Payload and Resistance Optimization of a SWATH Model via Design Space Dimensionality Reduction, CFD, and Multi-fidelity Surrogate Models

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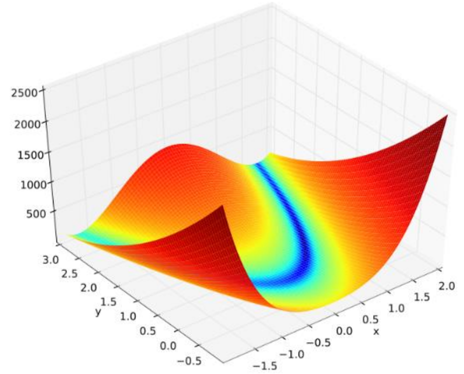
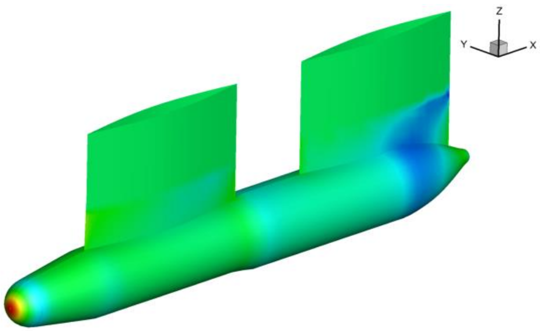
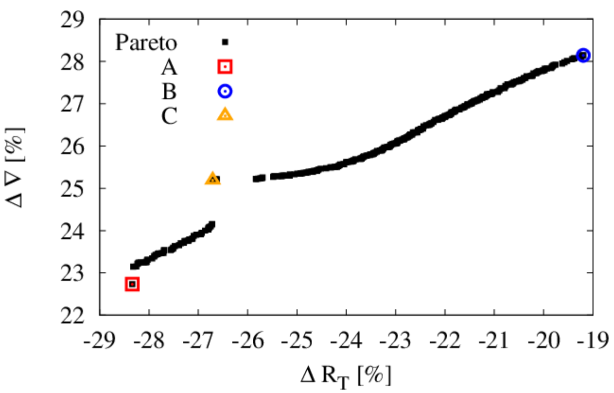
Outline

- Introduction
  - CNR-INSEAN
  - Background of simulation-based design optimization (SBDO)
  - Objective: multi-objective optimization problem
  - Approach
- Design-space dimensionality reduction by Karhunen-Loève Expansion
- SWATH geometry variations from CAESES
- CFD code WARP
- Adaptive multi-fidelity metamodel
- Multi-objective deterministic particle swarm optimization algorithm
- Numerical results
- Conclusions and future work



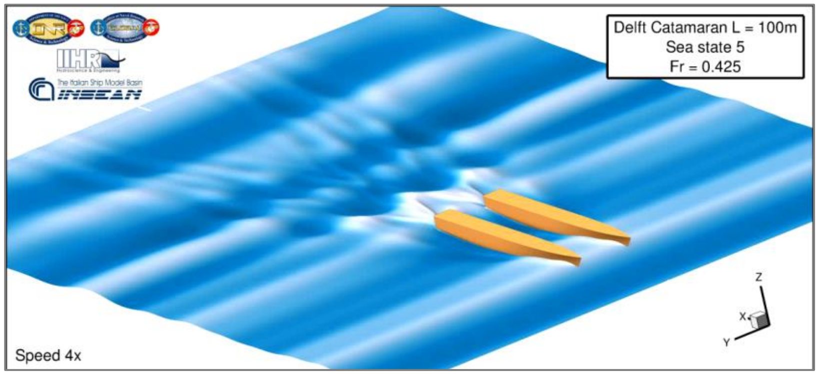


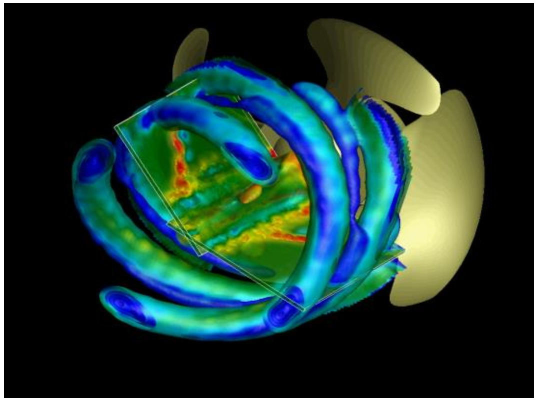


CNR-INSEAN: Marine Technology Research Institute, Italy

CNR-INSEAN: Numerical / Experimental research on naval hydrodynamics and marine engineering; **145** people (**65** researchers, research engineers and temporary positions); ***All in-house: simulation codes & hardware (design, production, testing).***

- **Numerical modeling and simulations for hydrodynamics of hull, propeller, wave breaking,sloshing, hydroacoustics, structures**
- **Simulation-based design methods including validation experiments**



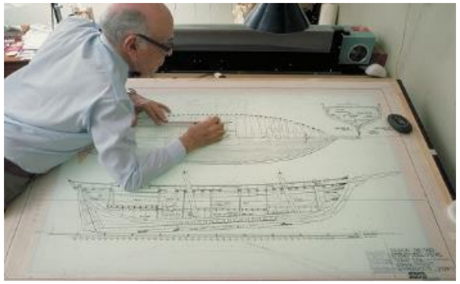


- **Towing tanks**
- **Circulating water channel**
- **Cavitation tunnel**
- **Maneuvering basin (Nemi Lake)**
- **Hydraulic channel**
- **Sloshing lab**
- **High-speed ditching**
- **Mechanical, electronic, equipment workshops**
- **Woodshop**

Simulation-based design optimization

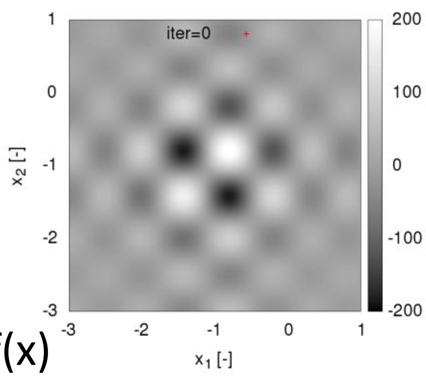
Build-and-test

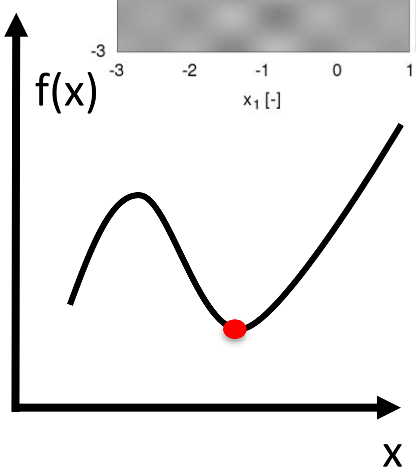
Design → *Build* → *Test*

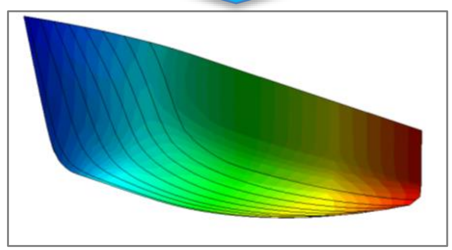


Increased computational resources

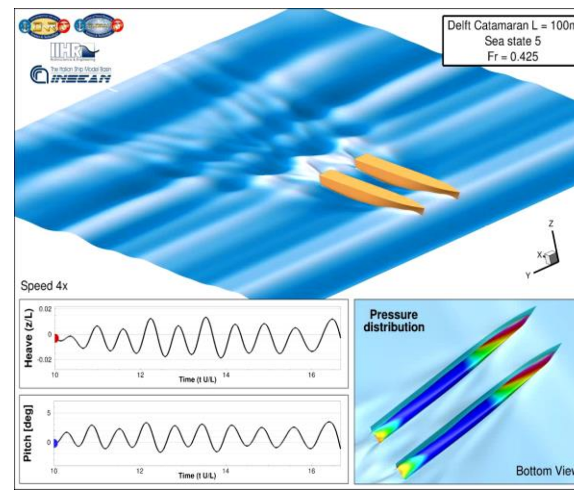
Simulation-based design optimization







Design → Simulation → Optimization



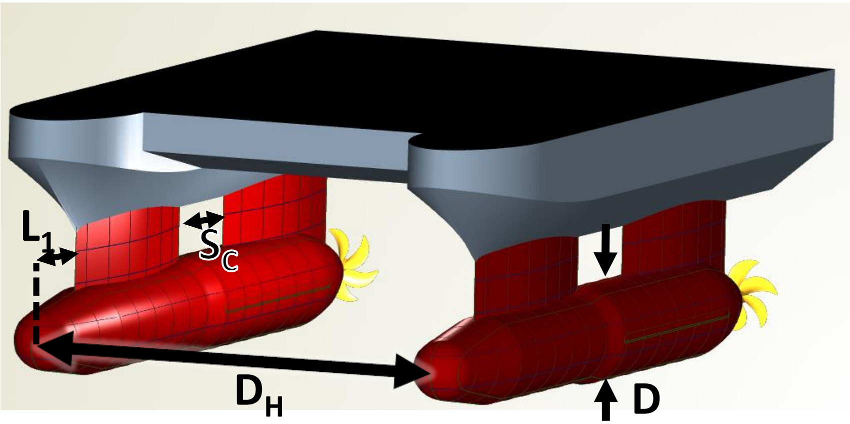
Multi-objective optimization problem

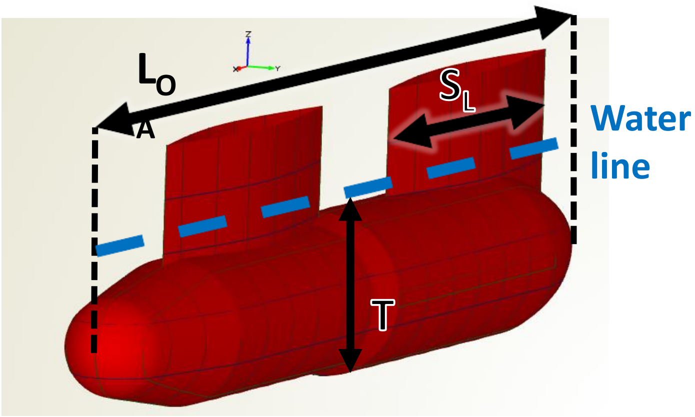
- The optimization addresses
  - total resistance (R_T) minimization (18 kn)
  - payload maximization (∇)

Dimension	Value [m]
L_{OA}	36.50
D	4.50
D_H	20.00
L_1	6.00
S_L	12.00
S_C	5.15
T	6.31
S_W	1064 [m^2]
A_{WP}	38.88 [m^2]

No constraints are imposed for this preliminary application

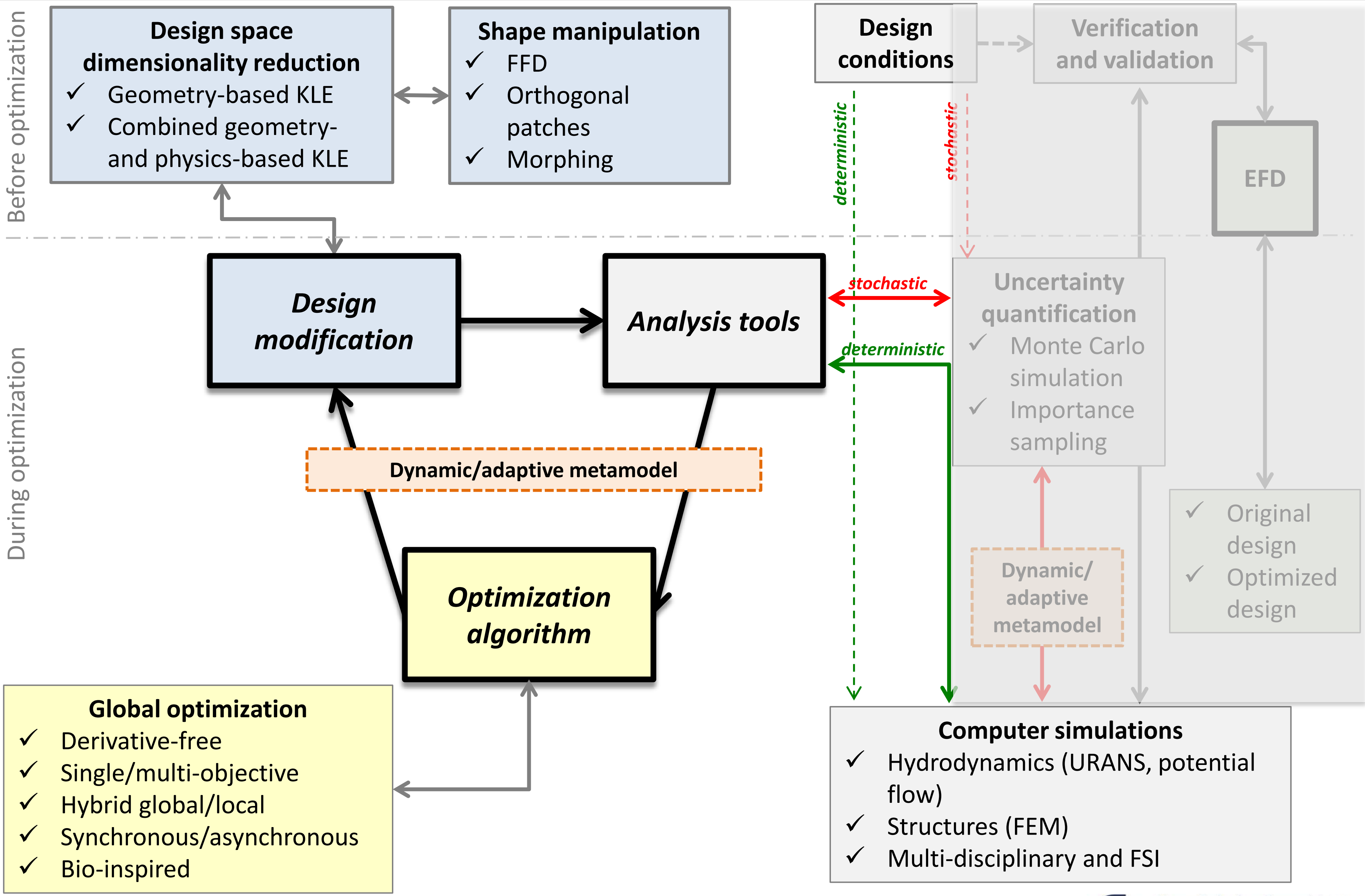
Objective functions	Value
∇	982.23 [m^3]
R_T (HF, 18 kn)	4.816E5 [N]





Pellegrini R., Serani A., Harries S., and Diez M. "Multi-objective hull-form optimization of a SWATH configuration via design-space dimensionality reduction, multi-fidelity metamodels, and swarm intelligence" In proceedings of 7th International conference on Computational Methods in Marine Engineering (MARINE 2017), 15-17 May 2017, Nantes, France.

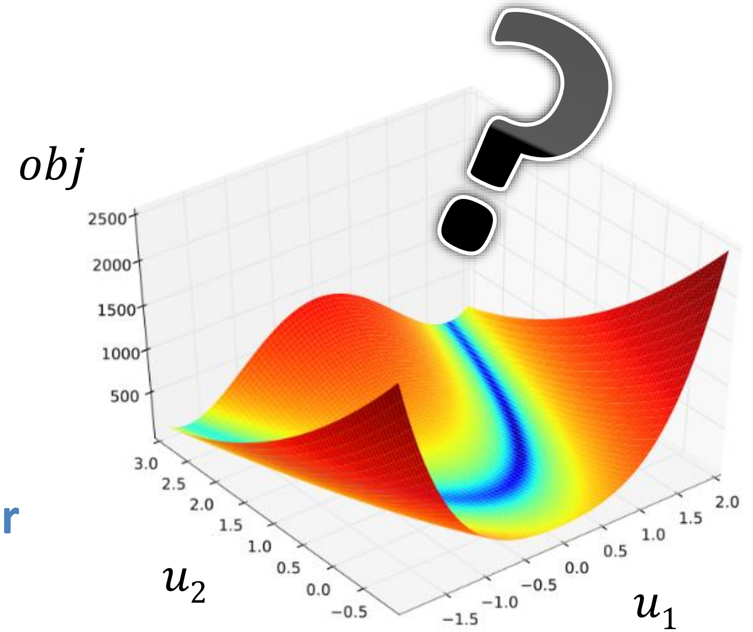
Approach - INSEAN SBDO Framework



Design-space dimensionality reduction - Underlying idea

$$\min_{\boldsymbol{u} \in \mathcal{U}} obj(\boldsymbol{u})$$

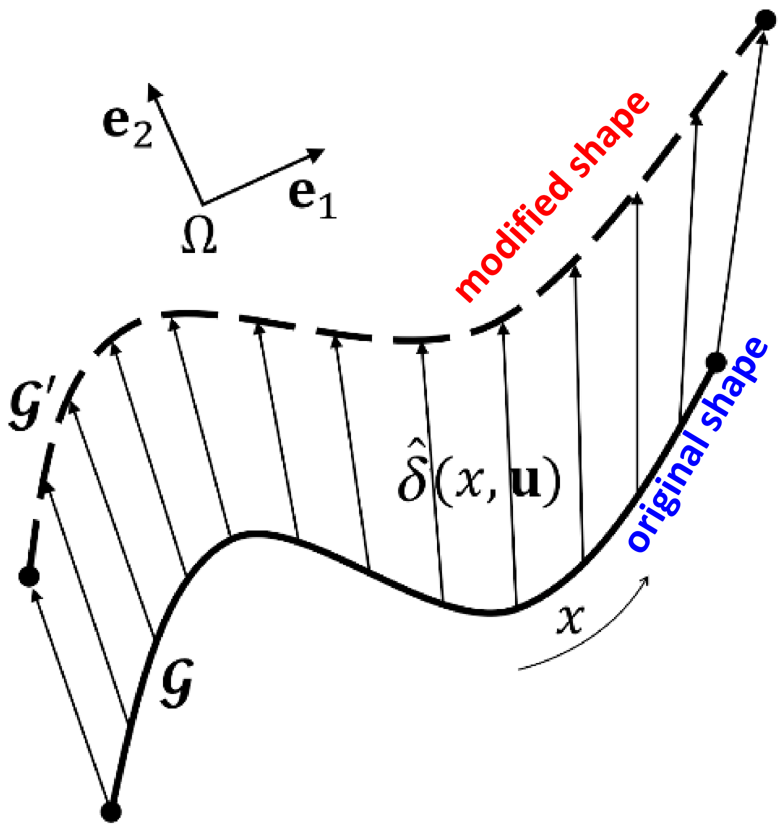
"uncertain" shape design variable vector



- Before going through the optimization process, one does not know (yet) where the optimal design is
- The optimum is unknown and its identification may be considered as a problem affected by *epistemic uncertainty* (Diez et al., CMAME, 2015)
- One may consider the (uncertain) design variable vector $\boldsymbol{u}$ as belonging to a stochastic domain $\mathcal{U}$ with associated probability density function $f(\boldsymbol{u})$, $\boldsymbol{u} \in \mathcal{U}$

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

Design-space dimensionality reduction - Definitions



$\boldsymbol{u}$ design variable (uncertain)
$\boldsymbol{x}$ spatial variable
$\langle\cdot\rangle$ ensamble average over $\boldsymbol{u}$
$\hat{\boldsymbol{\delta}} = \boldsymbol{\delta} - \langle\boldsymbol{\delta}\rangle$
$\rho(\boldsymbol{x})$ weight function

- Generalized inner product

$$(\boldsymbol{f}, \boldsymbol{g})_\rho = \int_{\mathcal{G}} \rho(\boldsymbol{x}) \boldsymbol{f}(\boldsymbol{x}) \cdot \boldsymbol{g}(\boldsymbol{x}) d\boldsymbol{x}$$

- Mean shape modification

$$\langle\boldsymbol{\delta}\rangle = \int_{\mathcal{U}} \boldsymbol{\delta}(\boldsymbol{x}, \boldsymbol{u}) f(\boldsymbol{u}) d\boldsymbol{u}$$

- Geometric variance (key element)

$$\sigma^2 = \langle ||\hat{\boldsymbol{\delta}}||^2 \rangle$$

$$= \int_{\mathcal{U}} \int_{\mathcal{G}} \rho(\boldsymbol{x}) \hat{\boldsymbol{\delta}}(\boldsymbol{x}, \boldsymbol{u}) \cdot \hat{\boldsymbol{\delta}}(\boldsymbol{x}, \boldsymbol{u}) f(\boldsymbol{u}) d\boldsymbol{x} d\boldsymbol{u}$$

Design-space dimensionality reduction – Problem statement

- Basis of orthonormal functions (KLE)

$$\hat{\boldsymbol{\delta}}(\boldsymbol{x},\boldsymbol{u}) = \sum_{k=1}^{\infty} \alpha_k(\boldsymbol{u})\boldsymbol{\varphi}_k(\boldsymbol{x})$$

$\boldsymbol{u}$ design variable (uncertain)
$\boldsymbol{x}$ spatial variable
$\langle\cdot\rangle$ ensamble average over $\boldsymbol{u}$
$\hat{\boldsymbol{\delta}} = \boldsymbol{\delta} - \langle\boldsymbol{\delta}\rangle$
$\rho(\boldsymbol{x})$ weight function

- Geometric variance expressed as

$$\sigma^2 = \sum_{k=1}^{\infty}\sum_{j=1}^{\infty}\langle\alpha_k\alpha_j\rangle\left(\boldsymbol{\varphi}_k,\boldsymbol{\varphi}_j\right)_\rho = \sum_{j=1}^{\infty}\langle\alpha_j{}^2\rangle = \sum_{j=1}^{\infty}\left\langle\left(\hat{\boldsymbol{\delta}},\boldsymbol{\varphi}_j\right)_\rho^2\right\rangle$$

- Formulation of a variational problem

$$\max_{\boldsymbol{\varphi}\in\mathcal{L}_\rho^2(\mathcal{G})} \boldsymbol{J}(\boldsymbol{\varphi}) = \left\langle\left(\hat{\boldsymbol{\delta}},\boldsymbol{\varphi}_j\right)_\rho^2\right\rangle$$

$$\text{subject to } (\boldsymbol{\varphi},\boldsymbol{\varphi})_\rho^2 = \mathbf{1}$$

- The variational problem solution is

$$\mathcal{L}\boldsymbol{\varphi}(\boldsymbol{x}) = \int_{\mathcal{G}} \langle\delta(\boldsymbol{x},\boldsymbol{u})\otimes\delta(\boldsymbol{y},\boldsymbol{u})\rangle\boldsymbol{\varphi}(\boldsymbol{y})d\boldsymbol{y} = \lambda\boldsymbol{\varphi}(\boldsymbol{x})$$

Design-space dimensionality reduction – Discretization

- Considering the variational problem solution

$$\mathcal{L}\boldsymbol{\varphi}(\boldsymbol{x}) = \int_{\mathcal{G}} \langle \delta(\boldsymbol{x},\boldsymbol{u}) \otimes \delta(\boldsymbol{y},\boldsymbol{u}) \rangle \boldsymbol{\varphi}(\boldsymbol{y}) d\boldsymbol{y} = \lambda \boldsymbol{\varphi}(\boldsymbol{x})$$

- Define a 3-D (cartesian) basis of orthogonal unit vector $\{\boldsymbol{e}_q\}_{q=1}^{3}$ is possible to write

$$\boldsymbol{\delta}(\boldsymbol{x},\boldsymbol{u}) = \sum_{q=1}^{3} \delta_q(\boldsymbol{x},\boldsymbol{u})\boldsymbol{e}_q\,, \qquad \boldsymbol{\varphi}(\boldsymbol{x}) = \sum_{q=1}^{3} \varphi_q(\boldsymbol{x})\boldsymbol{e}_q$$

- which yields

$$\sum_{q=1}^{3} \int_{\mathcal{G}} \left\langle \delta_p(\boldsymbol{x},\boldsymbol{u}) \delta_q(\boldsymbol{y},\boldsymbol{u}) \right\rangle \varphi_q(\boldsymbol{y}) d\boldsymbol{y} = \lambda \boldsymbol{\varphi}_p(\boldsymbol{x})$$

- Discretizing the variable of integration $\boldsymbol{y}$ (therefore the geometry) with L elements of dimension $\Delta\mathcal{G}_j$ and centroid at $\boldsymbol{x}_j, j = 1, \dots, L$

$$\sum_{q=1}^{3} \sum_{j=1}^{L} \left\langle \delta_p(\boldsymbol{x}_i,\boldsymbol{u}) \delta_q\left(\boldsymbol{x}_j,\boldsymbol{u}\right) \right\rangle \varphi_q\left(\boldsymbol{x}_j\right) \Delta\mathcal{G}_j = \lambda \varphi_p(\boldsymbol{x}_i)$$

Design-space dimensionality reduction – Implementation

- This form can be discretized as

$$\sum_{q=1}^{3}\sum_{j=1}^{L}\left\langle \boxed{\delta_p(\boldsymbol{x}_i,\boldsymbol{u})}\,\delta_q(\boldsymbol{x}_j,\boldsymbol{u})\right\rangle \overbrace{\boxed{\varphi_q(\boldsymbol{x}_j)}}^{\mathbf{z}_q}\Delta\mathcal{G}_j = \lambda \underbrace{\boxed{\varphi_p(\boldsymbol{x}_i)}}_{\mathbf{z}_p}$$

$$\mathbf{d}_p(\mathbf{u}) = \begin{Bmatrix} \gamma_p(\boldsymbol{x}_1,\boldsymbol{u}_k) \\ \vdots \\ \gamma_p(\boldsymbol{x}_L,\boldsymbol{u}_k) \end{Bmatrix} - \frac{1}{S}\sum_{k=1}^{S}\begin{Bmatrix} \gamma_p(\boldsymbol{x}_1,\boldsymbol{u}_k) \\ \vdots \\ \gamma_p(\boldsymbol{x}_L,\boldsymbol{u}_k) \end{Bmatrix}$$

$$\gamma_p = \boldsymbol{\gamma}\cdot\boldsymbol{e}_p$$

$$\boldsymbol{D}_p = [\mathbf{d}_p(\mathbf{u}_1) \quad \dots \quad \mathbf{d}_p(\mathbf{u}_S)]$$

S shape modifications

$$\boldsymbol{R}_{pq} = \frac{1}{S}\boldsymbol{D}_p\boldsymbol{D}_q^T$$

Covariance matrix

$$\boldsymbol{W} = [\Delta\mathcal{G}_i\delta_{ij}]$$

Kronecker delta

Design-space dimensionality reduction – Implementation

- This form can be discretized as

$$\sum_{q=1}^{3}\sum_{j=1}^{L}\langle \underbrace{\boxed{\delta_p(\boldsymbol{x}_i,\boldsymbol{u})}}_{\mathbf{d}_p(\mathbf{u})}\delta_q(\boldsymbol{x}_j,\boldsymbol{u})\rangle \overbrace{\boxed{\varphi_q(\boldsymbol{x}_j)}}^{\mathbf{z}_q}\Delta\mathcal{G}_j = \lambda \underbrace{\boxed{\varphi_p(\boldsymbol{x}_i)}}_{\mathbf{z}_p}$$

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Covariance matrix

$$\boldsymbol{W} = [\Delta\mathcal{G}_i\delta_{ij}]$$

$$\sum_{q=1}^{3}\sum_{j=1}^{L}\underbrace{[\boldsymbol{R}_{pq}W]_{ij}}_{\mathbf{A}_{ij}}\{\boldsymbol{z}_q\}_j = \lambda\{\boldsymbol{z}_p\}_i$$

Design-space dimensionality reduction – Implementation

- This form can be discretized as

$$\sum_{q=1}^{3}\sum_{j=1}^{L}\langle \boxed{\delta_p(\boldsymbol{x}_i,\boldsymbol{u})}\,\delta_q(\boldsymbol{x}_j,\boldsymbol{u})\rangle \overset{\mathbf{z}_q}{\boxed{\varphi_q(\boldsymbol{x}_j)}}\Delta\mathcal{G}_j = \lambda \underset{\mathbf{z}_p}{\boxed{\varphi_p(\boldsymbol{x}_i)}}$$

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$$\boldsymbol{R}_{pq} = \frac{1}{S}\boldsymbol{D}_p\boldsymbol{D}_q^T$$

Covariance matrix

$$\boldsymbol{W} = [\Delta\mathcal{G}_i\delta_{ij}]$$

$$\mathbf{A}\mathbf{z} = \lambda\mathbf{z}$$

Design-space dimensionality reduction – “How to use”

- Property: each eigenvalue (KL value) equal the variance retained by the associated eigenfunction (KL mode)

$$\lambda_k = \langle {\alpha_k}^2 \rangle \qquad \sigma^2 = \sum_{k=1}^{\infty} \lambda_k$$

variance retained by each KLE eigenfunction

total variance

- Dimensionality reduction with confidence level l

$$\hat{\boldsymbol{\delta}}(\boldsymbol{x}, \cancel{\boldsymbol{u}}) = \sum_{k=1}^{N} \alpha_k (\cancel{\boldsymbol{u}}) \boldsymbol{\varphi}_k(\boldsymbol{x})$$

New design variables

New representation of the shape modification (new design space, ROM)

$$\sum_{k=1}^{N} \lambda_k \geq l \sum_{k=1}^{\infty} \lambda_k = l\sigma^2$$

N is the new (reduced) dimensionality of the design space

Design-space dimensionality reduction – "How to use"

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variance retained by each KLE eigenfunction

total variance

- Dimensionality reduction with confidence level l

$$\hat{\boldsymbol{\delta}}(\boldsymbol{x}, \cancel{\xi}) = \sum_{k=1}^{N} \alpha_k(\cancel{\xi}) \boldsymbol{\varphi}_k(\boldsymbol{x})$$

The use of orthonormal basis allows for sensitivity analysis of not correlated variables

New representation of the shape modification (new design space, ROM)

$$\sum_{k=1}^{N} \lambda_k \geq l \sum_{k=1}^{\infty} \lambda_k = l\sigma^2$$

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Design-space dimensionality reduction – “How to use”

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variance retained by each KLE eigenfunction

total variance

- Dimensionality reduction with confidence level l

$$\hat{\boldsymbol{\delta}}(\boldsymbol{x}, \cancel{\boldsymbol{u}}) = \sum_{k=1}^{N} \alpha_k(\cancel{\boldsymbol{u}})\boldsymbol{\varphi}_k(\boldsymbol{x})$$

All the geometric constraints are respected

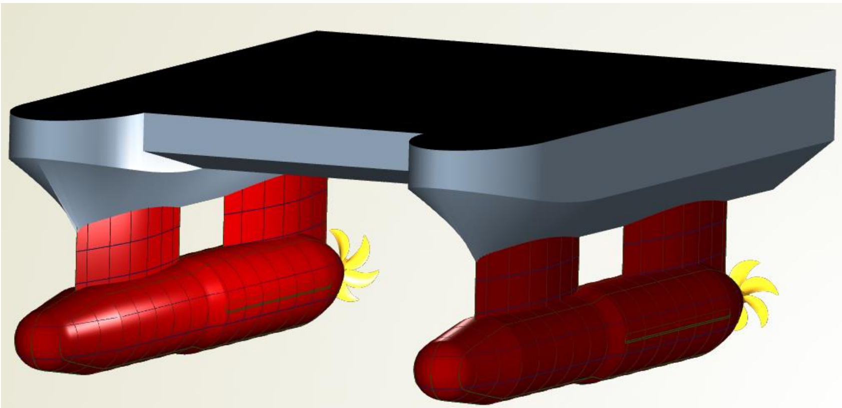
New representation of the shape modification (new design space, ROM)

$$\sum_{k=1}^{N} \lambda_k \geq l \sum_{k=1}^{\infty} \lambda_k = l\sigma^2$$

N is the new (reduced) dimensionality of the design space

Before optimization – Reference geometry modifications

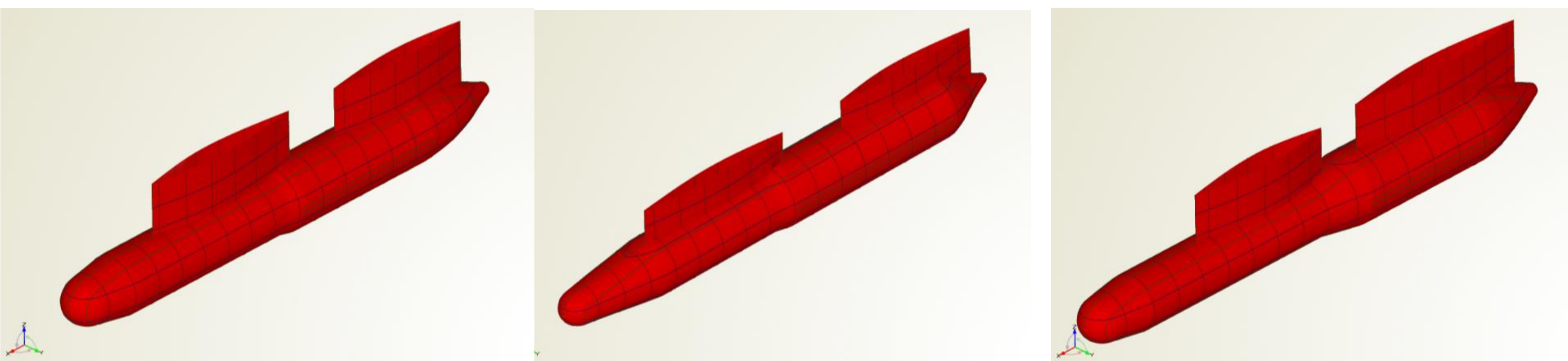
- Reference geometry variations



27 Parameters
- ±15% Range variation
- Definition of the geometric constraints (<u>to avoid infeasible geometries</u>!)

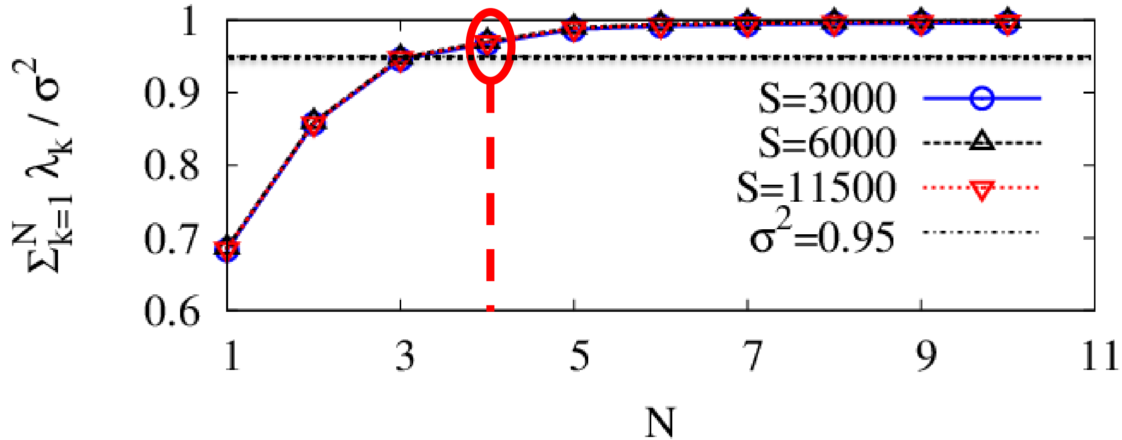
↓

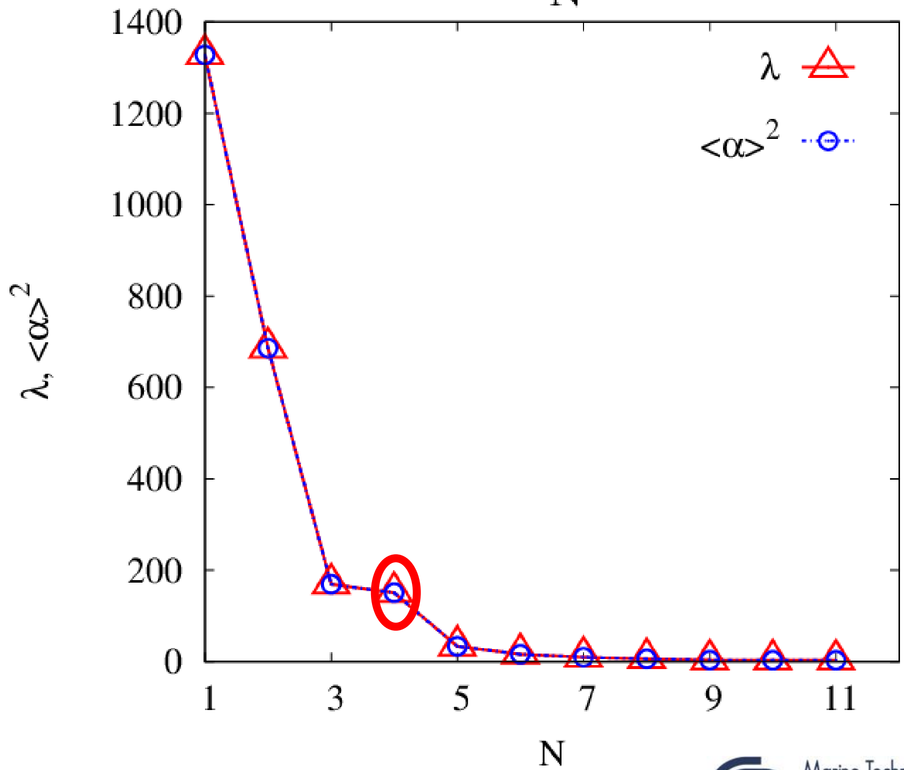
CAESES© Sobol engine
- 12000 geometry variations



Design-space dimensionality reduction by KLE - variables

- Results
  - The eigenvalues are convergent with respect to the number of designs,
  - 4 modes are sufficient for retaining more than 95% of the original variance,
  - From 27 to 4 variables, more than 85% dimensionality reduction.

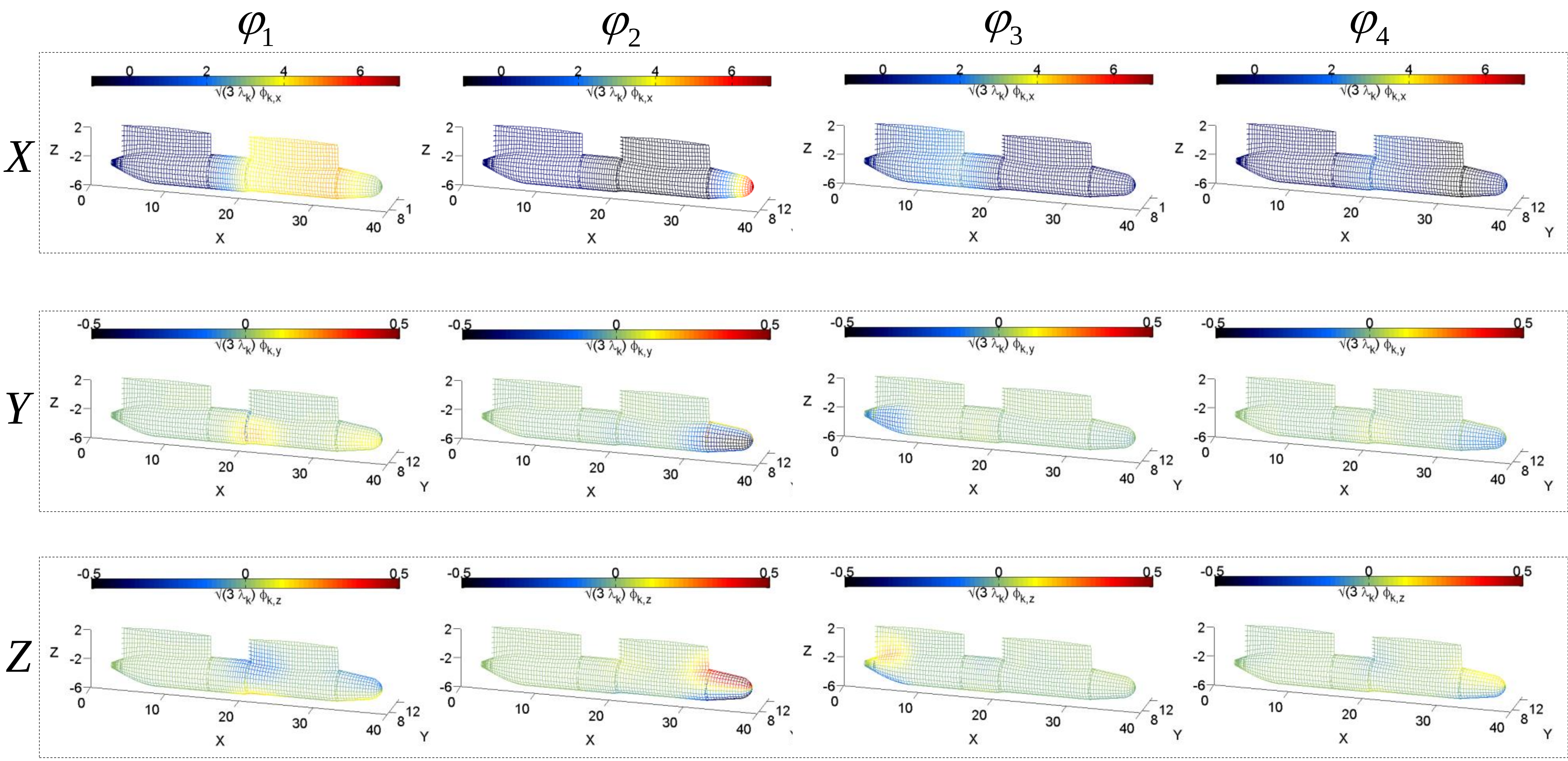




Marine Technology Research Institute

Design-space dimensionality reduction by KLE - modes

- First four KL modes φ



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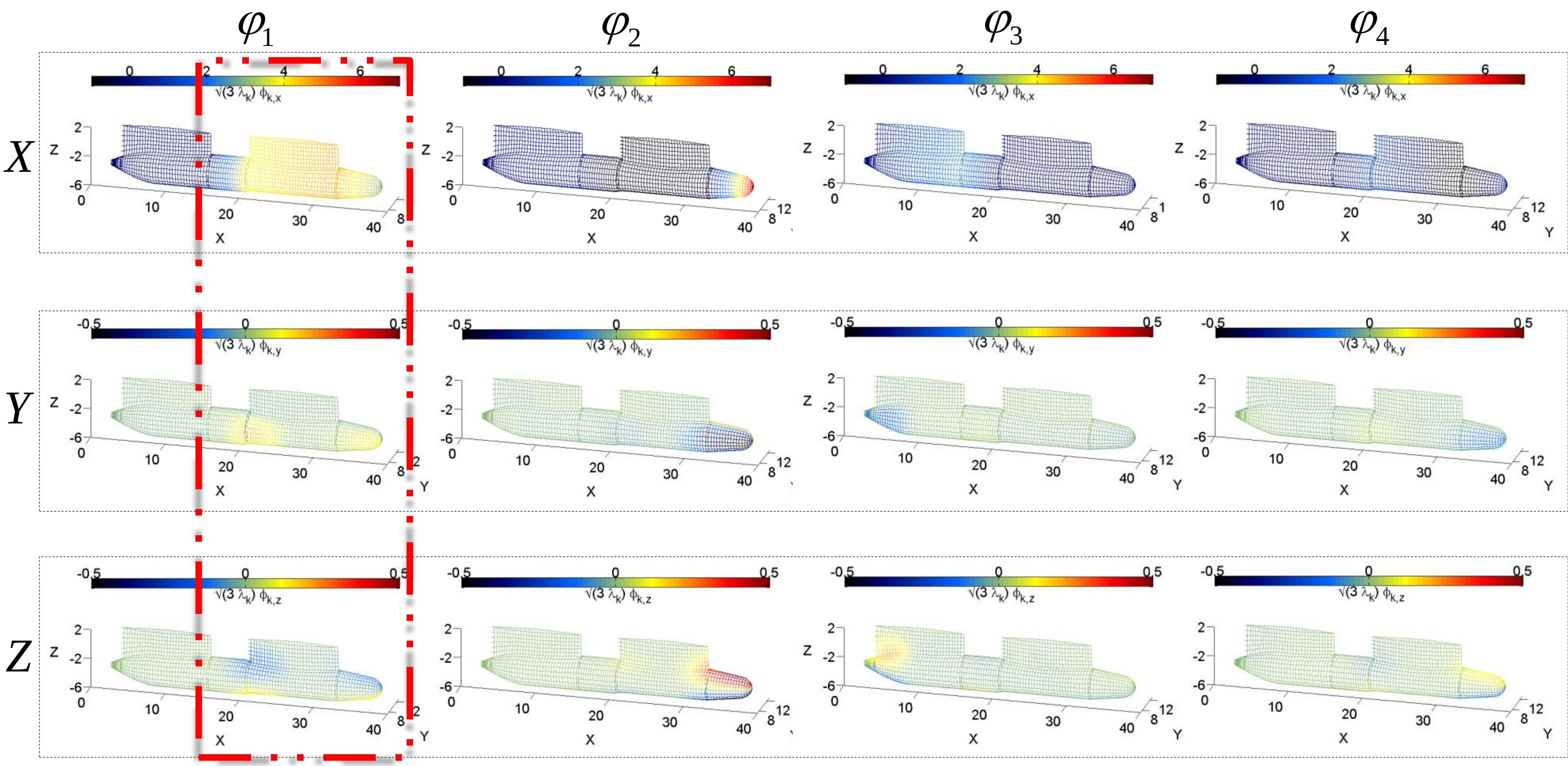
Design-space dimensionality reduction by KLE - modes

- First four KL modes φ



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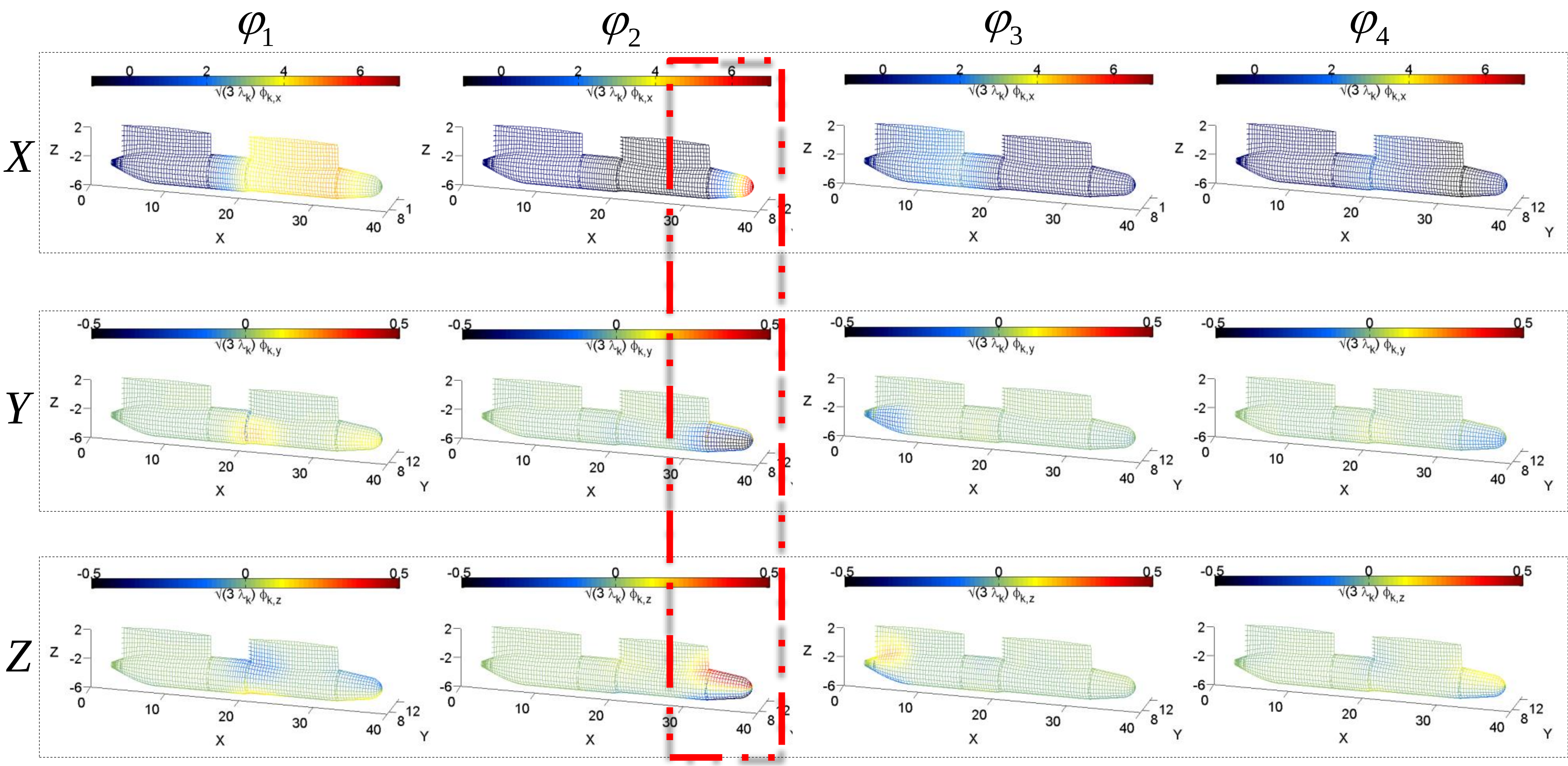
Design-space dimensionality reduction by KLE - modes

- First four KL modes φ



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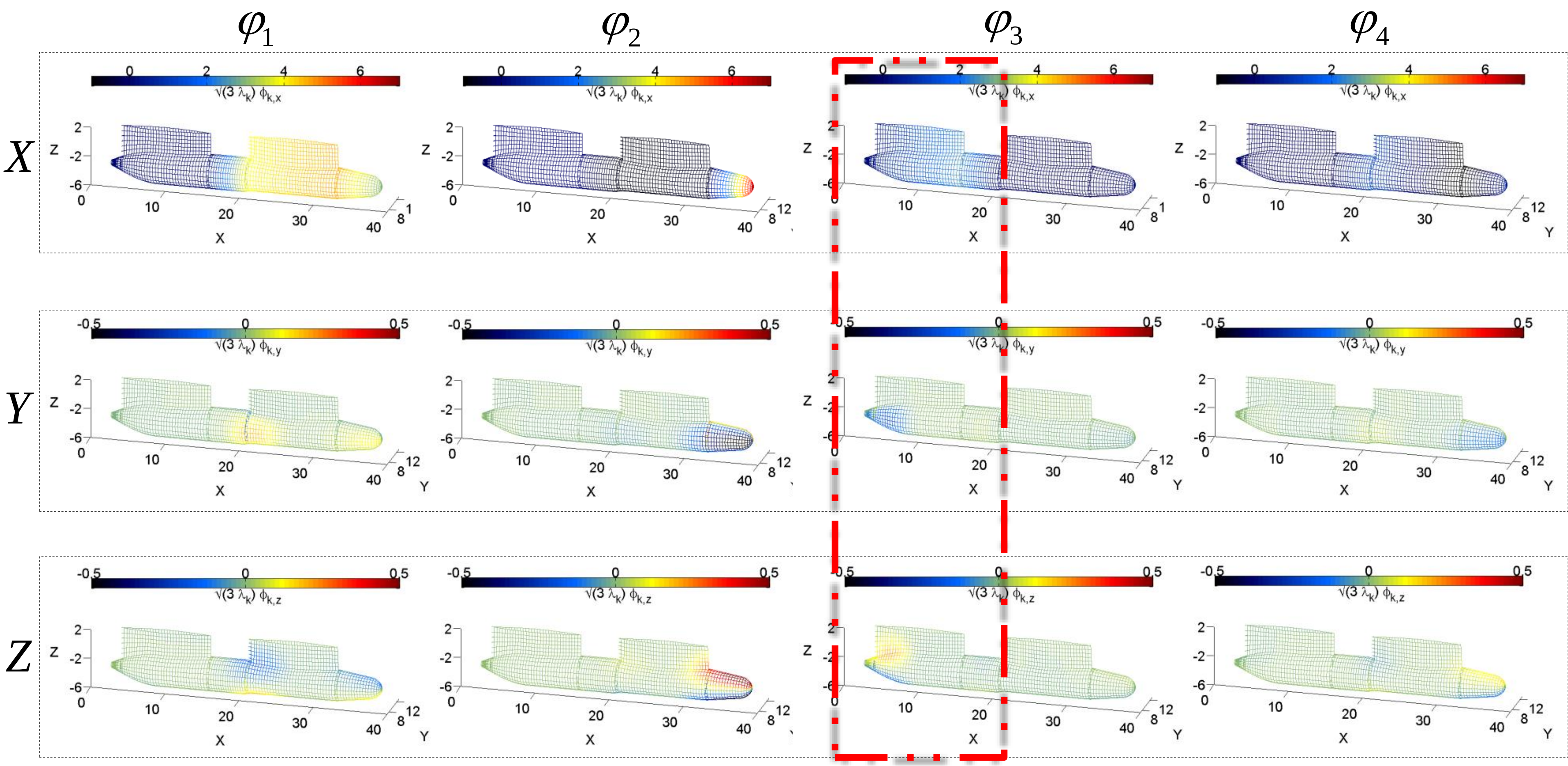
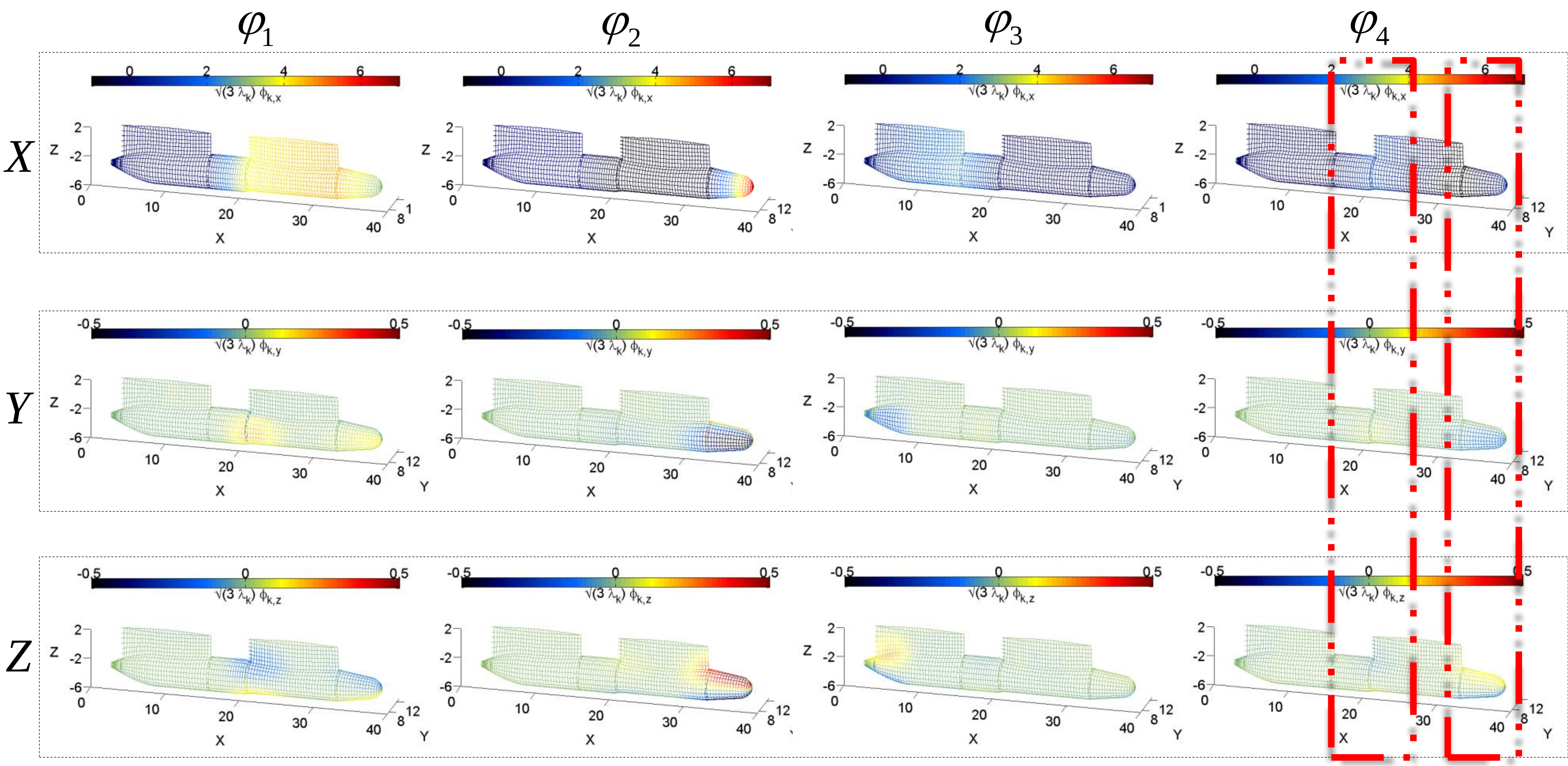
Design-space dimensionality reduction by KLE - modes

- First four KL modes φ



Design-space dimensionality reduction by KLE - modes

- First four KL modes φ



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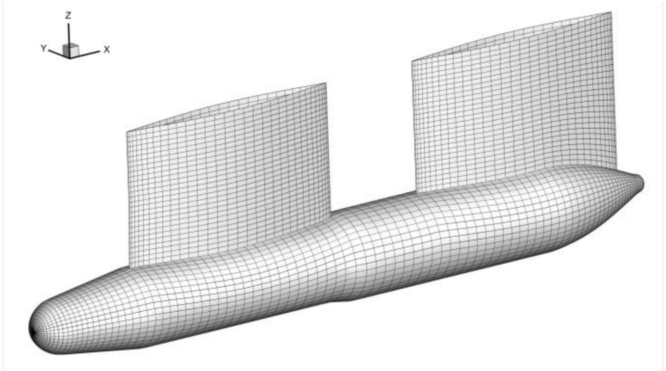
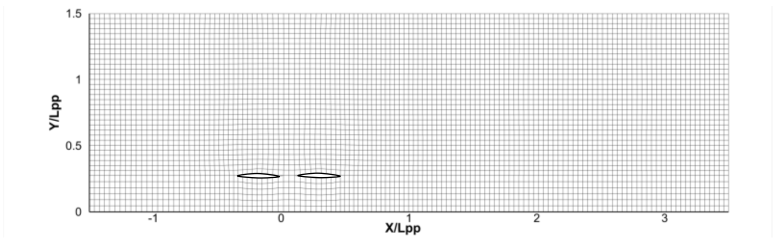
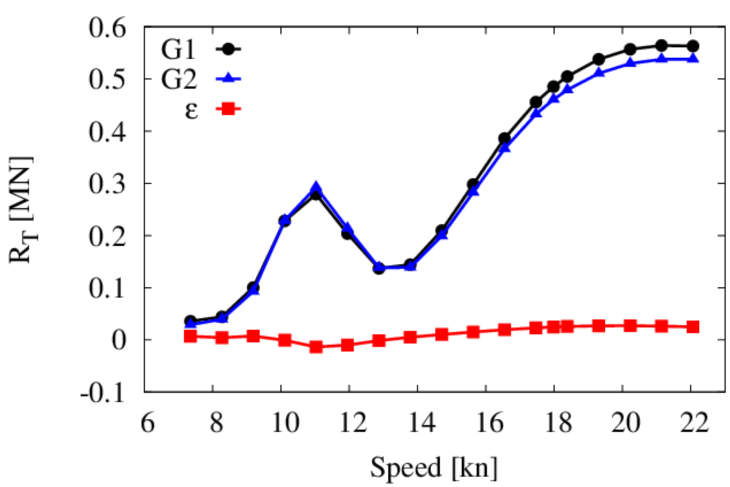
Potential flow solver

- Wave Resistance Program (WARP)
  - Fixed body
  - Double model linearization
  - Intel Xeon E5-1620 v2 @3.70GHz
  - HF steady linear potential flow code
    - fine body/surface grids
    - 4 minutes wall-clock time
  - LF steady linear potential flow code
    - coarse body/surface grids
    - 1 minute wall-clock time





Grid	G1	G2
Upstream extension	1.5 L_{OA}	
Downstream extension	3.5 L_{OA}	
Sideways extension	1.5 L_{OA}	
Body panels	5.2 k	2.6 k
Surface panels	6.0 k	3.0 k

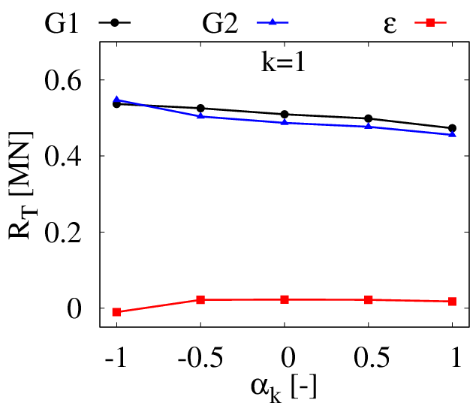


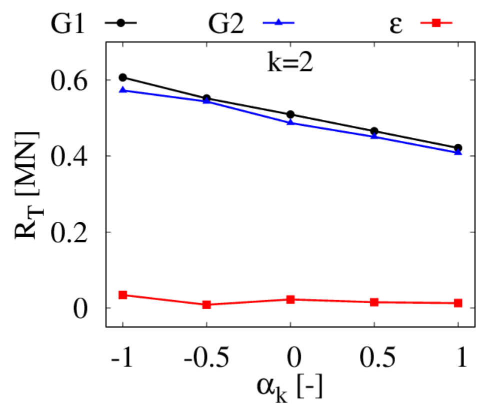
Bassanini et al., The Wave Resistance Problem in a Boundary Integral Formulation, Surveys on Mathematics for Industry, 4:151-194, 1994.

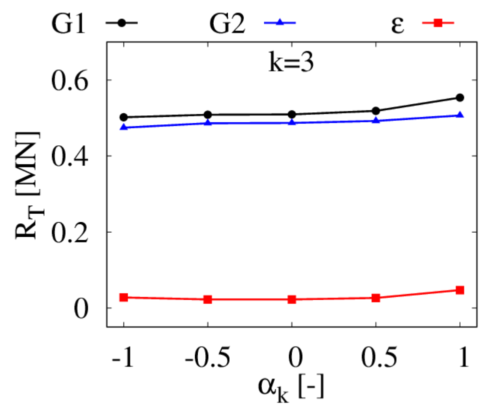
Potential flow solver

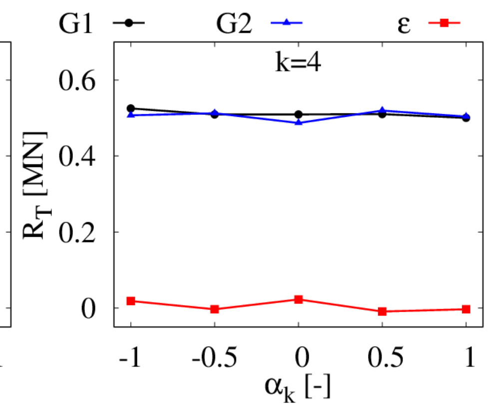
- Sensitivity analysis

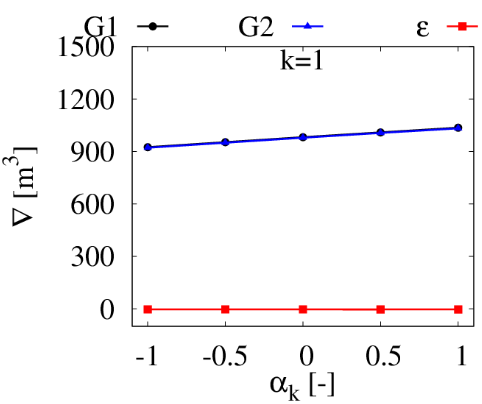
$\alpha_1 = \{-1,1\}$	$\alpha_1 = 0$	$\alpha_1 = 0$	$\alpha_1 = 0$
$\alpha_2 = 0$	$\alpha_2 = \{-1,1\}$	$\alpha_2 = 0$	$\alpha_2 = 0$
$\alpha_3 = 0$	$\alpha_3 = 0$	$\alpha_3 = \{-1,1\}$	$\alpha_3 = 0$
$\alpha_4 = 0$	$\alpha_4 = 0$	$\alpha_4 = 0$	$\alpha_4 = \{-1,1\}$

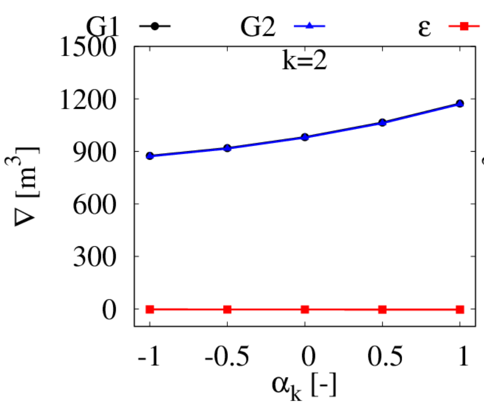


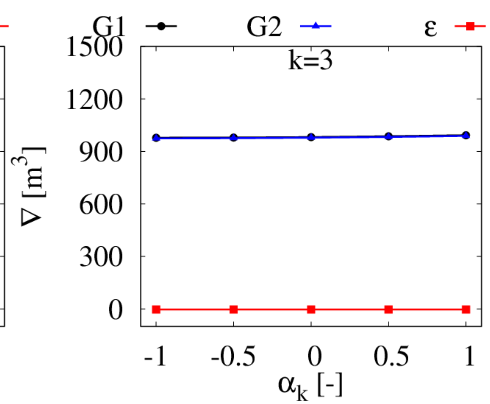


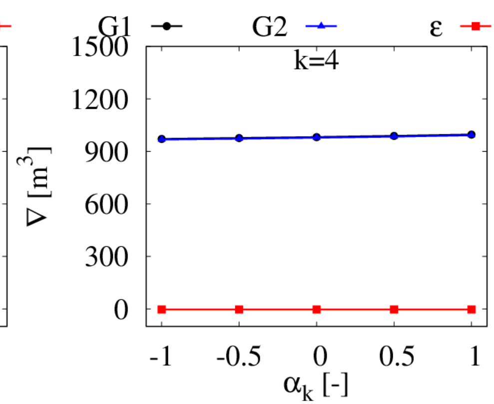












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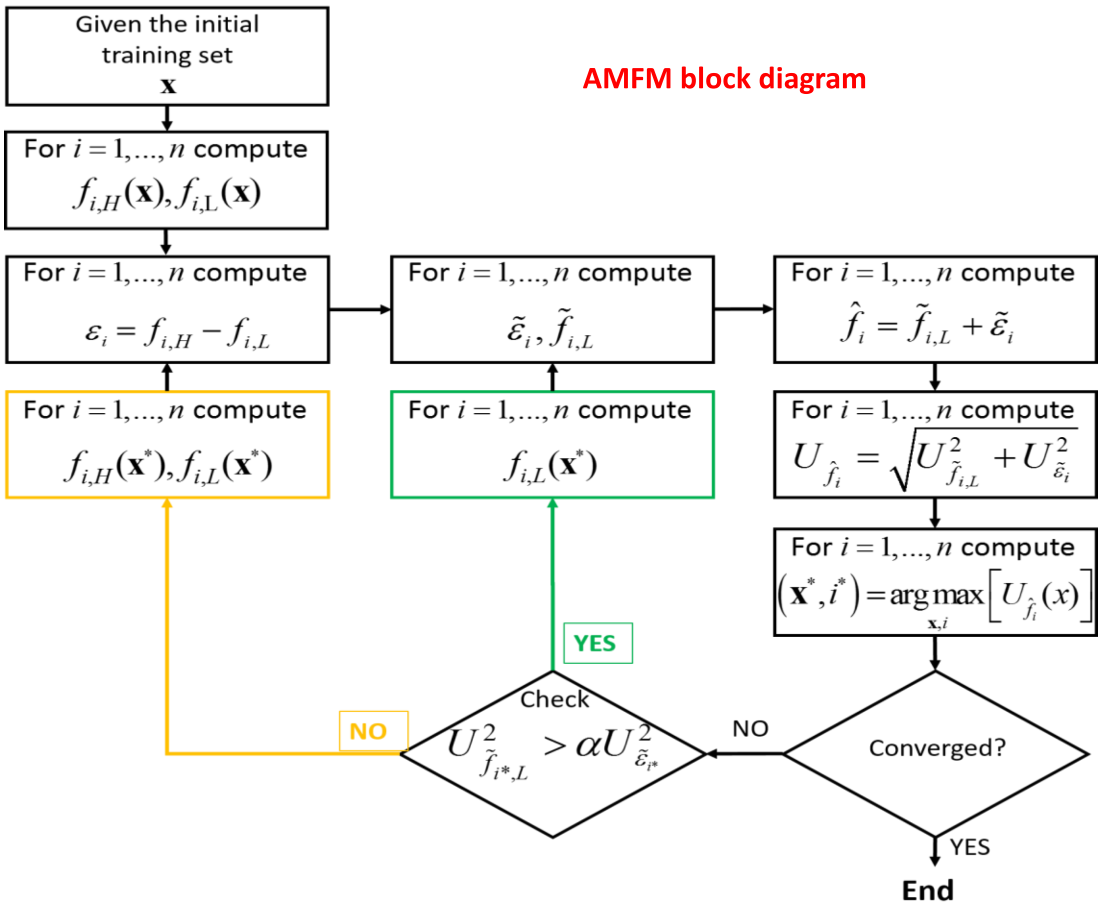
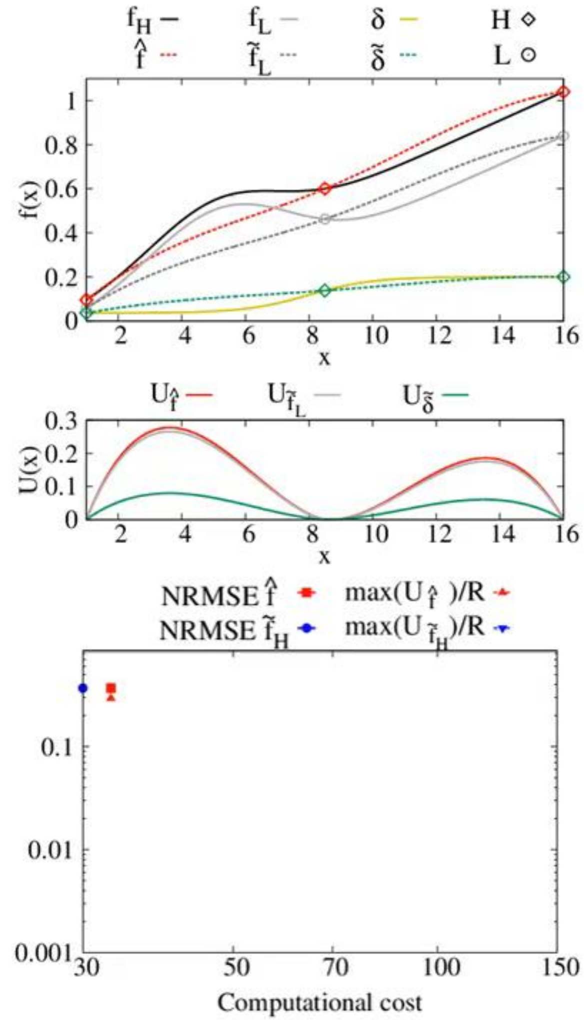
Adaptive multi-fidelity metamodel (AMFM)

- **AMFM**
  - The adaptive sampling procedure is based on metamodel uncertainty minimization.



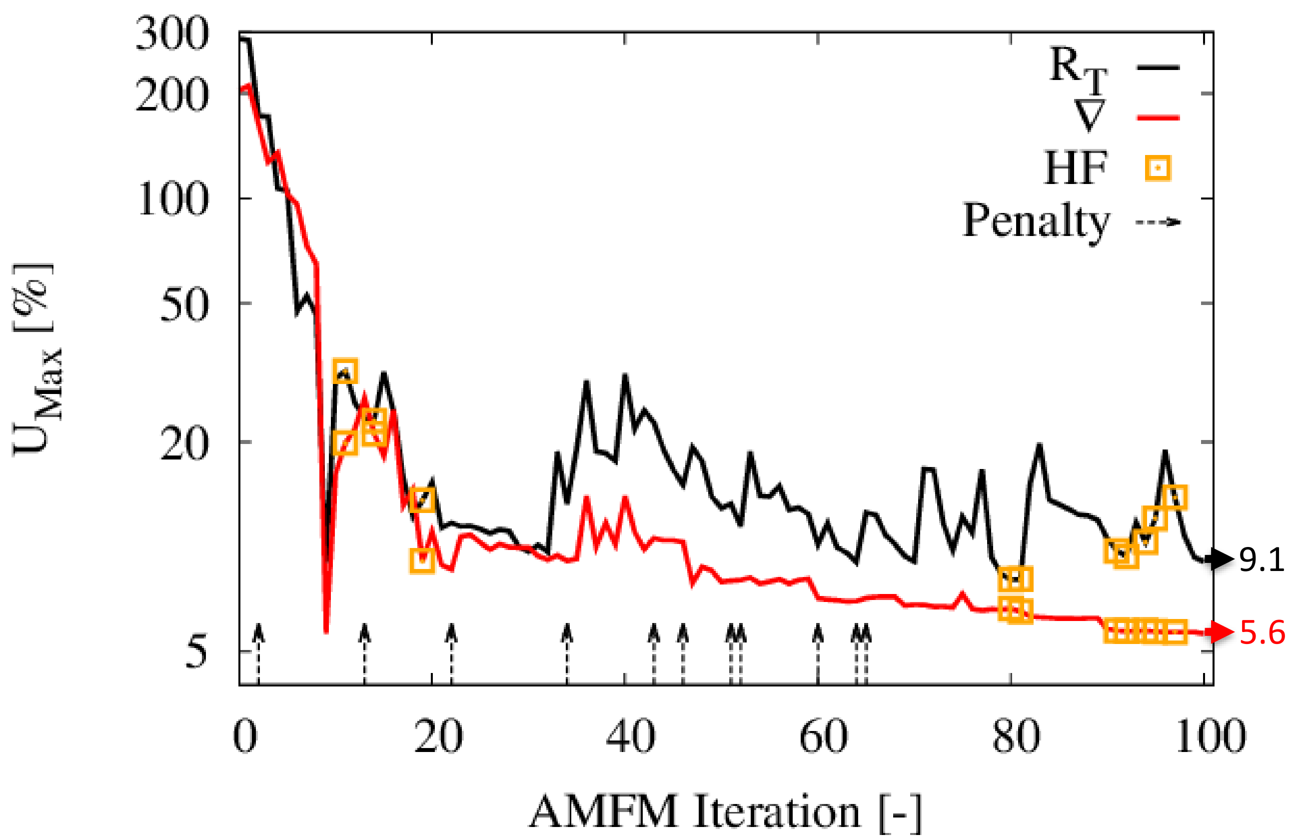
AMFM block diagram



Pellegrini R., Iemma U., Leotardi C., Campana E.F., Diez M., "*Multi-fidelity adaptive global metamodel of expensive computer simulations*", in Proceedings of IEEE World congress on computational intelligence (WCCI) 24-29 July 2016, Vancouver, Canada.

Adaptive multi-fidelity metamodel (AMFM) - Results

- AMFM uncertainty convergence
  - The sensitivity analysis is also the training set (17 HF and LF simulations)
  - Available budget of 100 iterations



Fidelity	Number of simulations
H	17+10
L	17+100

117 LF simulations

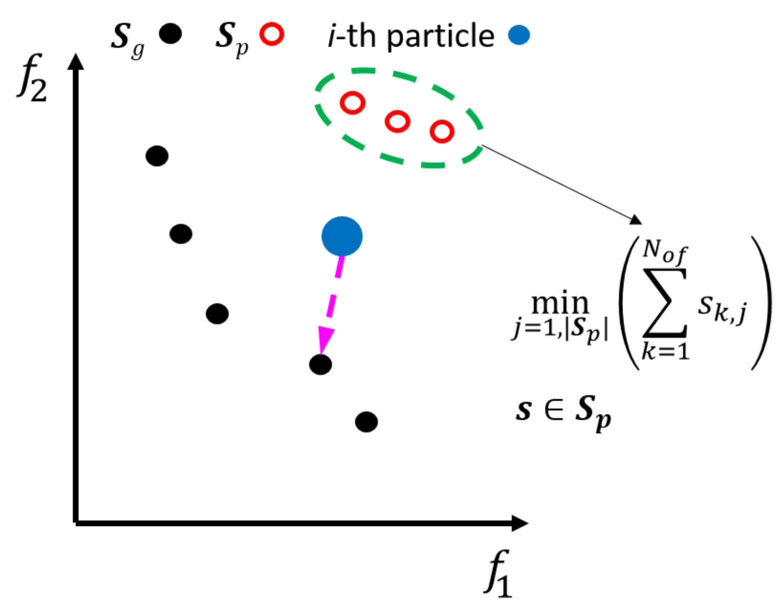
About 3 samples per direction

Multi-objective deterministic particle swarm optimization

- MODPSO
  - Meta-heuristic algorithm based on the metaphor of a flock of bird or bees searching for food [2]
  - **Personal attractor**: minimum of the aggregated function
  - **Global attractor**: closest point of social solution set
  - Hammersley sequence sampling initialization over domain and boundaries, with non-null velocity
  - $8 N_{dv} N_{of}$ particles
  - χ=0.721
  - $c_1 = c_2$ =1.655

$$\begin{cases} v_i^{k+1} = \chi[v_i^k + c_1(\underline{x_{i,pb}} - x_i^k) + c_2(\underline{x_{i,gb}} - x_i^k)] \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases}$$

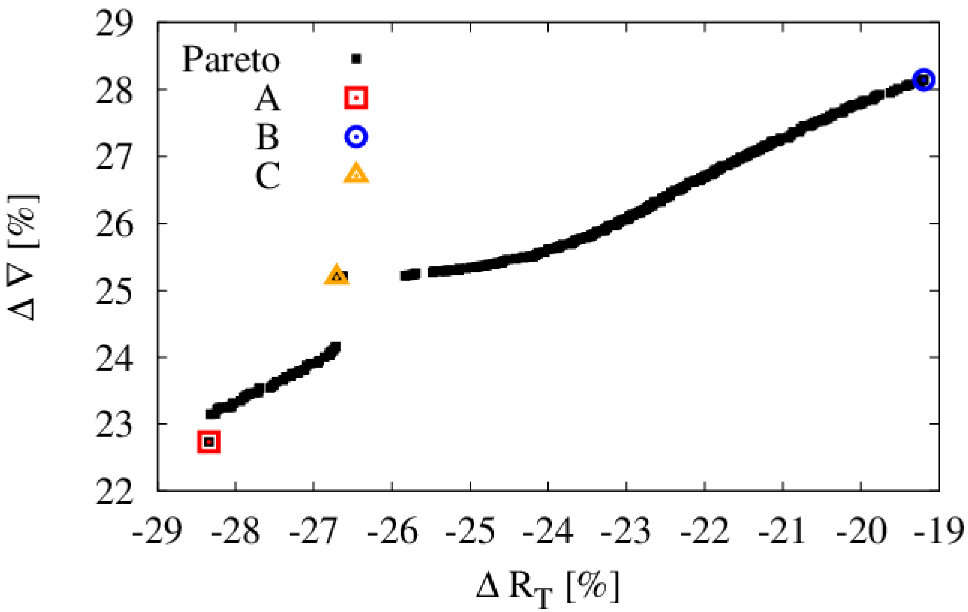
k is iteration counter *i* is the particle index *v* is the particle velocity *x* is the particle position

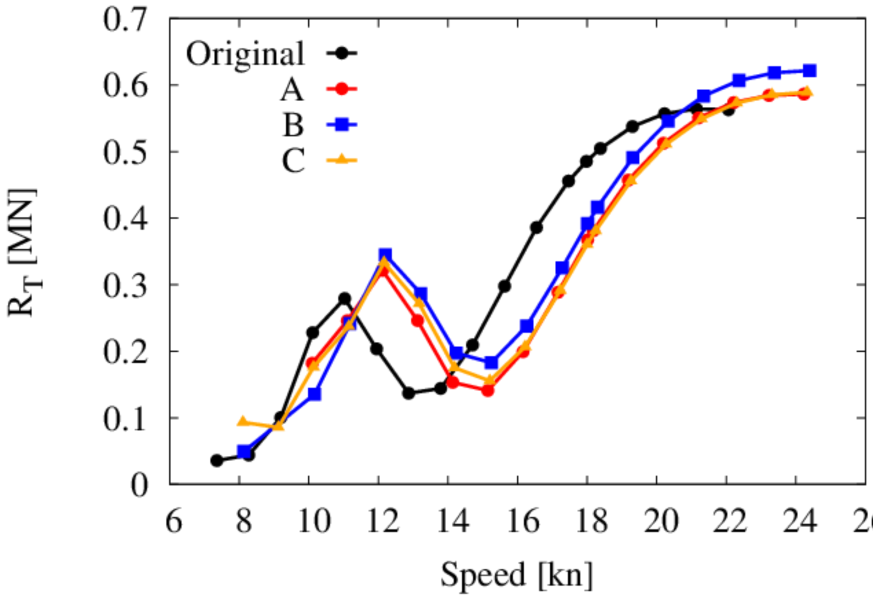


R. Pellegrini, A. Serani, C. Leotardi, U. Iemma, E.F. Campana, M. Diez, “Formulation and parameter selection in multi-objective deterministic particle swarm for simulation-based optimization”, Applied Soft Computing 58 (2017) 714-731. pp. 1942–1948.

Simulation-based hull-form optimization

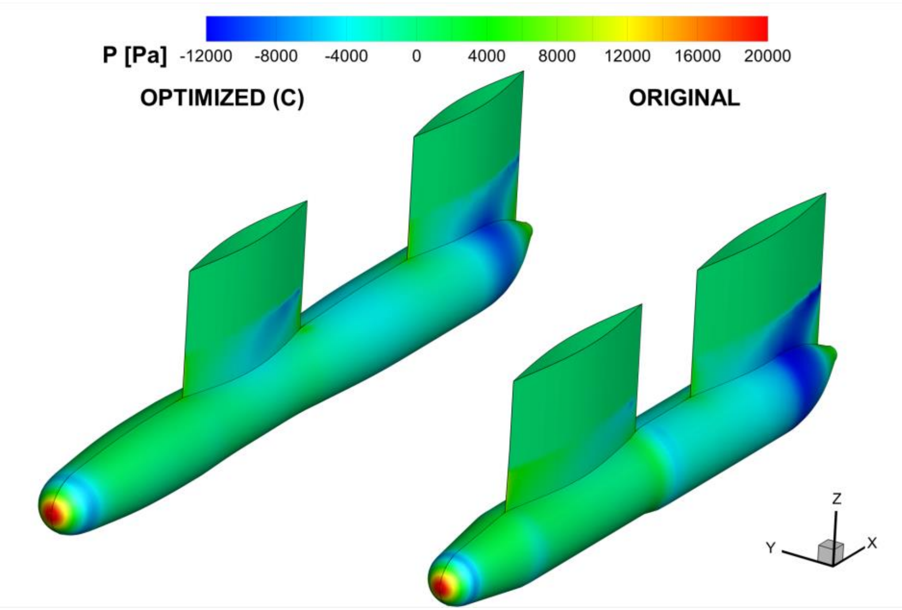
- Non-dominated solution set and most promising configurations performances
  - ✓ The optimization is pèrformed with a deterministic formulation of multi-objective particle swarm optimization algorithm

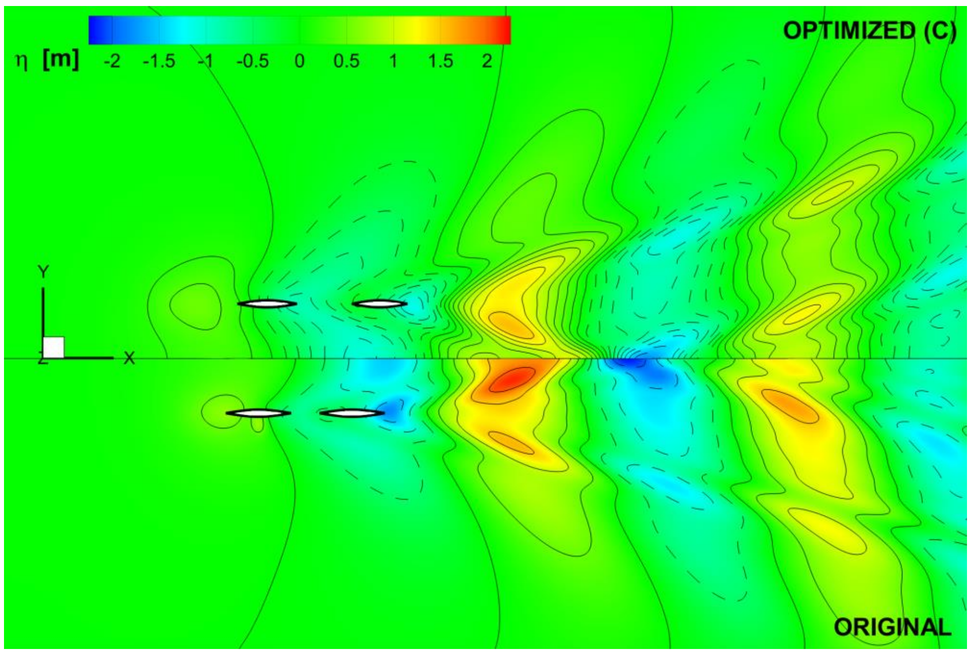


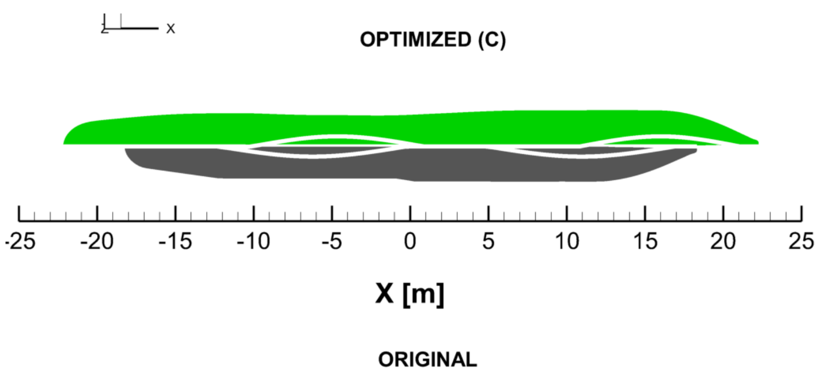


				ΔR_T%		$\Delta\nabla$ %	
Design	ΔL_{OA}%	ΔS_W%	ΔA_{WP}%	AMFM	WARP	AMFM	WARP
A	20.55	19.60	-5.65	-28.30	-24.30	22.70	22.80
B	22.19	24.33	1.27	-19.20	-19.20	28.10	28.20
C	21.64	20.10	-11.42	-26.70	-25.70	25.20	25.10

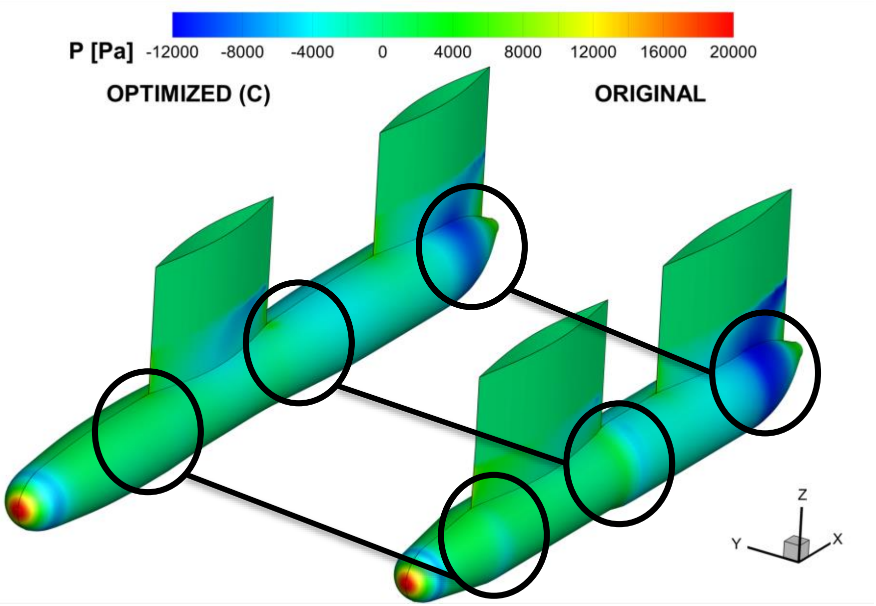
Optimized hull-form



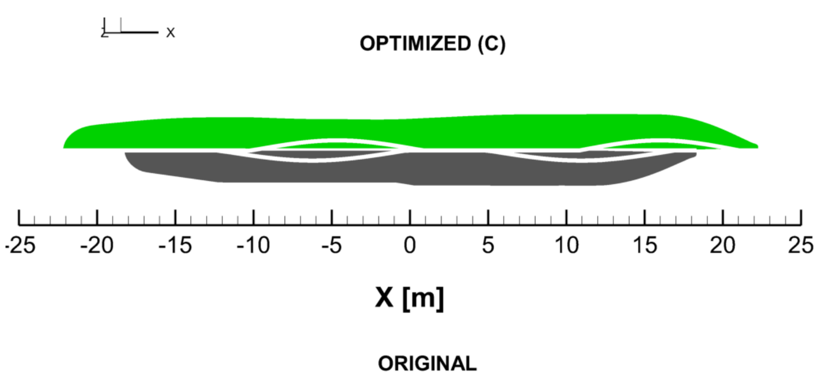


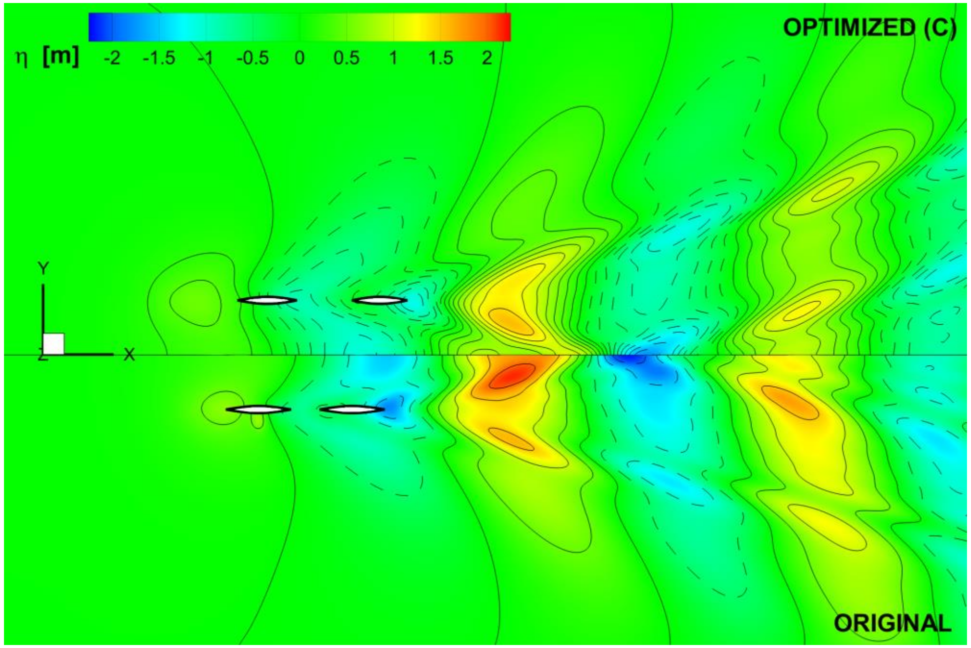


Optimized hull-form



Lower pressure gradients on hull





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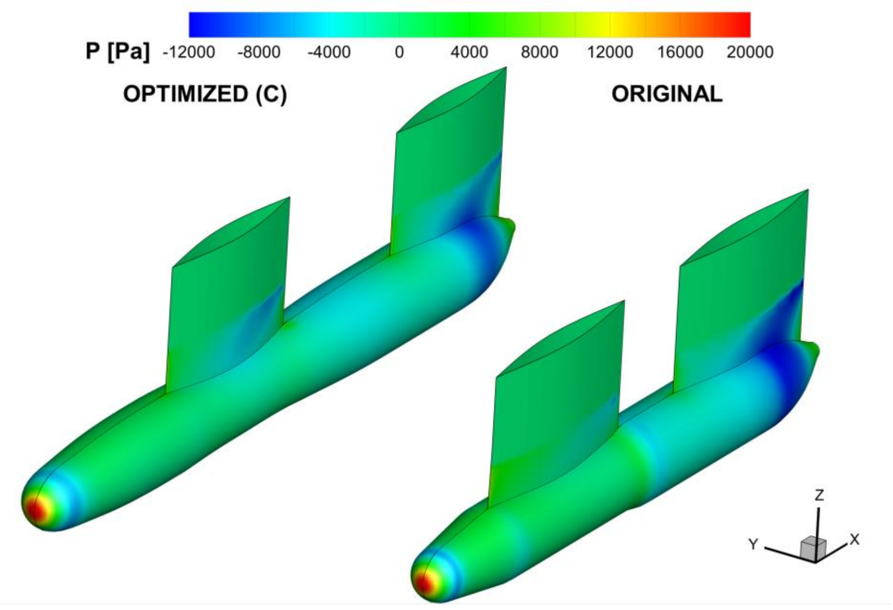
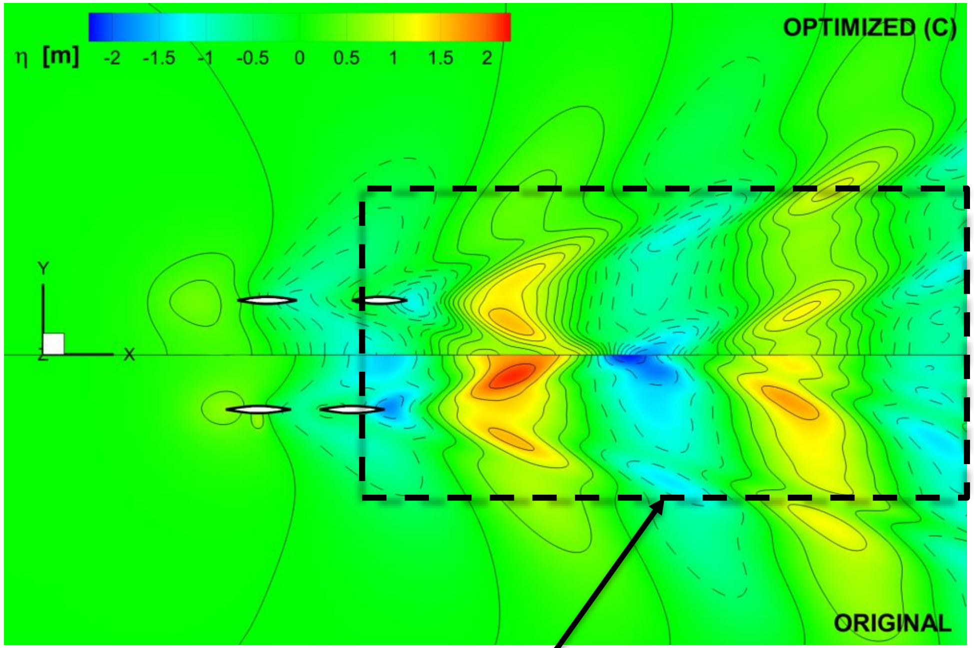
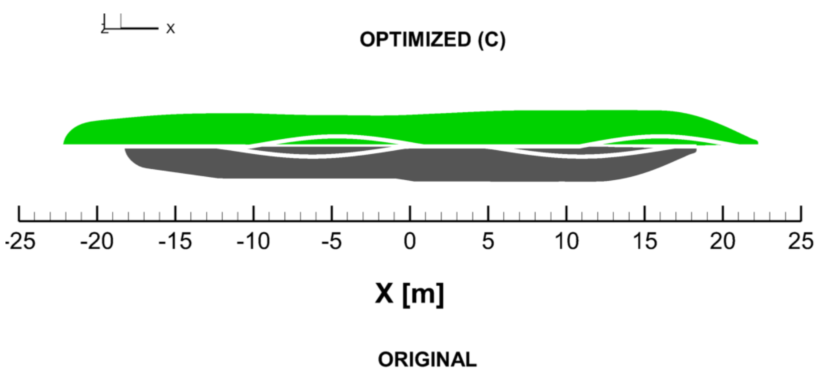
Optimized hull-form



Lower pressure gradients on hull

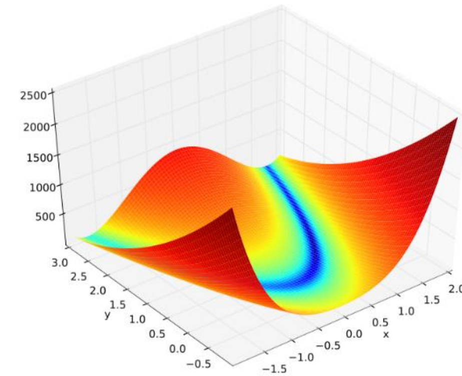


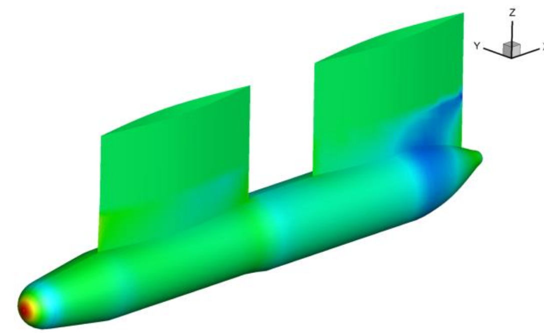


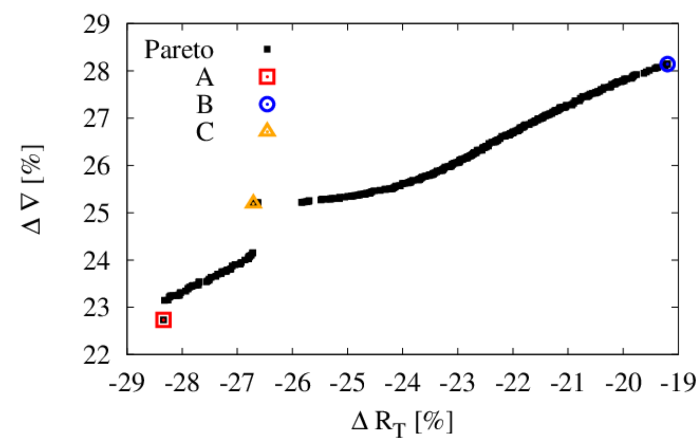
Reduced diverging Kelvin wave

Conclusions

- The hull-form optimization of a SWATH model, addressing the total resistance reduction (at 18 kn) and the displacement maximization, has been presented
  - The parametric CAD models has been produced with CAESES© software
  - The geometric variations have been produced with the CAESES © Sobol engine
  - The design-space has been reduced with the KLE method
  - The stochastic radial basis functions based multi-fidelity metamodel has been used to predict the model performances
  - The optimization has been performed with a deterministic formulation of multi-objective particle swarm optimization algorithm
- The design variables has been reduced from 27 to 4 (85% of reduction), retaining more than 95% of the original variance
- The AMFM maximum uncertainty has been reduced to 9.1% and 5.6% of the original function range for the total resistance and displacement, respectively
- 27 high- and 117 low-fidelity evaluations have been performed
- The optimal design achieves a reduction of the total resistance about 25% and an increase of the displacement about 25%

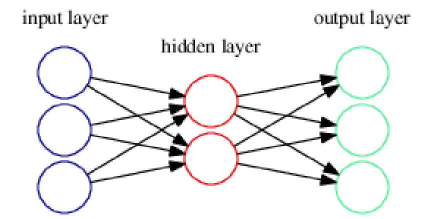


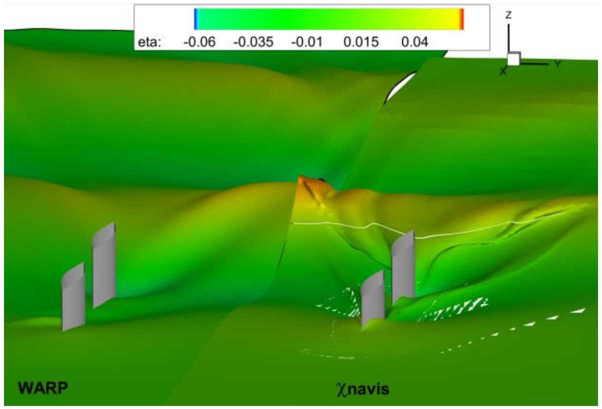


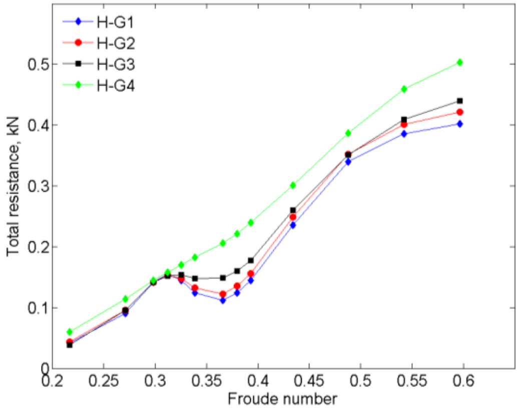


Ongoing/Future work

- Non-linear KLE [1]
  - E.g. deep auto-encoder
- Inclusion of physical parameters in KLE
  - The variational analysis takes into account also the physical effects of the geometry modification
- Use of high-fidelity CFD codes [2]
  - Xnavis, developed at CNR-INSEAN
- Use of hybrid global/local algorithms
  - Combination of MODPSO and linesearch-type algorithms
- Development of parallel strategies for the AMFM update
  - Take advantage of HPC cluster







[1]D'Agostino D., Serani A., Campana E.F., and Diez M. "*Nonlinear Methods for Design-Space Dimensionality Reduction in Shape Optimization* ", In proceedings of 3rd International conference on Machine learning, Optimization and Big Data (MOD 2017) 14-17 September, Volterra, Italy, 2017.
[2]Pellegrini R., Serani A., Broglia R., Harries S., and Diez M., "Payload Optimization of a Sea Vehicle by Multi-Fidelity Surrogate Models", In preparation for 2018 AIAA SciTech Forum, 8–12 January 2018, Gaylord Palms, Kissimmee, Florida.

Thank you!

Questions ??
Suggestions ?!?!?!

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