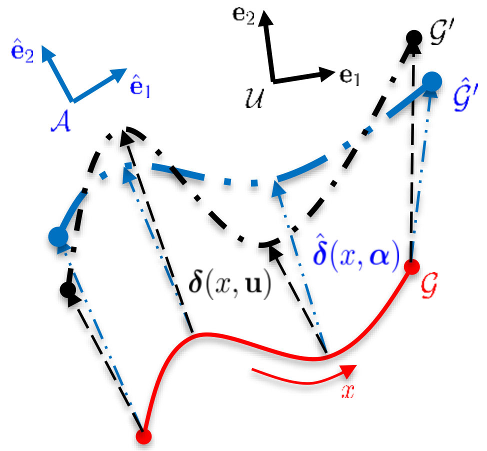
The optimization/analysis algorithmic performance deteriorates with increasing dimension (Bellman, 1957)

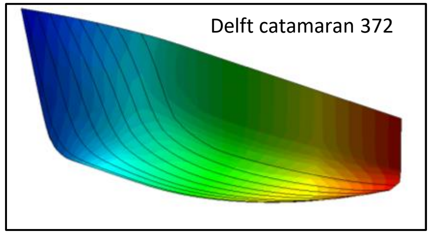
M.C. Escher, Relativity, 1953

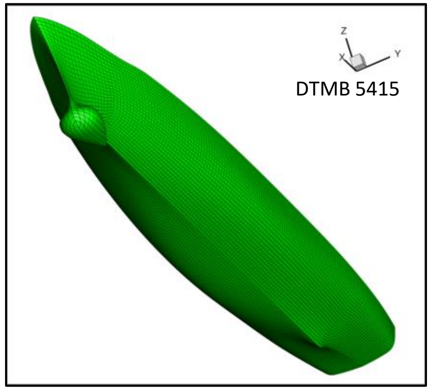
Design-space Dimensionality Reduction via Machine Learning

$\mathbf{x} \in \mathcal{G} \subset \mathbb{R}^3$
$\mathbf{u} \in \mathcal{U} \subset \mathbb{R}^M$
$\boldsymbol{\alpha} \in \mathcal{A} \subset \mathbb{R}^N$






Delft catamaran 372

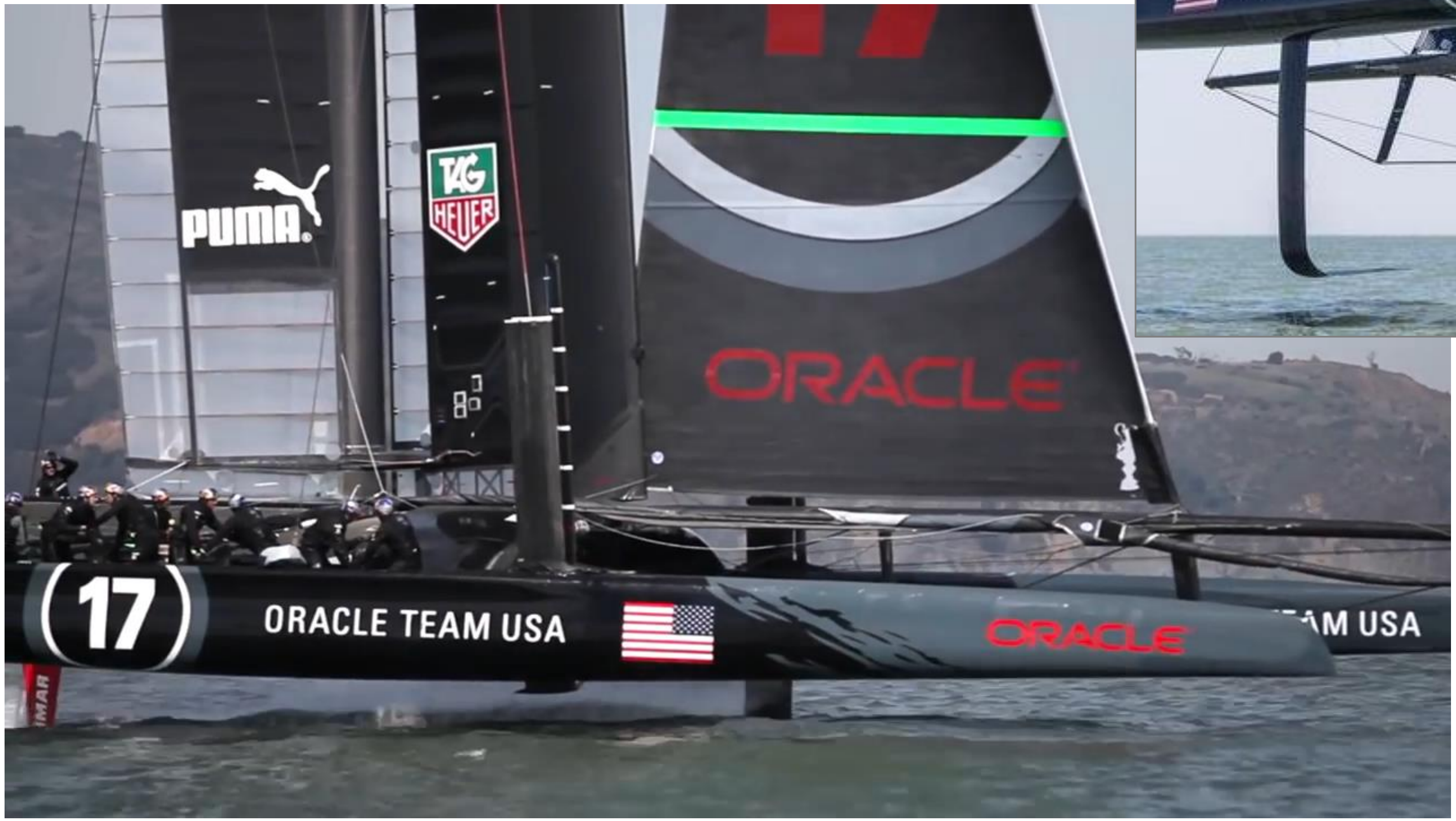


DTMB 5415

- Offline machine learning approaches have been developed with the aim of assessing and reducing the design-space dimensionality before optimization is performed
- Dimensionality reduction of shape modification vector
  - Karhunen-Loève expansion/principal component analysis (PCA)
  - Local principal component analysis (LPCA)
  - Kernel principal component analysis (KPCA)
  - Deep autoecoders (DAE)

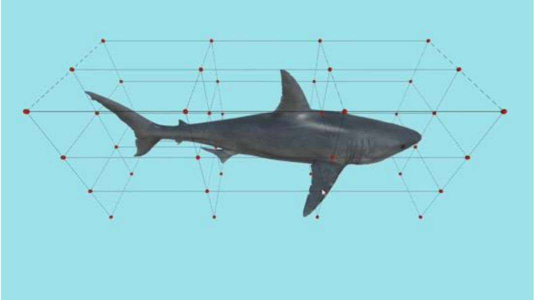
- Diez, M., Campana, E.F. and Stern, F., 2015. Design-space dimensionality reduction in shape optimization by Karhunen–Loève expansion. *Computer Methods in Applied Mechanics and Engineering*, *283*, pp.1525-1544.
- Diez, M., Serani, A., Stern, F. and Campana, E.F., 2016, September. Combined geometry and physics based method for design-space dimensionality reduction in hydrodynamic shape optimization. In *Proceedings of the 31st Symposium on Naval Hydrodynamics, Monterey, CA, USA*.
- D'Agostino, D., Serani, A., Campana, E.F. and Diez, M., 2017, September. Nonlinear methods for design-space dimensionality reduction in shape optimization. In International Workshop on Machine Learning, Optimization, and Big Data (pp. 121-132). Springer, Cham.

Application: 3D Hydrofoil

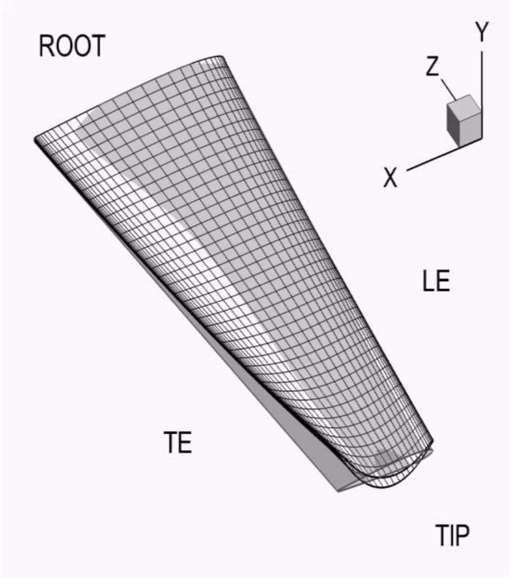


https://www.youtube.com/watch?v=Y6dnOlE9sjk

Application: 3D Hydrofoil



https://www.youtube.com/watch?v=MwtIj5QoKLE



Shape modification by FFD

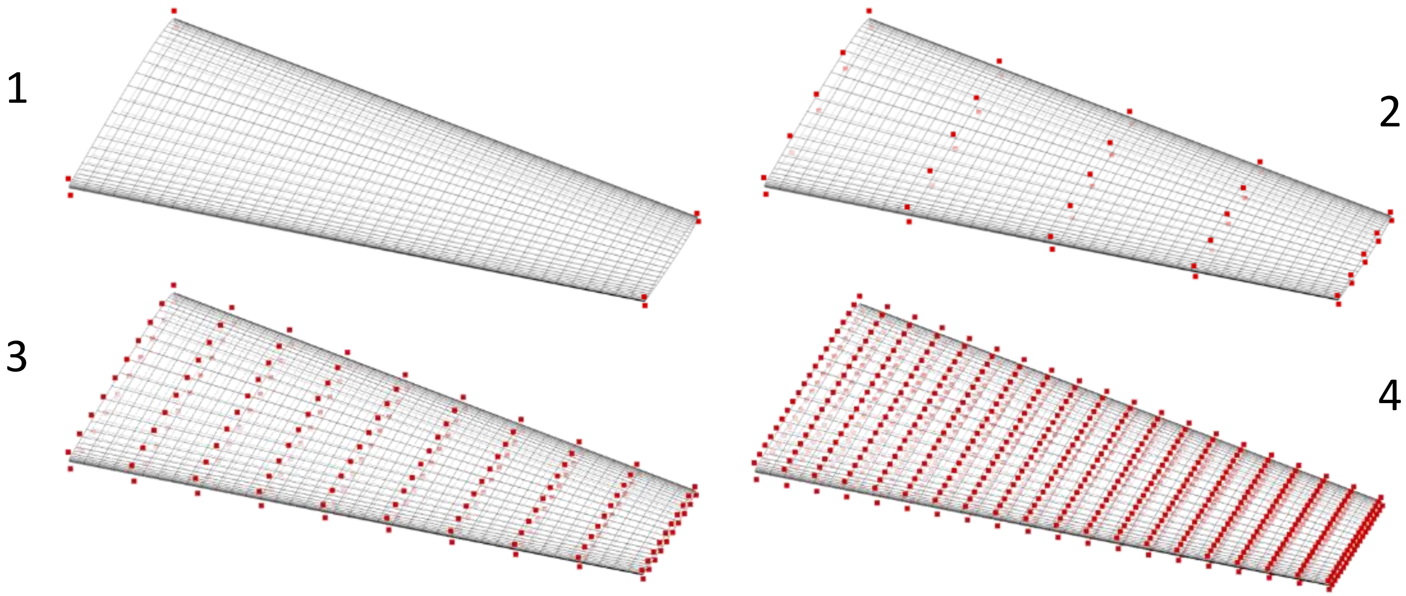
- Free form deformation (FFD) originally developed by Sederberg and Parry (1986)
- FFD control points are moved and the modification is interpolated using trivariate Bernstein polynomials

$$\mathbf{x}_{\text{ffd}} = \sum_{i=0}^{l} \binom{l}{i} (1-s)^{l-i} s^i \left[\sum_{j=0}^{m} \binom{m}{j} (1-t)^{m-j} t^i \left[\sum_{k=0}^{n} \binom{n}{k} (1-u)^{n-k} u^i \mathbf{P}_{ijk} \right] \right]$$

- The design space is bounded by +/- 20% mid-chord displacement of control points
- +/- 5 degrees of twist angle at the tip section is added to the design variables. Twist is interpolated along the span and is zero at the root section

- Sederberg, T. W. and Parry, S. R., "Free-form deformation of solid geometric models," *ACM SIGGRAPH computer graphics*, Vol. 20, No. 4, 1986, pp. 151–160

Application: 3D Hydrofoil



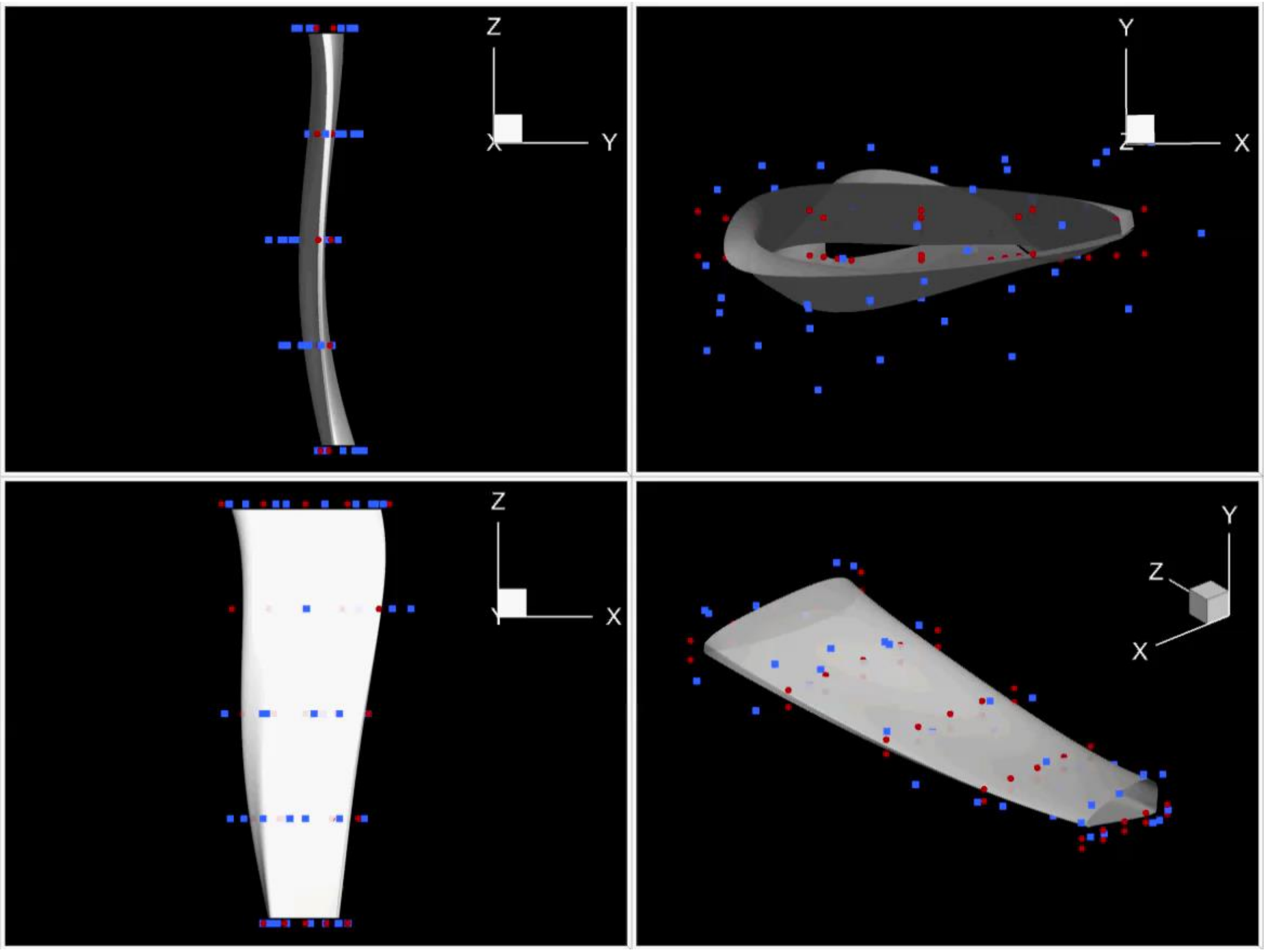
Design space	$l+1$	$m+1$	$n+1$	N_{CP}	DOF_{CP}	DOF_{twist}	M
1	2	2	2	8	2 $(\hat{\mathbf{s}},\hat{\mathbf{t}})$	1 (θ)	17
2	5	2	5	50	2 $(\hat{\mathbf{s}},\hat{\mathbf{t}})$	1 (θ)	101
3	10	2	10	200	2 $(\hat{\mathbf{s}},\hat{\mathbf{t}})$	1 (θ)	401
4	20	2	20	800	2 $(\hat{\mathbf{s}},\hat{\mathbf{t}})$	1 (θ)	1601

- Four design spaces are compared, which have a different number of control points

- Volpi, S., Diez, M. and Stern, F., 2018. Multidisciplinary design optimization of a 3D composite hydrofoil via variable accuracy architecture. In *2018 Multidisciplinary Analysis and Optimization Conference* (p. 4173).

Application: 3D Hydrofoil

- MC sampling of the design space (uniform random distribution)



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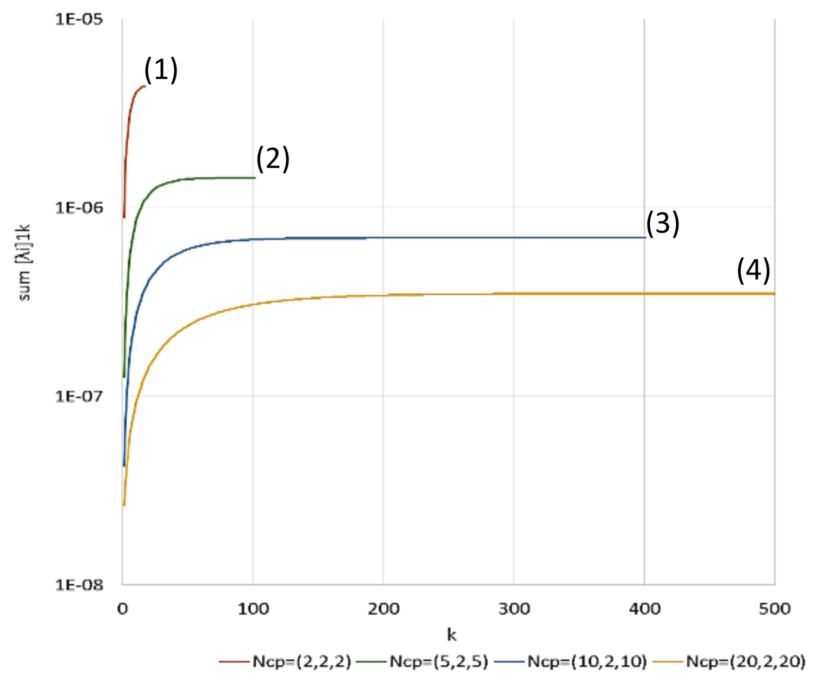
Application: 3D Hydrofoil

PCA eigenvalues (cumulative sum): design/geometric variability



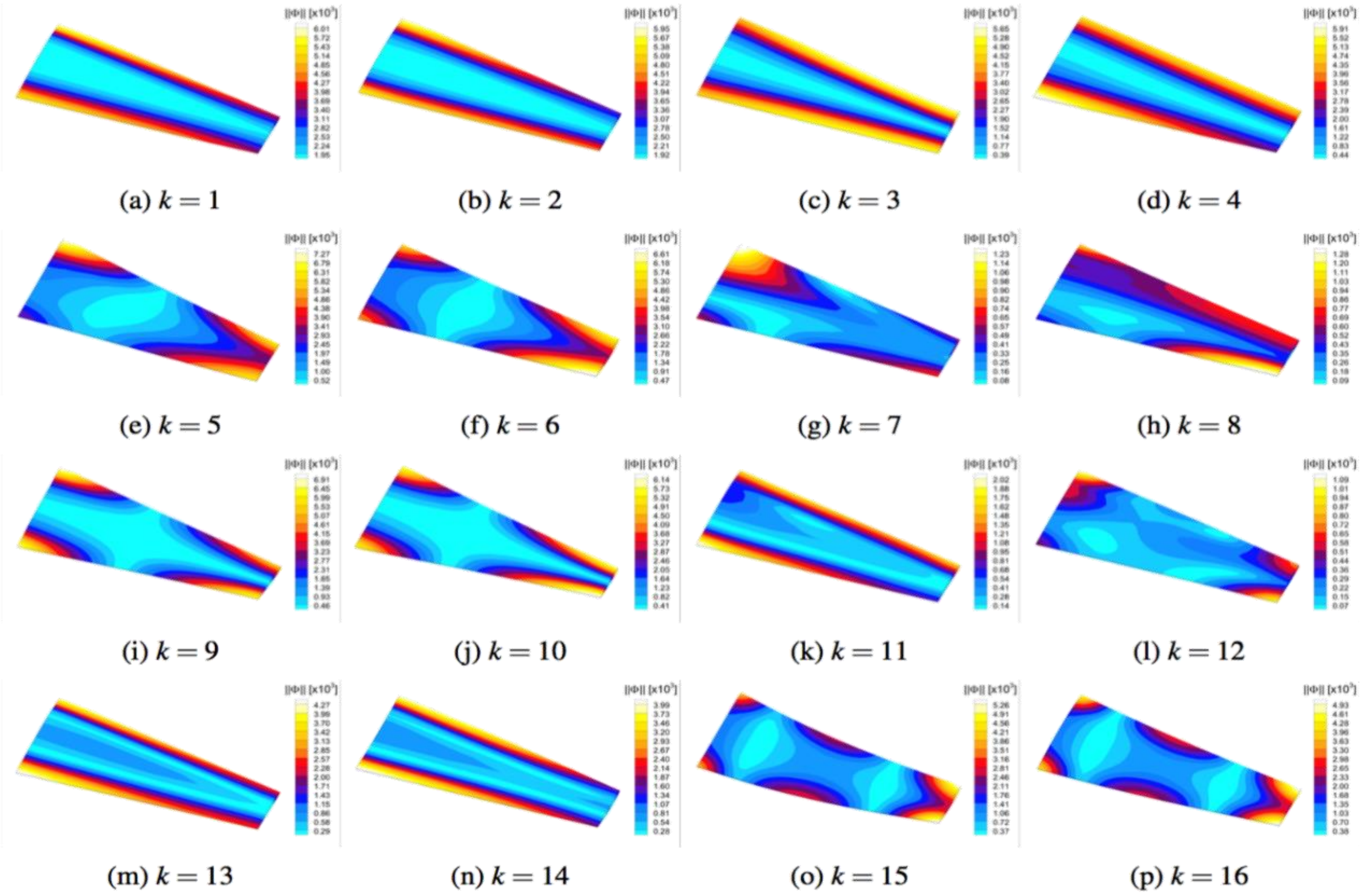
Design space	σ^2	$N\vert\sum_{k=1}^{N} = 50\%\sigma^2$	$N\vert\sum_{k=1}^{N} = 75\%\sigma^2$	$N\vert\sum_{k=1}^{N} = 90\%\sigma^2$	$N\vert\sum_{k=1}^{N} = 99\%\sigma^2$
1	4.4E-6	3 (18%)	7 (41%)	10 (59%)	14 (82%)
2	1.4E-6	8 (8%)	16 (17%)	28 (28%)	55 (55%)
3	6.9E-7	16 (4%)	33 (8%)	57 (14%)	120 (30%)
4	3.5E-7	29 (2%)	64 (4%)	113 (7%)	243 (15%)

- Increasing the number of FFD control points reduces the geometric variance of the design space (assuming equally defined design variable bounds for each space)
- The potentiality of the dimensionality reduction becomes very significant as the number of FFD control points increases

- Volpi, S., Diez, M. and Stern, F., 2018. Multidisciplinary design optimization of a 3D composite hydrofoil via variable accuracy architecture. In *2018 Multidisciplinary Analysis and Optimization Conference* (p. 4173).

Application: 3D Hydrofoil

Eigenfunctions: new basis for design space



(a) $k = 1$ (b) $k = 2$ (c) $k = 3$ (d) $k = 4$

(e) $k = 5$ (f) $k = 6$ (g) $k = 7$ (h) $k = 8$

(i) $k = 9$ (j) $k = 10$ (k) $k = 11$ (l) $k = 12$

(m) $k = 13$ (n) $k = 14$ (o) $k = 15$ (p) $k = 16$

(First 16 PCA modes for the design space 2)

Application: High-Speed Catamaran

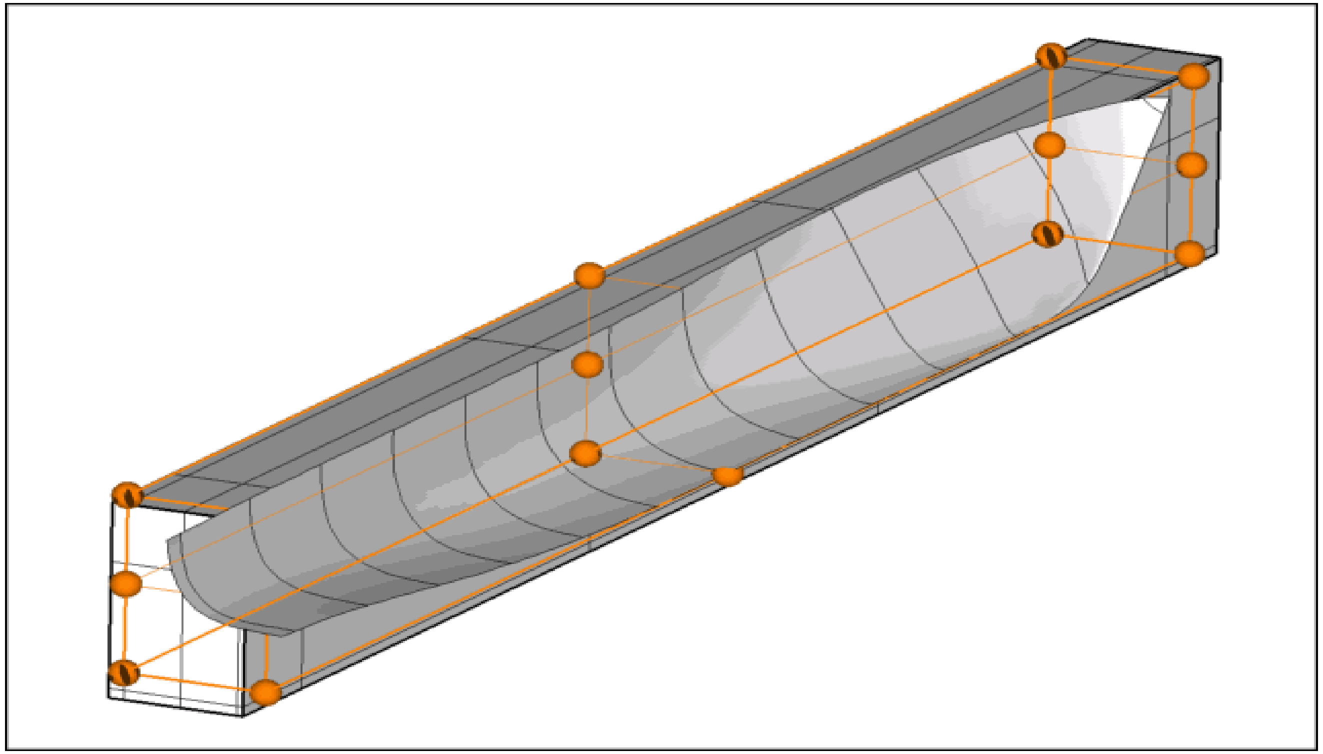
Littoral Surface Craft-Experimental LSC(X), developed by the Office of Naval Research and christened Sea Fighter (FSF 1)

Application: High-Speed Catamaran

Delft catamaran 372 hull-form **optimization** in calm water at Fr=0.5

Shape parameters

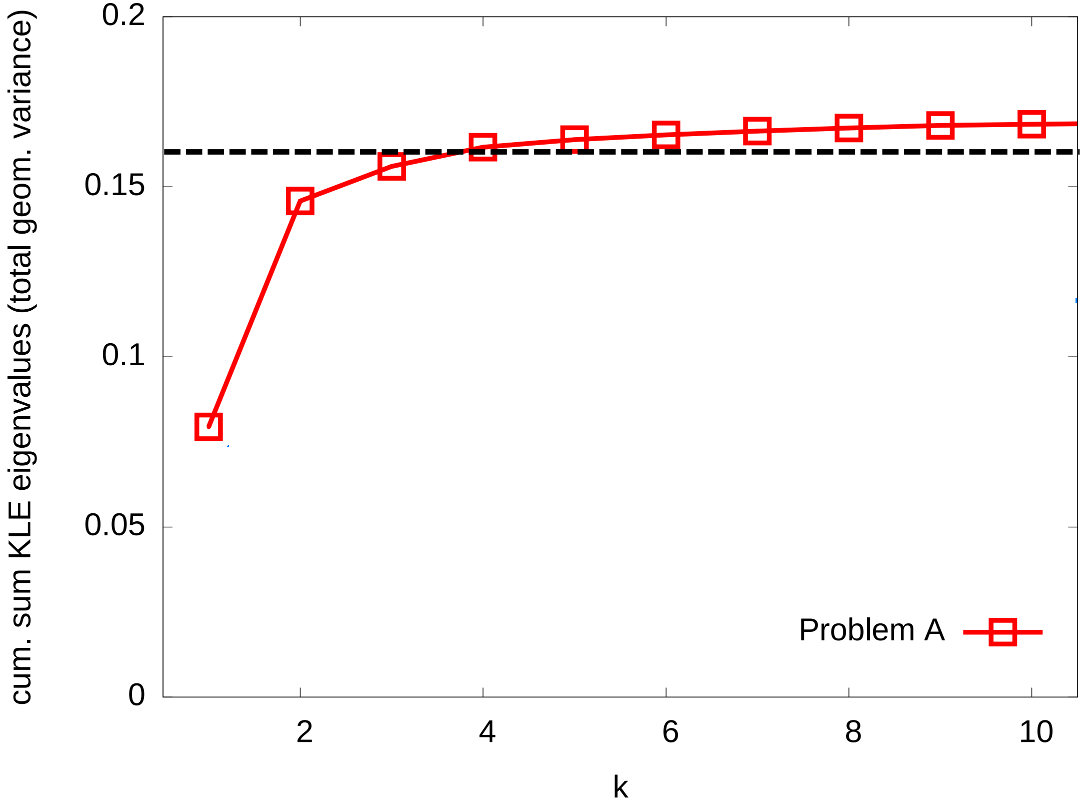
- Free-form deformation (FFD)
- 20 design variables
- 2 geometric constraint sets (design spaces)



- Diez M, Campana EF, Stern F (2015) *Design-space dimensionality reduction in shape optimization by Karhunen–Loève expansion*, Computer Methods in Applied Mechanics and Engineering 283, 1525–1544

Application: High-Speed Catamaran

Design/geometric variability

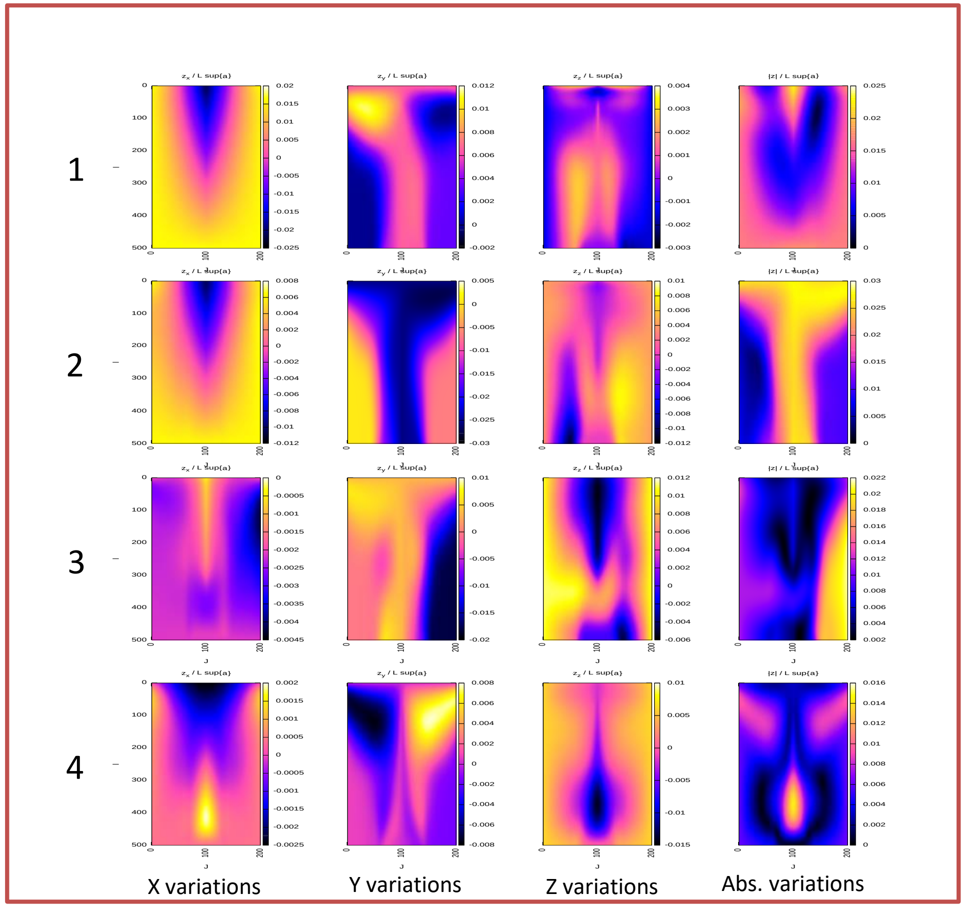


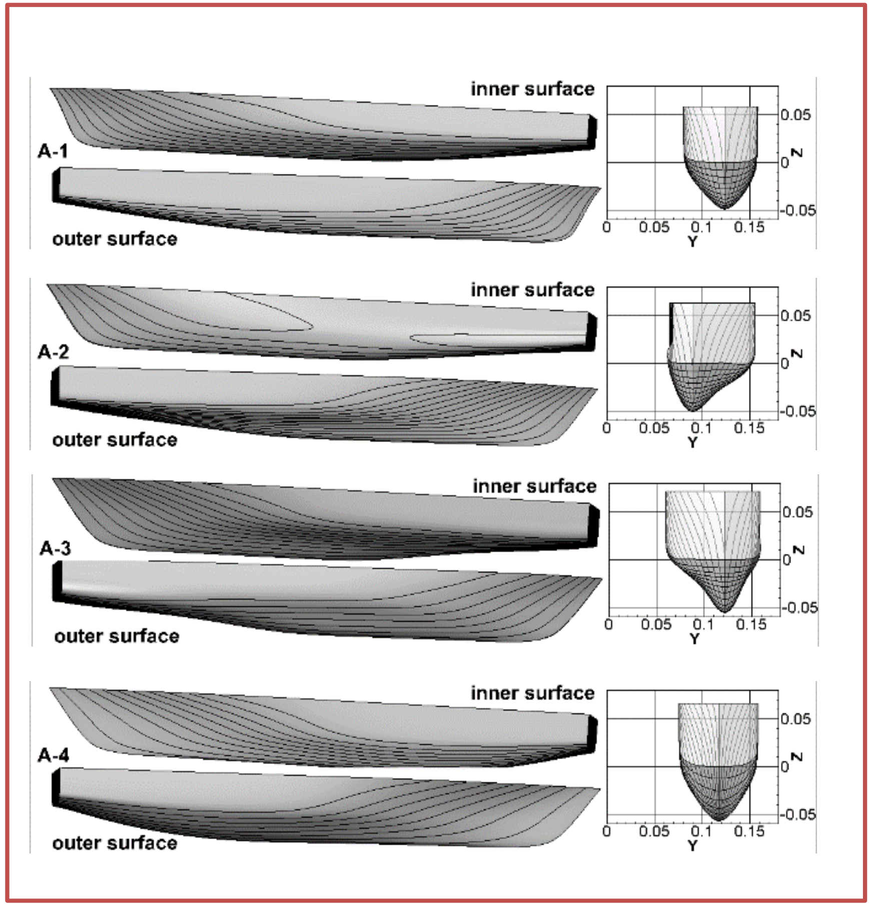
- The original design space is sampled using a random uniform distribution of 10,000 hull-form designs
- Design space A: **4 variables** are needed to retain the 95% of original geometric variance

Design space	Dimensionality
Original	22
Reduced	**4**

Application: High-Speed Catamaran

New basis for design space



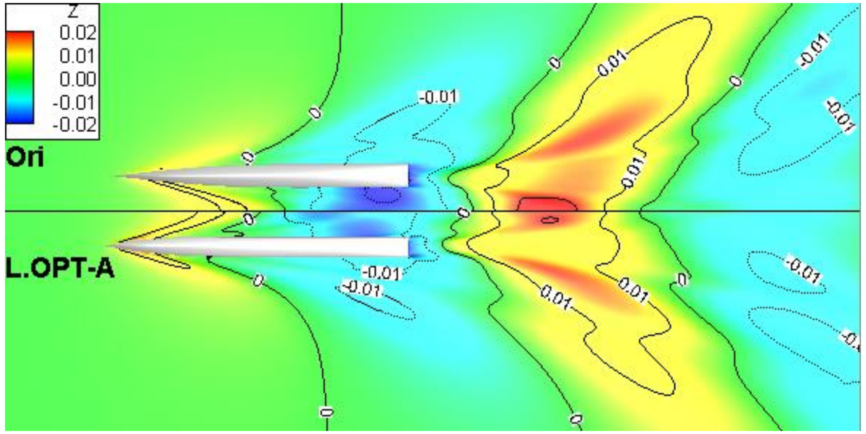


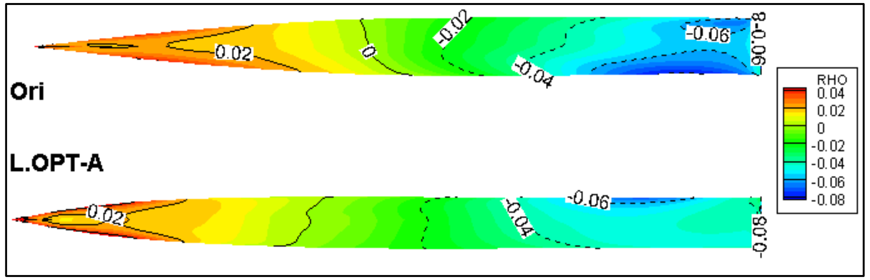
- PCA functions are variations in X, Y, Z direction

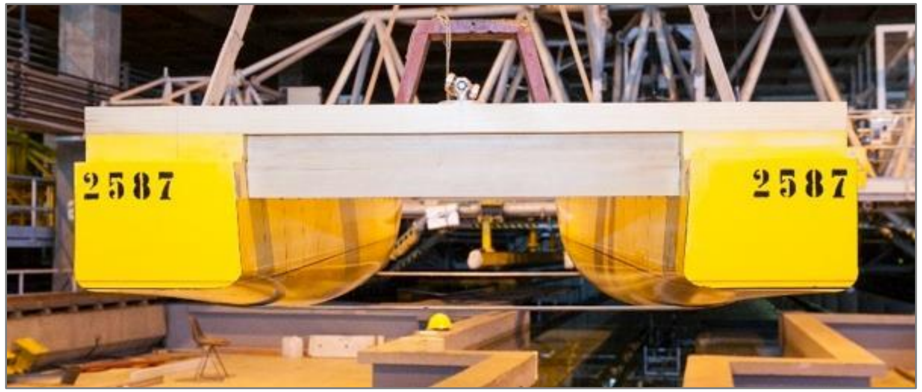
Design space	Dimensionality
Original	22
Reduced	**4**

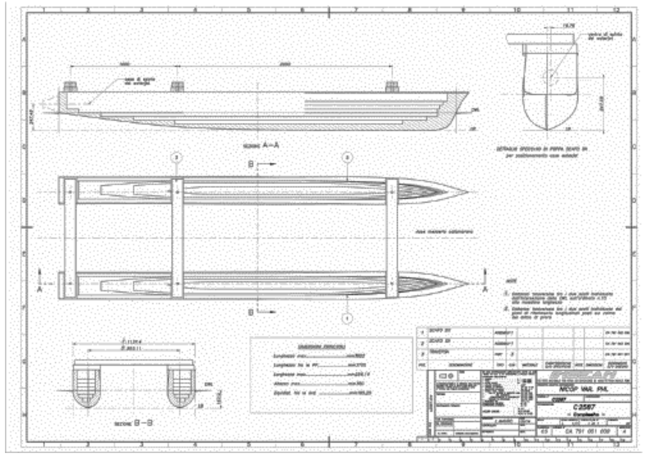
Application: High-Speed Catamaran

- Comparing to the original design, optimized designs slenderize the entire geometry while moving more volume to the bow and the stern (especially at the inner side)









Application: High-Speed Catamaran


Fr=0.15


Fr=0.20


Fr=0.25


Fr=0.30


Fr=0.35


Fr=0.40


Fr=0.45


Fr=0.50


Fr=0.55

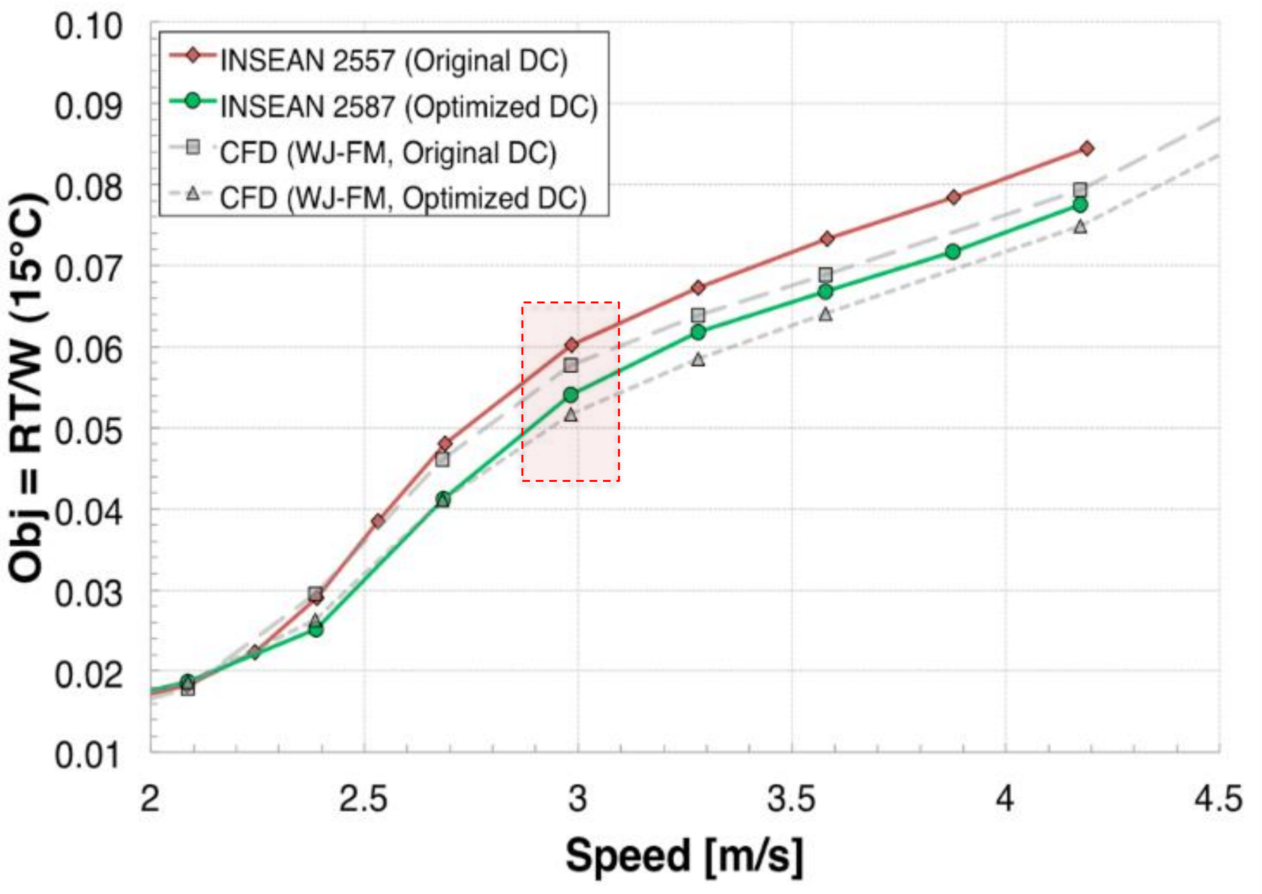

Fr=0.60


Fr=0.65


Fr=0.70

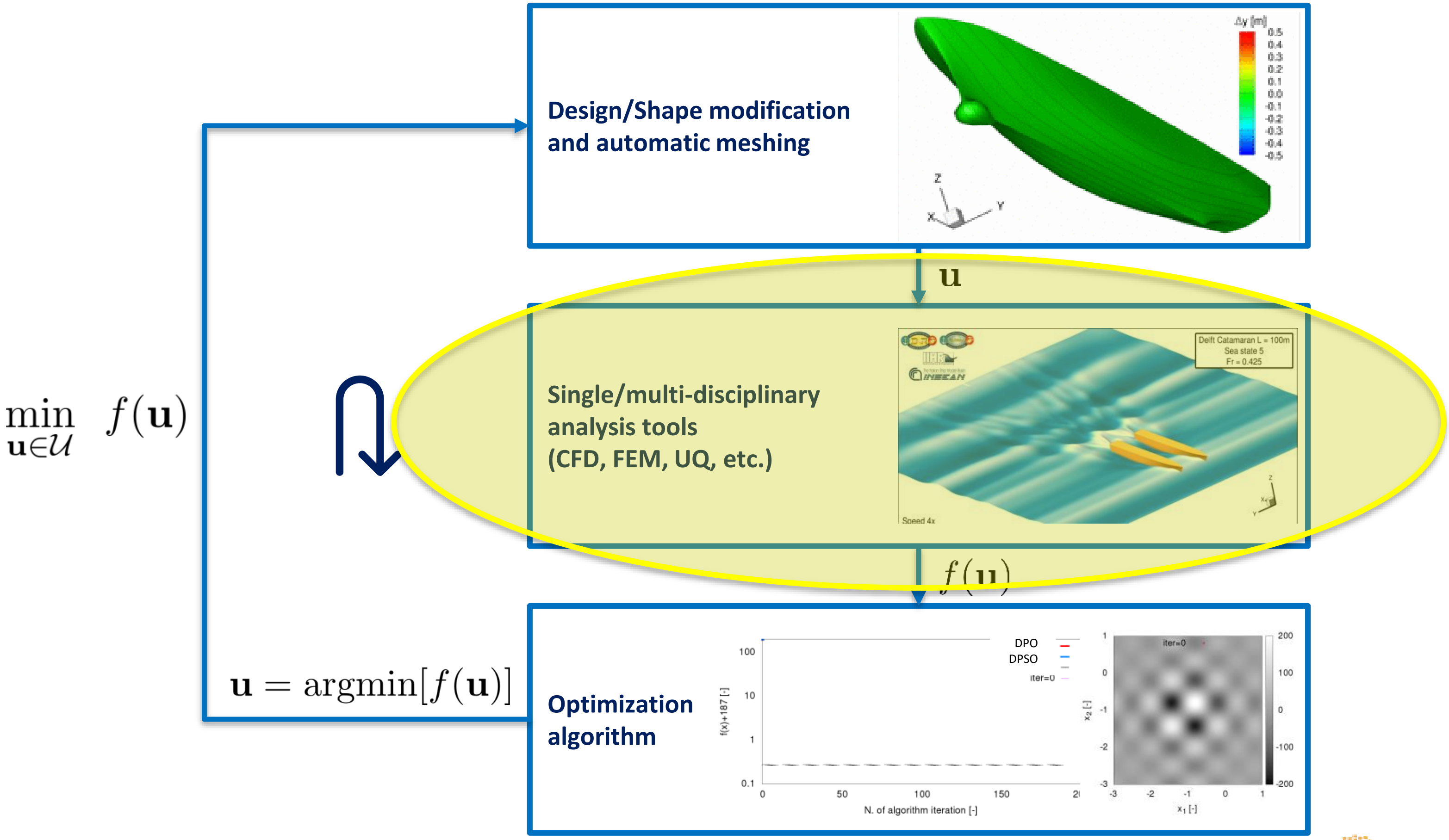
Application: High-Speed Catamaran

- EFD: **8.9% reduction** at Fr = 0.5; U%D small (<1%)
- CFD: 10.0% reduction; U%S = 3.7% (original) and 2.6% (optimized)
- Error for reduction prediction E = 1.1%

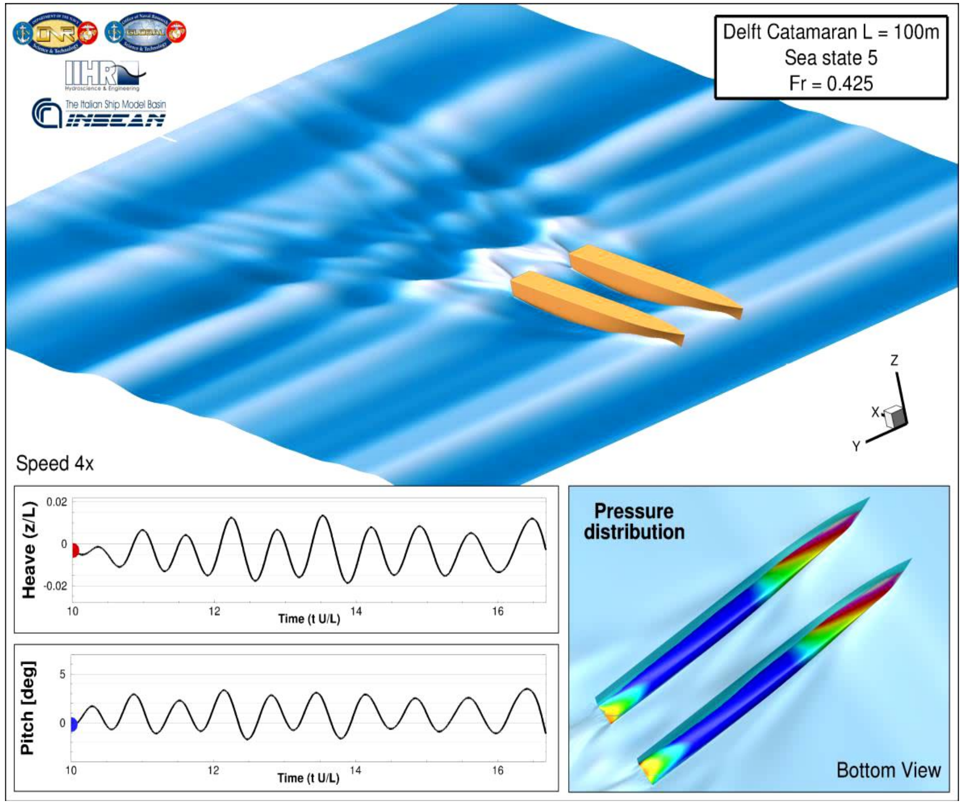


Simulation-Based Design Optimization

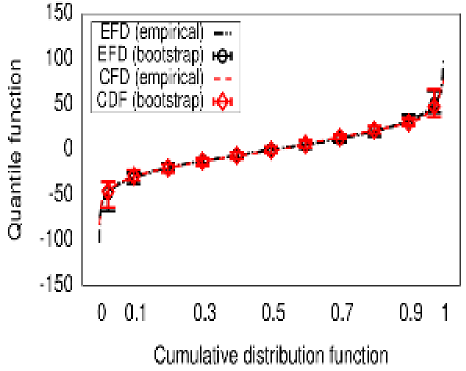
$$\begin{aligned} \text{Minimize} \quad & f(\mathbf{x}) \\ \text{subject to} \quad & l_k \le x_k \le u_k, \quad k = 1,\dots,n \\ \text{and to} \quad & g_j(\mathbf{x}) \le 0, \quad j = 1,\dots,N_g \end{aligned}$$

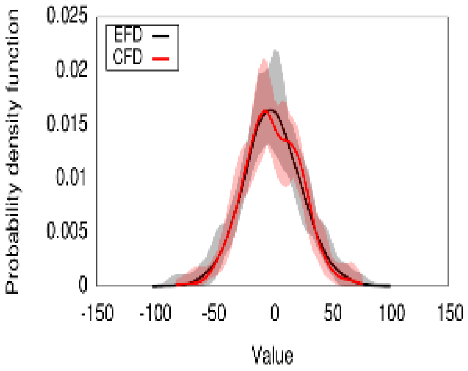


Simulations and Uncertainty Quantification



	No. of wave components, N_w	Run time at model scale [s]	No. of encounter waves	No. of modal periods	m_0 [mm^2]	E(m_0) %Theory
EFD	993	240	361	143	599	0.2
CFD	50	50	88	30	571	-2.5





- URANS/FE
- MC methods with metamodels
- Auto-covariance analysis
- Bootstrap methods

- Diez, M., Broglia, R., Durante, D., Olivieri, A., Campana, E. and Stern, F., 2017. Validation of Uncertainty Quantification Methods for High-Fidelity CFD of Ship Response in Irregular Waves. J. Verif. Valid. Uncert. (2018); doi: 10.1115/1.404137.

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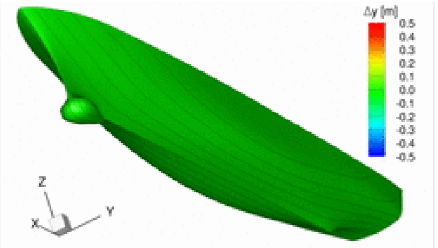

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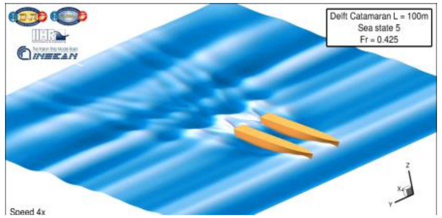
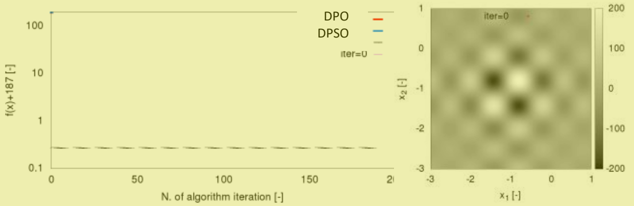


$f(\mathbf{u})$

$$\min_{\mathbf{u}\in\mathcal{U}} \quad f(\mathbf{u})$$

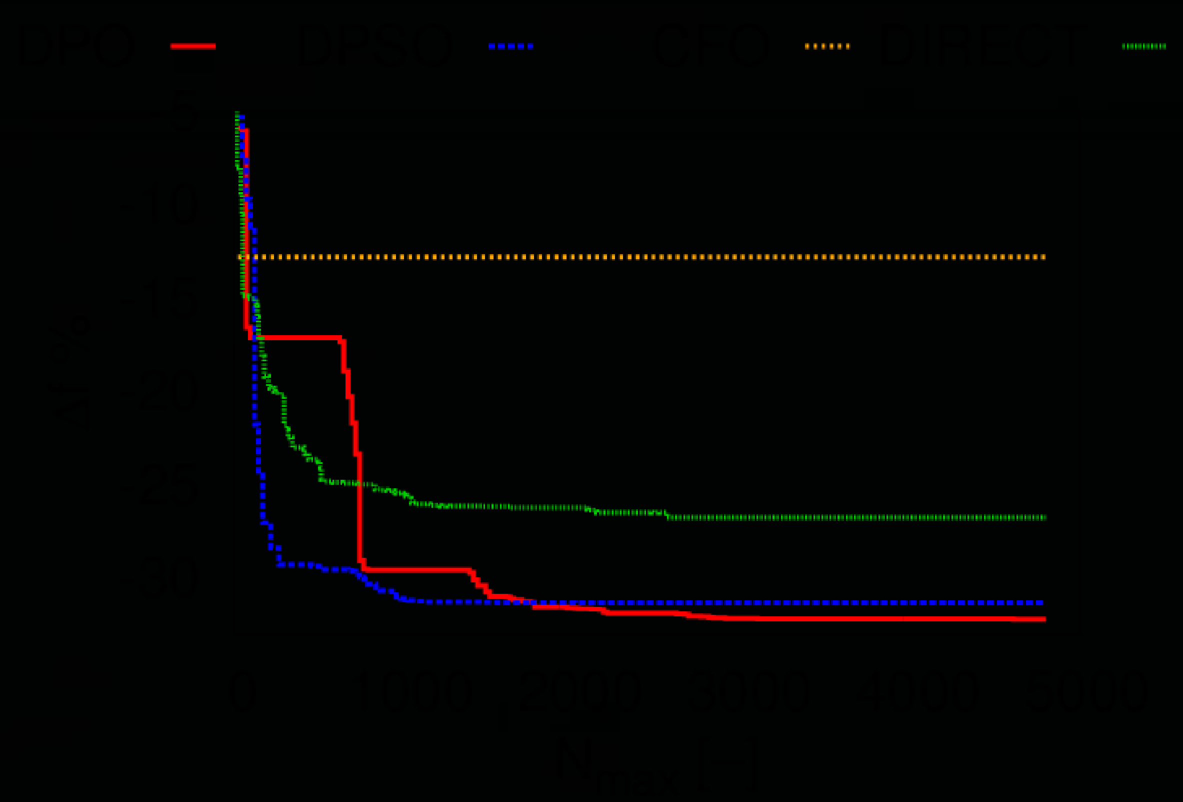
Optimization algorithm

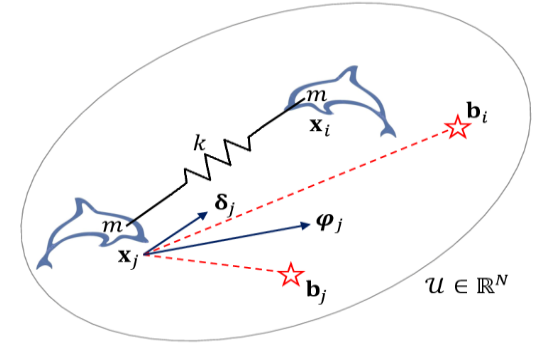


$$\mathbf{u} = \operatorname{argmin}[f(\mathbf{u})]$$

Optimization Algorithm: Dolphin Pod Optimization

- Based on a simplified social model of a dolphin pod in search for food
- Formulated for unconstrained single-objective minimization and intended for SBD optimization problems with costly objective functions.
- The novelty stems from formulating the global search by defining the pod dynamics as a spring-mass system subject to internal and external forces
- DPO is formulated considering the essential elements of the cetacean intelligence:
  - ✓ *Congregation*
  - ✓ *Self-awareness*
  - ✓ *Communication*
  - ✓ *Memory*





"Individual feeding may be enhanced by the presence of the group due to rapid and efficient information transfer concerning where, for example, the major concentration of prey is and what the extent of the prey school may be."
(Würsig, *Delphinid Foraging Strategies* 2013)

- Serani, A. and Diez, M., 2017, September. Dolphin pod optimization. In *International Workshop on Machine Learning, Optimization, and Big Data* (pp. 50-62). Springer, Cham.

Simulation-Based Design Optimization

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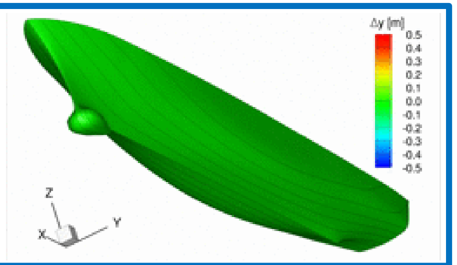

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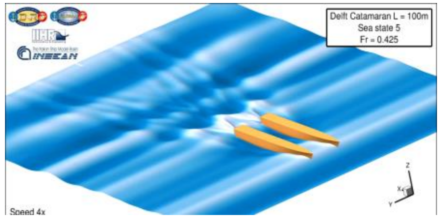
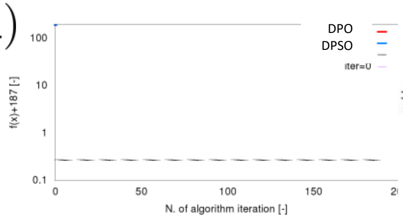


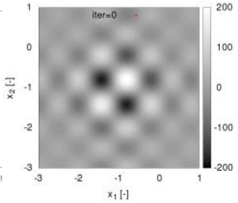
Metamodels

$f(\mathbf{u})$

$\min_{\mathbf{u} \in \mathcal{U}} f(\mathbf{u})$

Optimization algorithm





$\mathbf{u} = \text{argmin}[f(\mathbf{u})]$

Radial Basis Function (RBF) Metamodel

- **Standard RBF**

number of training points

$$\tilde{f}(\mathbf{x}) = \sum_{i=1}^{N} w_i \varphi(r) \quad \text{with} \quad r = \|\mathbf{x} - \mathbf{x}_i\|$$

unknown coefficients

training points with associated $f(\mathbf{x})$

Kernel

- Power law

$$\varphi(r) = r^\tau$$

- Multiquadric

$$\varphi(r) = \sqrt{1 + (\tau r)^2}$$

- Inverse multiquadric

$$\varphi(r) = \frac{1}{\sqrt{1 + (\tau r)^2}}$$

- Gaussian

$$\varphi(r) = \exp^{-(\tau r)^2}$$

- Inverse quadratic

$$\varphi(r) = \frac{1}{1 + (\tau r)^2}$$

$$\mathbf{A}\mathbf{w} = \mathbf{f}$$

$$\text{with} \quad \mathbf{w} = \{w_i\}, \quad a_{ij} = \varphi(r) \quad \text{and} \quad \mathbf{f} = \{f(\mathbf{x}_i)\}$$

Stochastic Radial Basis Function (SRBF) Metamodel

- **Stochastic RBF**

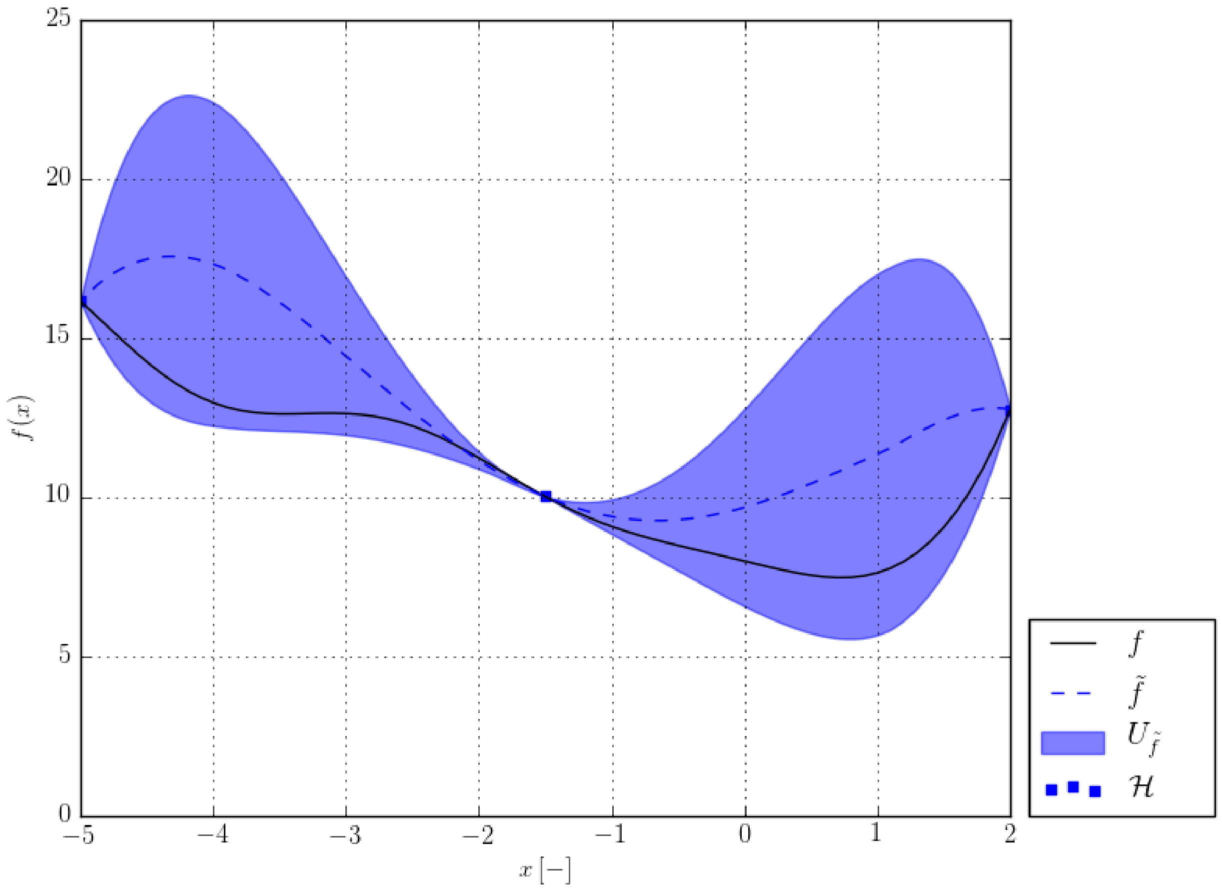
$$\tilde{f}(\mathbf{x}) = \sum_{i=1}^{N} w_i \varphi(r) \quad \text{with} \quad r = \|\mathbf{x} - \mathbf{x}_i\|^{\tau}$$

- Monte Carlo sampling of τ is performed, providing a stochastic ensemble of metamodels

$$\boxed{\tilde{f}(\mathbf{x}) = \mathrm{EV}[\tilde{f}(\mathbf{x}, \tau)]}$$

- It provides predictions as mean value and 95% uncertainty band

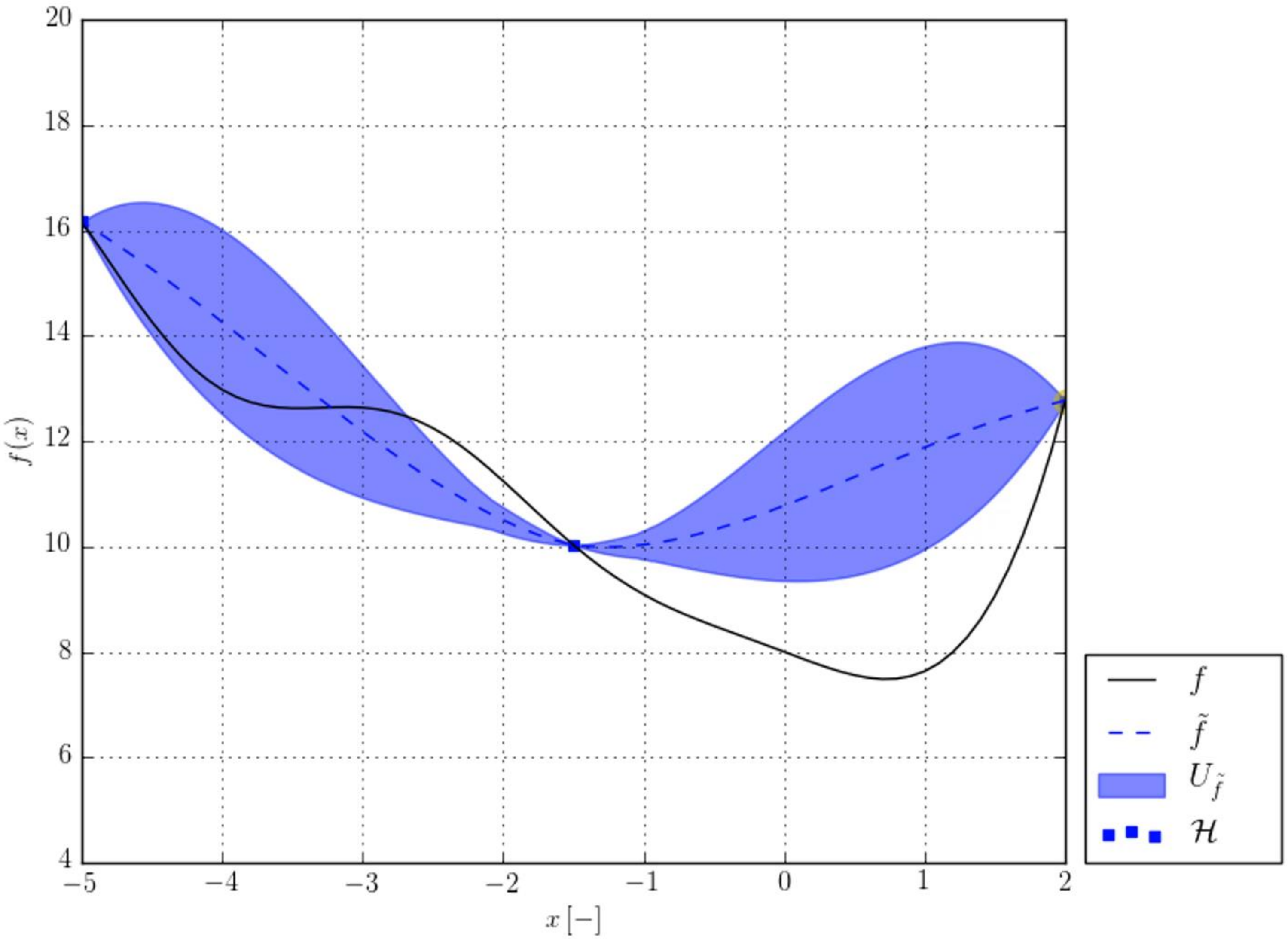
$$\boxed{U_{\tilde{f}} = \mathrm{CDF}^{-1}(0.975) - \mathrm{CDF}^{-1}(0.025)}$$



- Volpi, S., Diez, M., Gaul, N.J., Song, H., Iemma, U., Choi, K.K., Campana, E.F. and Stern, F., 2015. Development and validation of a dynamic metamodel based on stochastic radial basis functions and uncertainty quantification. *Structural and Multidisciplinary Optimization*, *51*(2), pp.347-368.

Adaptivity Through Sampling

- Adaptive exploration of design/operational spaces
- Focus on interesting regions and useful evaluations
- Sequential sampling procedure



Extension to Two Fidelity Levels

$f_H(\mathbf{x})$ High-fidelity function

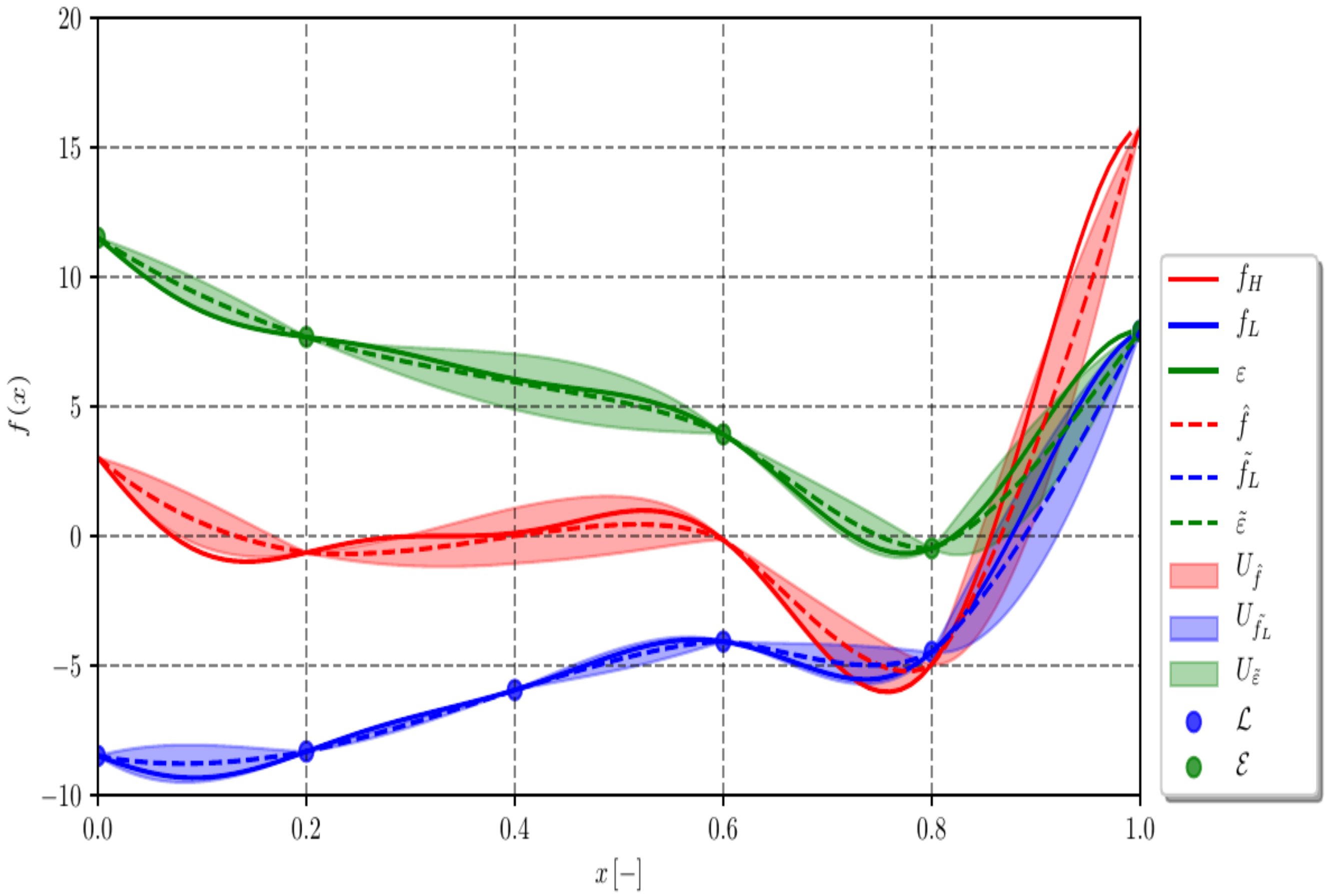
$f_L(\mathbf{x})$ Low-fidelity function

$\varepsilon(\mathbf{x}) = f_H(\mathbf{x}) - f_L(\mathbf{x})$ Error function

Multi-fidelity metamodel

$$\hat{f}(\mathbf{x}) = \tilde{f}_L(\mathbf{x}) + \tilde{\varepsilon}(\mathbf{x})$$

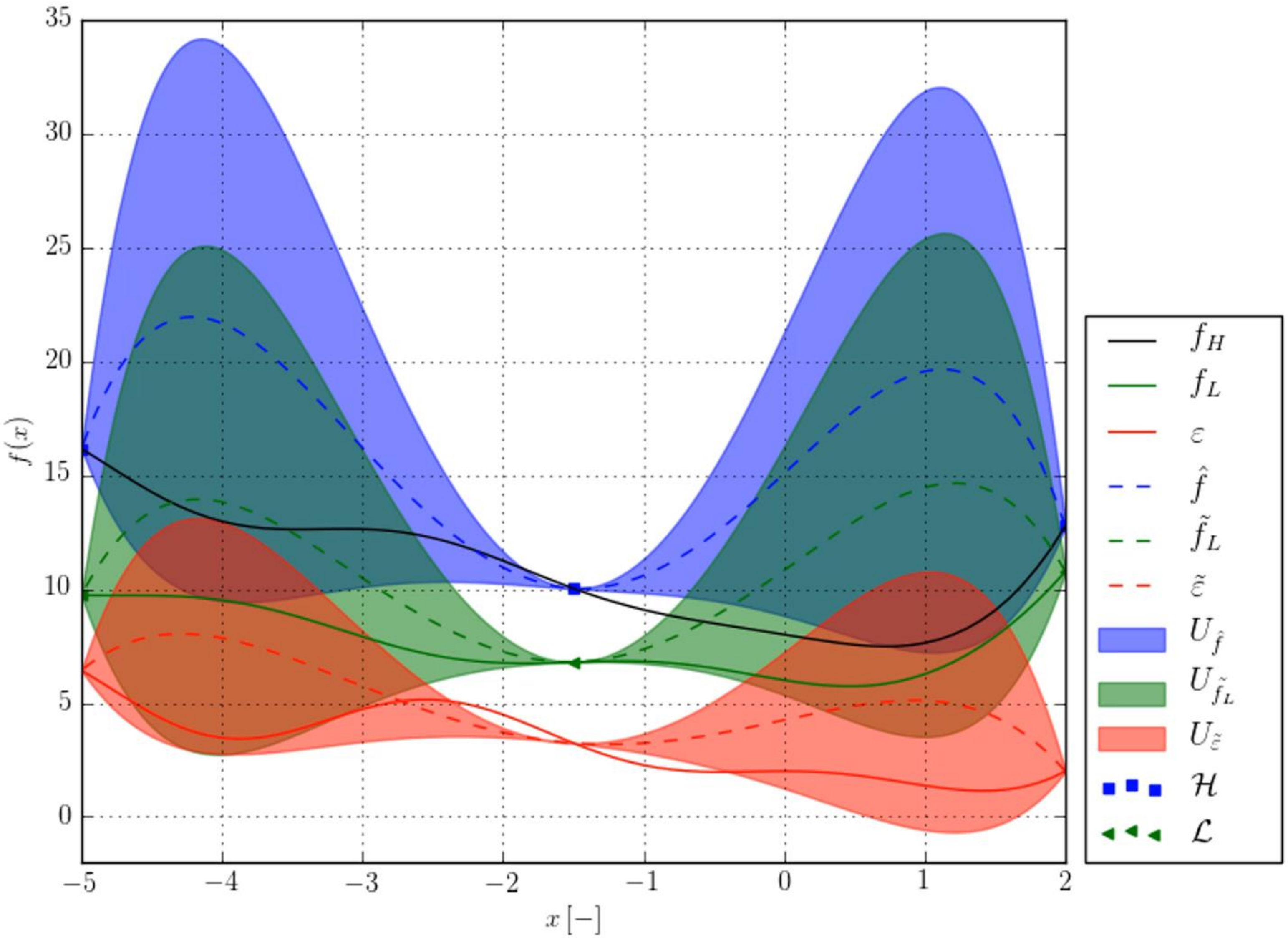
$$U_{\hat{f}}(\mathbf{x}) = \sqrt{U^2_{\tilde{f}_L}(\mathbf{x}) + U^2_{\tilde{\varepsilon}}(\mathbf{x})}$$



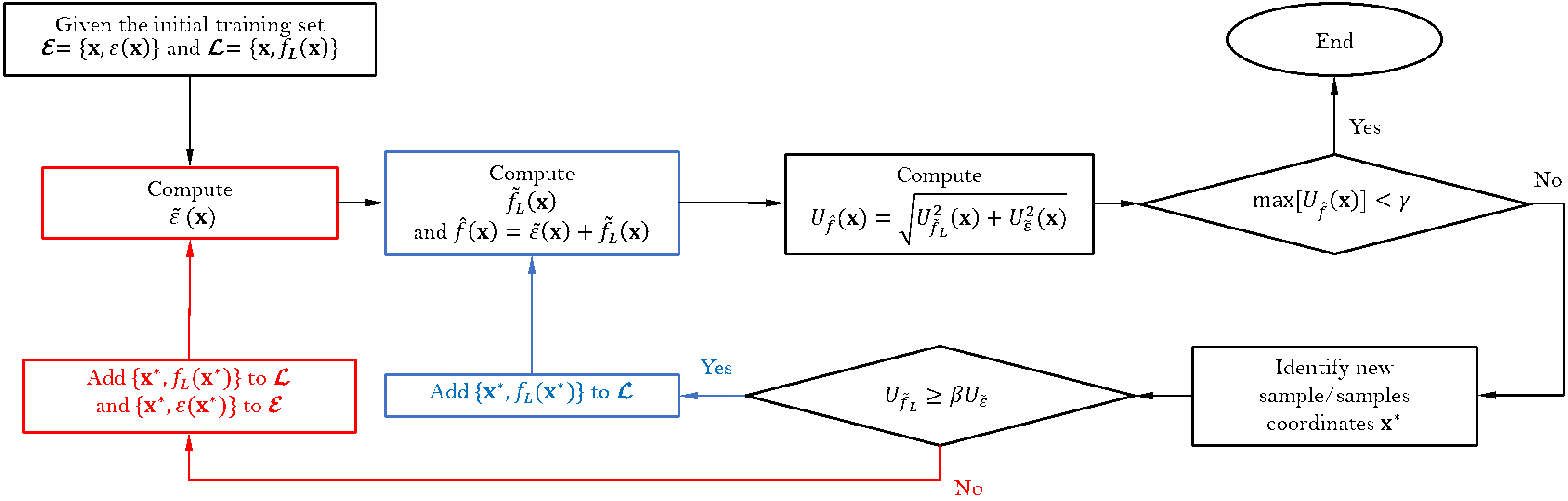
- Serani A., Pellegrini R., Broglia R., Wackers J., Visonneau M., Diez M. (2019). *Adaptive multi-fidelity sampling for CFD-based optimization via radial basis functions*, submitted to International Journal of Computational Fluid Dynamics, special issue on CFD-enabled Design Optimisation of Industrial Flows: Theory and Practice

Adaptivity with Two Fidelity Levels

- Adaptive exploration of design/operational spaces
- Focus on interesting zones and useful evaluations
- Sequential sampling procedure
- Adaptive selection of data fidelity



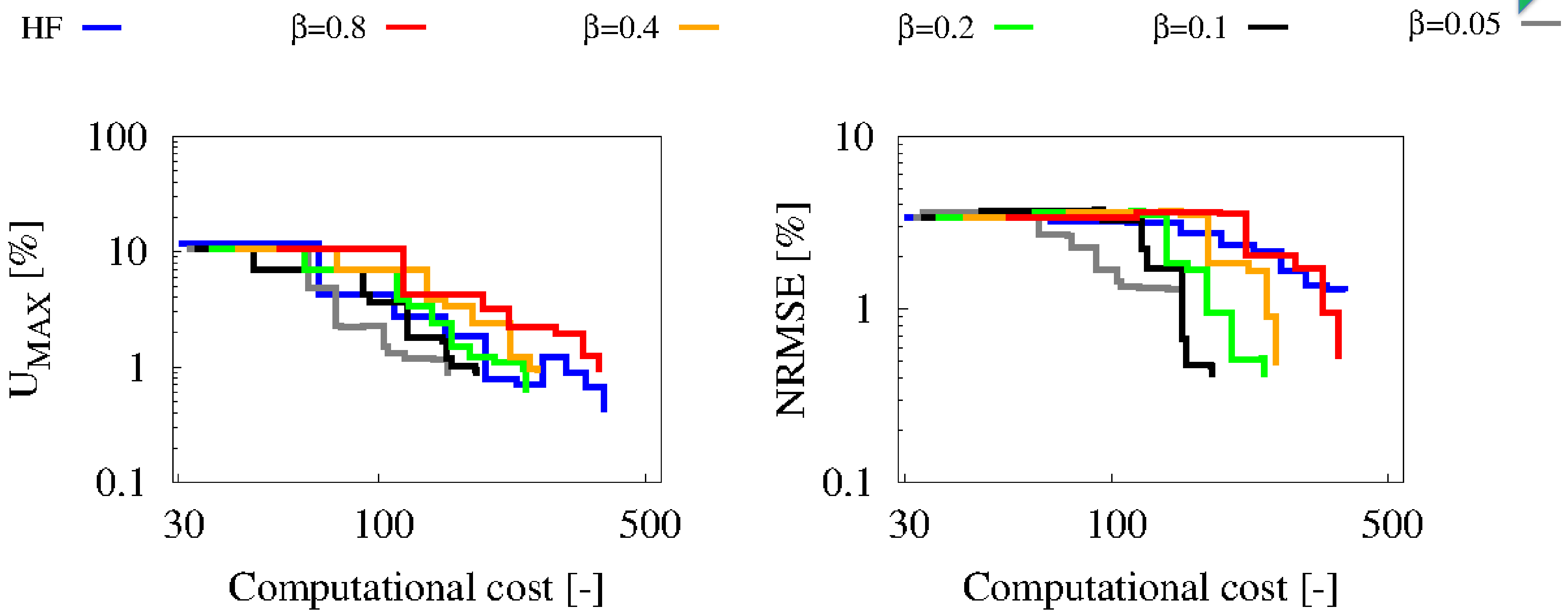
Two-Fidelity Metamodel Block Diagram



LF/HF computational cost ratio

$$\begin{cases} \text{If } U_{\tilde{f}_L}(\mathbf{x}^\star) \geq \beta U_{\tilde{\varepsilon}}(\mathbf{x}^\star), & \text{add } \{\mathbf{x}^\star, f_L(\mathbf{x}^\star)\} \text{ to } \mathcal{L} \\ \text{else,} & \text{add } \{\mathbf{x}^\star, f_L(\mathbf{x}^\star)\} \text{ to } \mathcal{L} \text{ and } \{\mathbf{x}^\star, \varepsilon(\mathbf{x}^\star)\} \text{ to } \mathcal{E} \end{cases}$$

Effect of Computational Cost in Two-Fidelity Metamodel

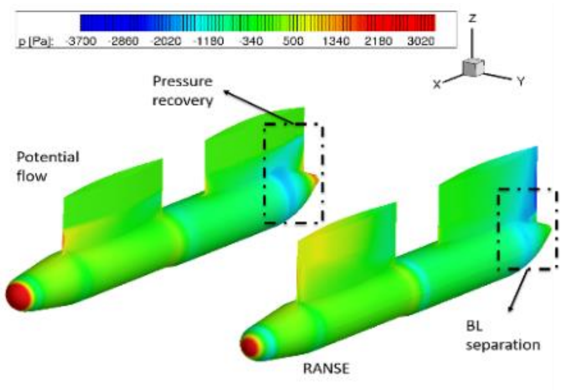


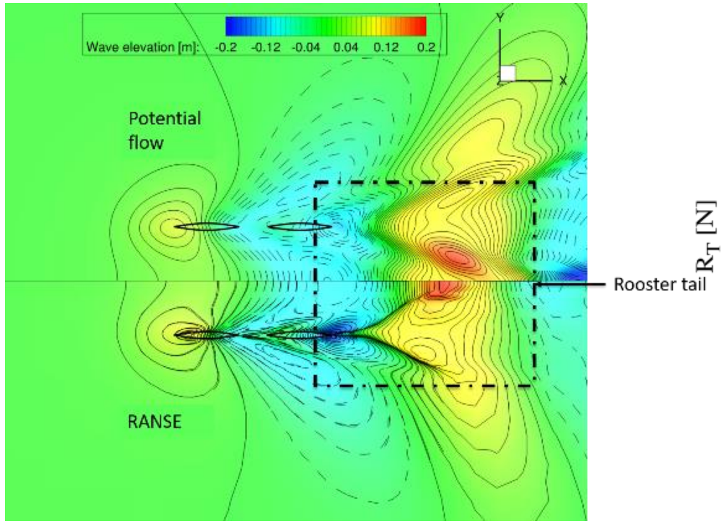
- Serani A., Pellegrini R., Broglia R., Wackers J., Visonneau M., Diez M. (2019). *Adaptive multi-fidelity sampling for CFD-based optimization via radial basis functions*, submitted to International Journal of Computational Fluid Dynamics, special issue on CFD-enabled Design Optimisation of Industrial Flows: Theory and Practice

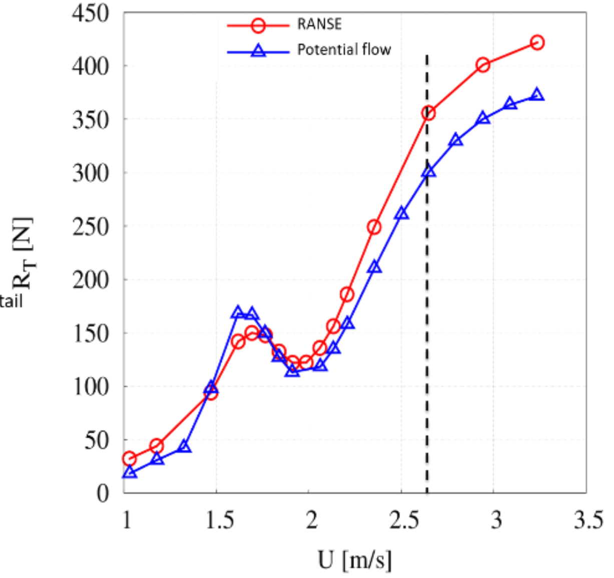
Application: Two-fidelity Optimization of a SWATH

Figure from http://www.bluebird-electric.net/
SWASH_Submerged_Single_Hull_Active_Surface_Stabilization.htm

Two-fidelity analysis

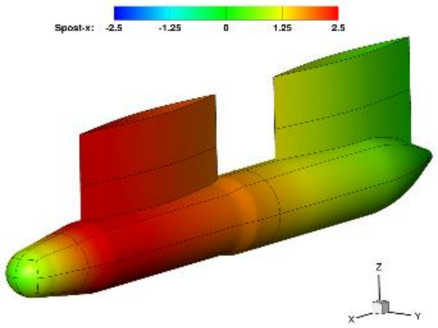




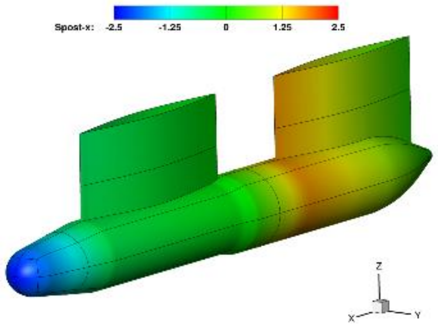


- Objective: resistance reduction at Fr=0.49
- Solvers: RANSE and potential flow/BEM
- Computational cost ratio: 0.3
- *N*-fidelity approach: adaptive two-fidelity metamodel
- Sampling: maximum uncertainty based
- Metamodel: stochastic radial basis functions, providing prediction and associated uncertainty

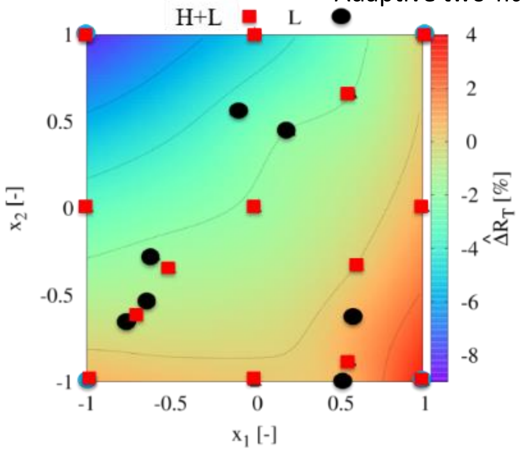
Design variable 1



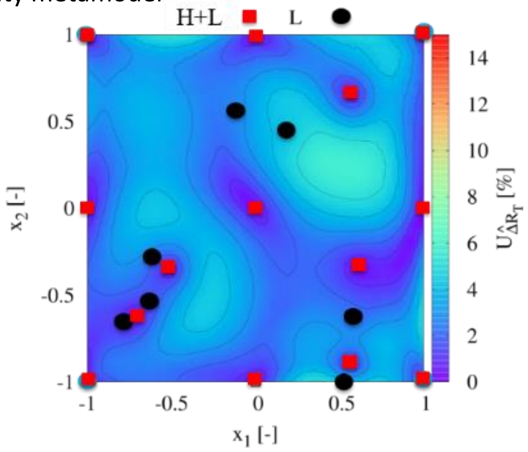
Design variable 2



Adaptive two-fidelity metamodel



Prediction



Uncertainty

- Pellegrini, R., Serani, A., Broglia, R., Diez, M. and Harries, S., 2018. *Resistance and Payload Optimization of a Sea Vehicle by Adaptive Multi-Fidelity Metamodeling*. In 2018 AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference (p. 1904).

Generalization to *N* Fidelity Levels

$f_M(\mathbf{x})$ additional-fidelity function

$f_H(\mathbf{x})$ High-fidelity function

$f_L(\mathbf{x})$ Low-fidelity function

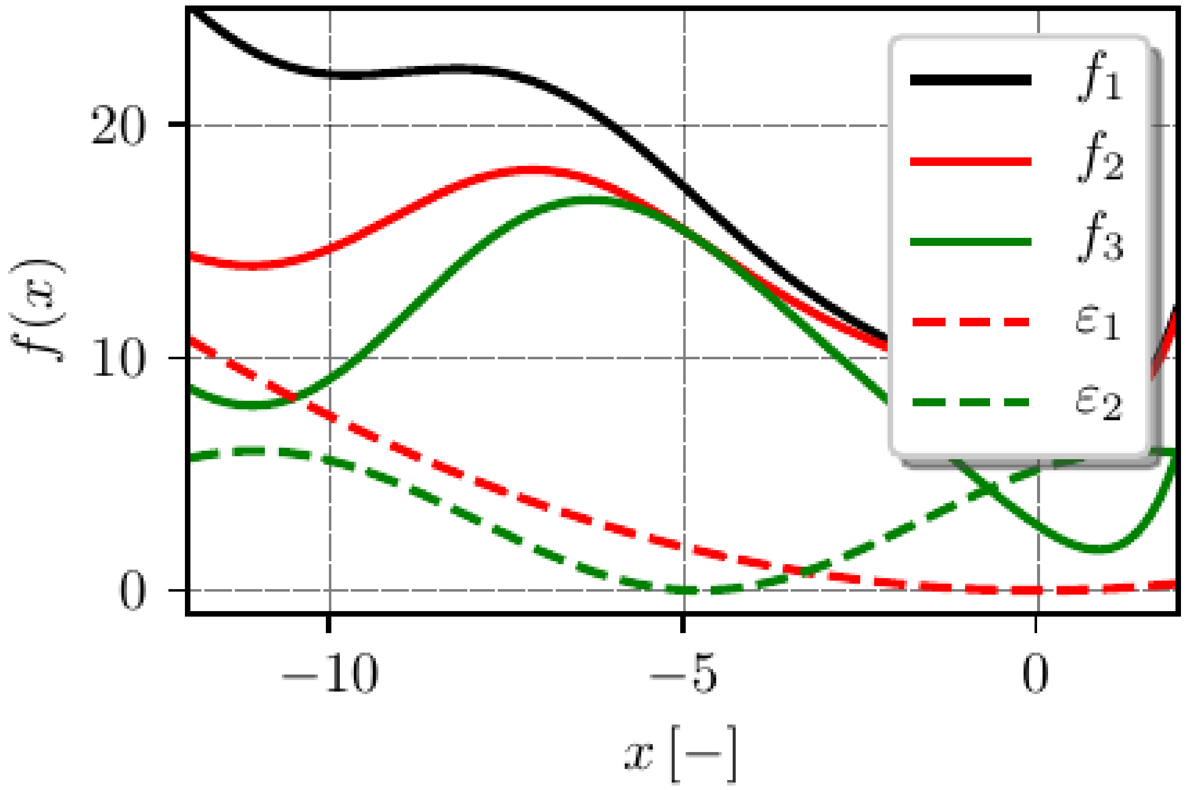
$$\varepsilon_1(\mathbf{x}) = f_H(\mathbf{x}) - f_M(\mathbf{x})$$
$$\varepsilon_2(\mathbf{x}) = f_M(\mathbf{x}) - f_L(\mathbf{x})$$

Error functions

***N*-fidelity metamodel**

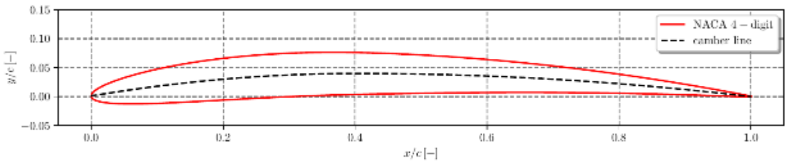
$$\hat{f}(\mathbf{x}) = \tilde{f}_N(\mathbf{x}) + \sum_{i=1}^{N-1} \tilde{\varepsilon}_i(\mathbf{x})$$

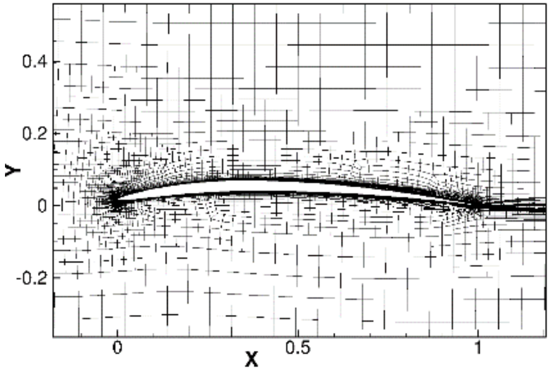
$$U_{\hat{f}}(\mathbf{x}) = \sqrt{U^2_{\tilde{f}_N}(\mathbf{x}) + \sum_{i=1}^{N-1} U^2_{\tilde{\varepsilon}_i}(\mathbf{x})}$$

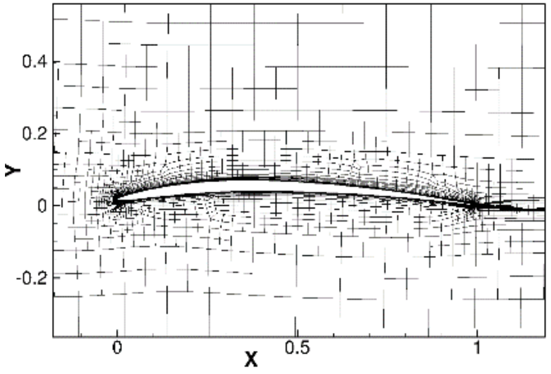


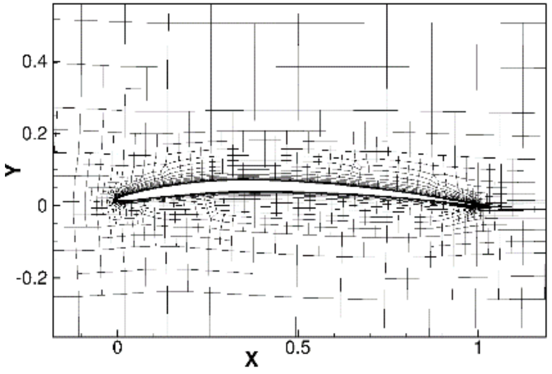
- Serani A., Pellegrini R., Broglia R., Wackers J., Visonneau M., Diez M. (2019). *An Adaptive N-fidelity Metamodel for Design and Operational-Uncertainty Space Exploration of Complex Industrial Problems*, to be presented at VIII International Conference on Computer Methods in Marine Engineering, Goteborg, Sweden

Application: Three-fidelity Optimization of a NACA Hydrofoil



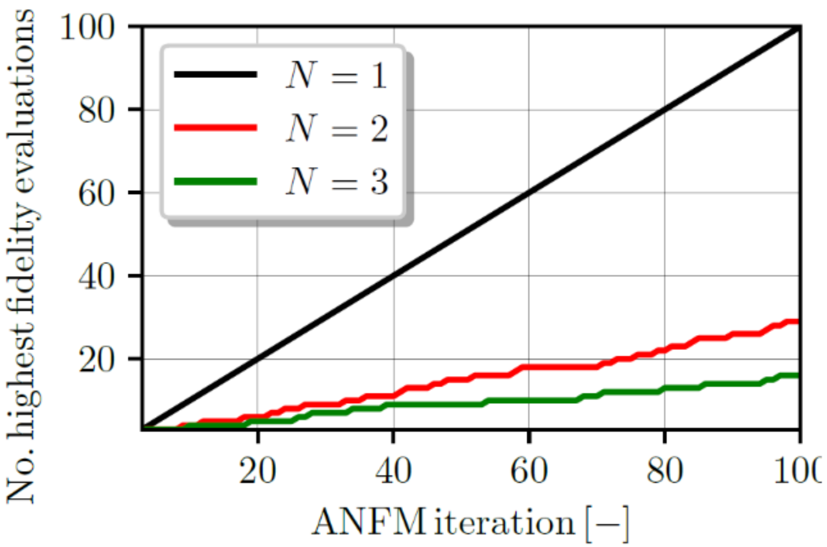

Fine grid


Medium grid

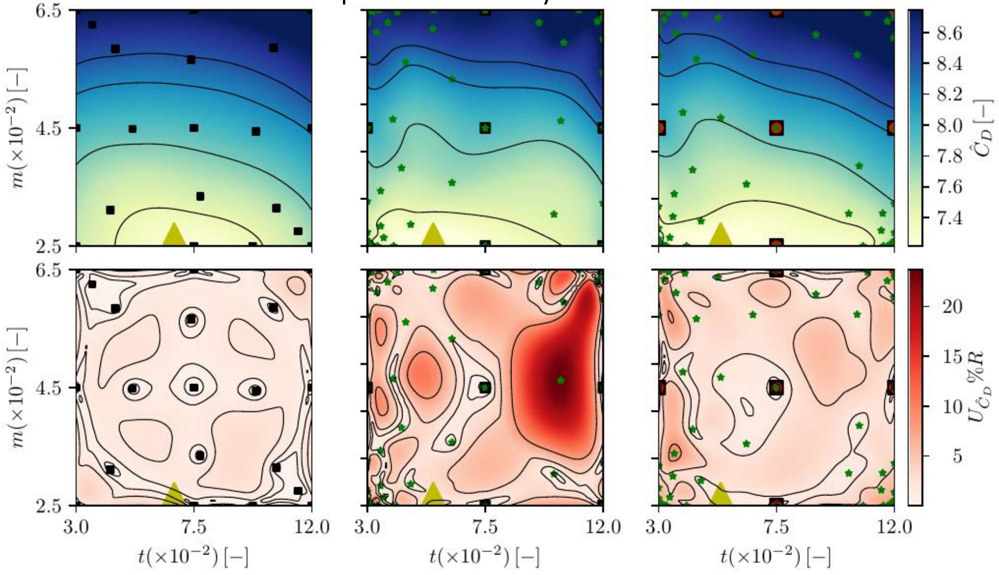

Coarse grid

- Objective: resistance reduction at C_L=0.6
- Solvers: RANSE with adaptive grid refinement
- Computational cost ratio: 0.5 and 0.3
- *N*-fidelity approach: adaptive three-fidelity metamodel
- Sampling: maximum uncertainty based
- Metamodel: stochastic radial basis functions, providing prediction and associated uncertainty

Number of high-fidelity evaluations to achieve optimum

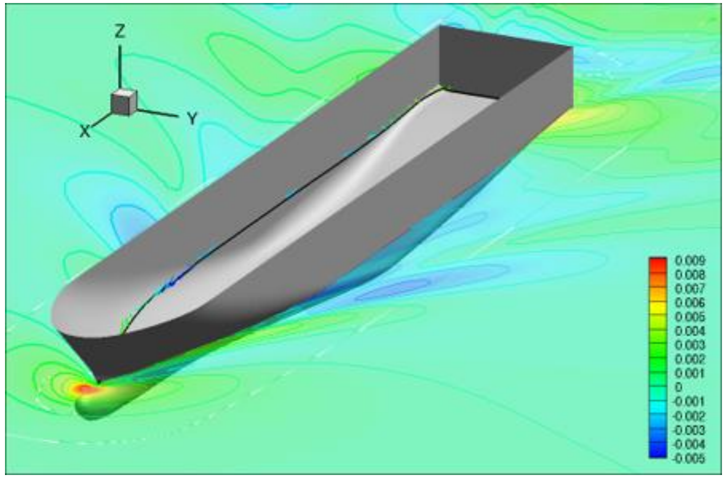


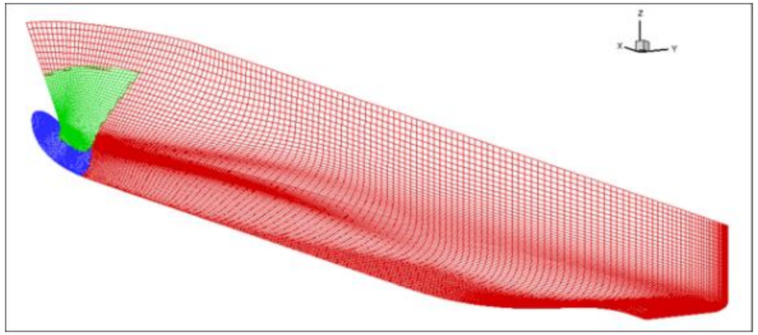
Adaptive three-fidelity metamodel



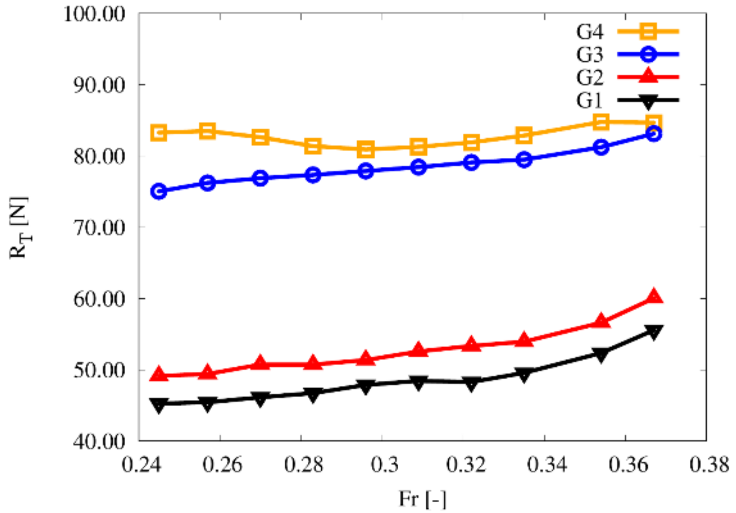
○ Serani A., Pellegrini R., Broglia R., Wackers J., Visonneau M., Diez M. (2019). *An Adaptive N-fidelity Metamodel for Design and Operational-Uncertainty Space Exploration of Complex Industrial Problems*, to be presented at VIII International Conference on Computer Methods in Marine Engineering, Goteborg, Sweden

Application: Three-fidelity Uncertainty Quantification of a RoPax Ferry

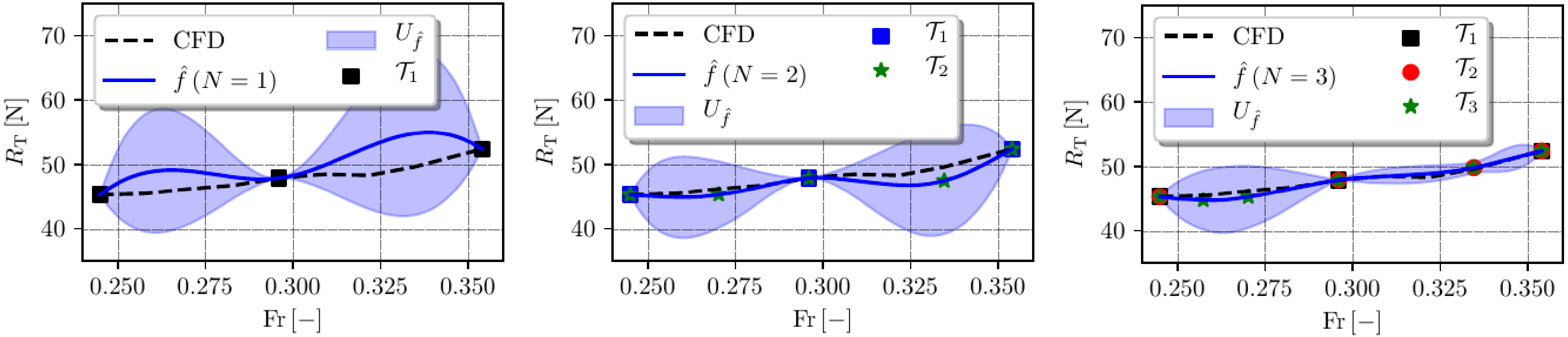




Fine body grid



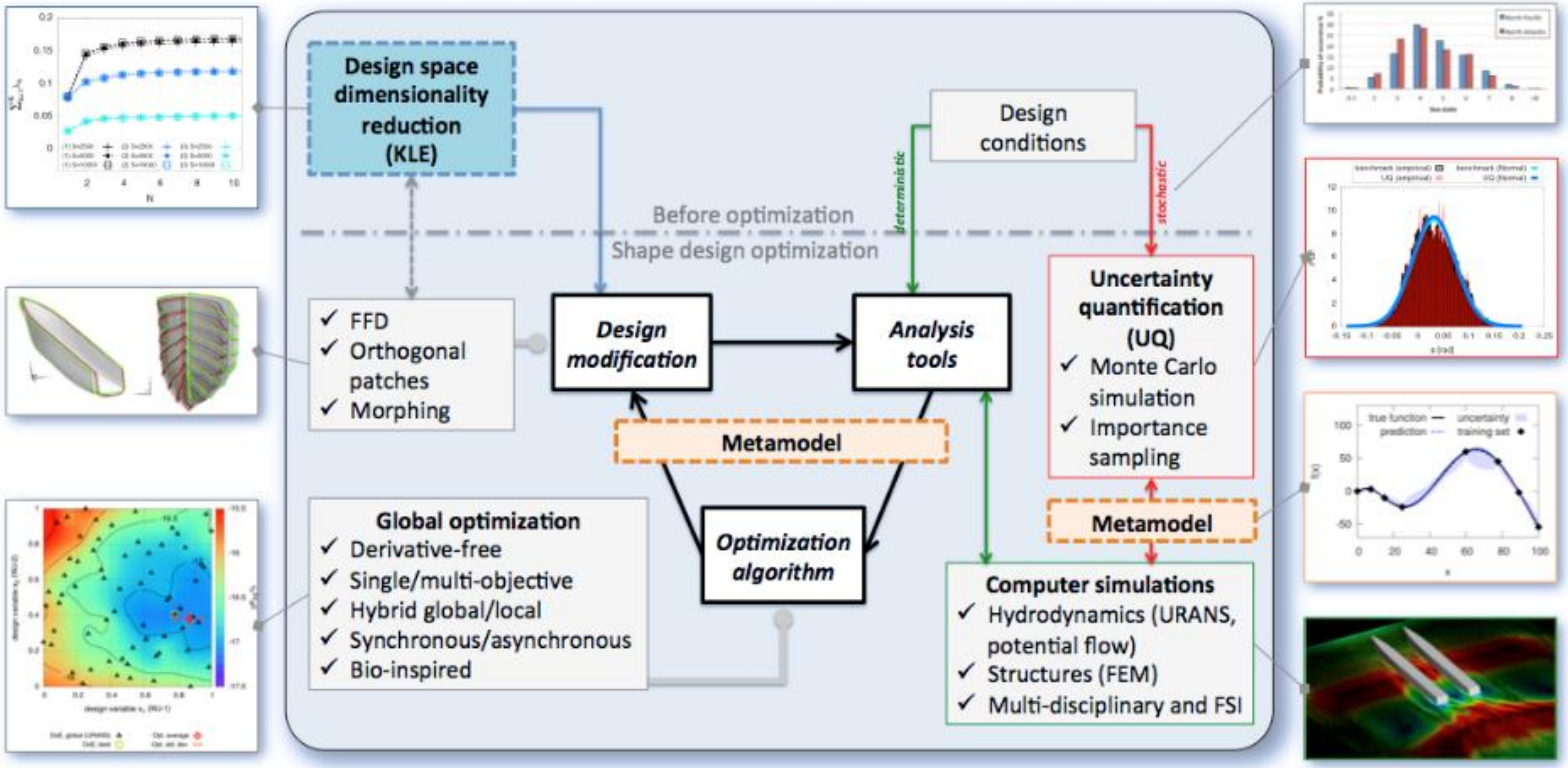
- Objective: resistance reduction at Fr=0.295
- Solvers: RANSE with multi-grid acceleration
- Computational cost ratio: 0.125 and 0.0625
- *N*-fidelity approach: adaptive three-fidelity metamodel
- Sampling: maximum uncertainty based
- Metamodel: stochastic radial basis functions, providing prediction and associated uncertainty



N-fidelity metamodel uncertainty for *N*=1, 2, and 3 from left to right

- Serani A., Pellegrini R., Broglia R., Wackers J., Visonneau M., Diez M. (2019). *An Adaptive N-fidelity Metamodel for Design and Operational-Uncertainty Space Exploration of Complex Industrial Problems*, to be presented at VIII International Conference on Computer Methods in Marine Engineering, Goteborg, Sweden

Closing remarks



- SBDO represents a viable paradigm shift for more efficient/safer ships and has a broad field of application (hull, propeller, ESD, etc.)
- Modularity and portability of tools is of interest to industries
- Extensions to
  - Multidisciplinary (hydroelasticity/FSI; routing; life cycle cost/assessment; combined design and operation; virtual/augmented reality)
  - More complex/realistic applications (self-propelled; manoeuvring; slamming in stochastic environment; autonomous/under-water vehicles; MDO)
  - Multi-fidelity including experimental data (URANS/DES; multi-grid; linear/nonlinear FE)