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

Design
Build
Test

Build-and-test

Increased computational resources

Simulation-based design optimization

Design
Optimization
Simulation

CAESES European Users' Meeting 2017
03/10/2017
Multi-objective optimization problem

The optimization addresses

- total resistance ($R_T$) minimization (18 kn)
- payload maximization ($\nabla$)

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<th>Value [m]</th>
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<tr>
<td>$D$</td>
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<tr>
<td>$T$</td>
<td>6.31</td>
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<td>$S_W$</td>
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<tr>
<td>$A_{WP}$</td>
<td>38.88 [m²]</td>
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No constraints are imposed for this preliminary application

Objectives functions

<table>
<thead>
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<th>Value</th>
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<tbody>
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<td>$\nabla$</td>
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<tr>
<td>$R_T$ (HF, 18 kn)</td>
<td>4.816E5 [N]</td>
</tr>
</tbody>
</table>

Approach - INSEAN SBDO Framework

**Design space dimensionality reduction**
- Geometry-based KLE ✓
- Combined geometry- and physics-based KLE ✓

**Shape manipulation**
- FFD ✓
- Orthogonal patches ✓
- Morphing ✓

**Design conditions**
- Deterministic 
- Stochastic

**Uncertainty quantification**
- Monte Carlo simulation ✓
- Importance sampling ✓

**Dynamic/adaptive metamodel**
- Stochastic
- Deterministic

**Before optimization**

**Verify and validation**
- Original design ✓
- Optimized design ✓

**Global optimization**
- Derivative-free ✓
- Single/multi-objective ✓
- Hybrid global/local ✓
- Synchronous/asynchronous ✓
- Bio-inspired ✓

**Analysis tools**

**Before optimization**

**Hydrodynamics (URANS, potential flow)** ✓
- Structures (FEM) ✓
- Multi-disciplinary and FSI ✓
Design-space dimensionality reduction - Underlying idea

\[ \min_{\mathbf{u} \in \mathcal{U}} \text{obj}(\mathbf{u}) \]

“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 \( \mathbf{u} \) as belonging to a stochastic domain \( \mathcal{U} \) with associated probability density function \( f(\mathbf{u}) \), \( \mathbf{u} \in \mathcal{U} \)

Design-space dimensionality reduction - Definitions

- Generalized inner product
\[(f, g)_\rho = \int_{\mathcal{G}} \rho(x)f(x) \cdot g(x)dx\]

- Mean shape modification
\[
\langle \delta \rangle = \int_{\mathcal{U}} \delta(x,u)f(u)du
\]

- Geometric variance (key element)
\[
\sigma^2 = \langle ||\hat{\delta}||^2 \rangle = \int_{\mathcal{U}} \int_{\mathcal{G}} \rho(x)\hat{\delta}(x,u) \cdot \hat{\delta}(x,u)f(u)dxdu
\]

- Design variable (uncertain)
\[u\]

- Spatial variable
\[x\]

- Ensemble average over \(u\)
\[\hat{\delta} = \delta - \langle \delta \rangle\]

- Weight function
\[\rho(x)\]
Design-space dimensionality reduction – Problem statement

- Basis of orthonormal functions (KLE)

\[ \tilde{\delta}(x,u) = \sum_{k=1}^{\infty} \alpha_k(u)\varphi_k(x) \]

- Geometric variance expressed as

\[ \sigma^2 = \sum_{k=1}^{\infty} \sum_{j=1}^{\infty} \langle \alpha_k \alpha_j \rangle (\varphi_k, \varphi_j)_{\rho} = \sum_{j=1}^{\infty} \langle \alpha_j^2 \rangle = \sum_{j=1}^{\infty} \langle (\tilde{\delta}, \varphi_j)^2 \rangle_{\rho} \]

- Formulation of a variational problem

\[ \max_{\varphi \in L^2_\rho(G)} J(\varphi) = \left\langle (\tilde{\delta}, \varphi_j)^2 \right\rangle_{\rho} \]

subject to \( (\varphi, \varphi)^2_{\rho} = 1 \)

- The variational problem solution is

\[ \mathcal{L}\varphi(x) = \int_{G} \langle \delta(x,u) \otimes \delta(y,u) \rangle \varphi(y) dy = \lambda \varphi(x) \]
Design-space dimensionality reduction – Discretization

- Considering the variational problem solution

\[ \mathcal{L} \varphi(x) = \int_G \langle \delta(x,u) \otimes \delta(y,u) \rangle \varphi(y) dy = \lambda \varphi(x) \]

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

\[ \delta(x,u) = \sum_{q=1}^{3} \delta_q(x,u) e_q, \quad \varphi(x) = \sum_{q=1}^{3} \varphi_q(x) e_q \]

- which yields

\[ \sum_{q=1}^{3} \int_G \langle \delta_p(x,u) \delta_q(y,u) \rangle \varphi_q(y) dy = \lambda \varphi_p(x) \]

- Discretizing the variable of integration \( y \) (therefore the geometry) with \( L \) elements of dimension \( \Delta G_j \) and centroid at \( x_j, j = 1, \ldots, L \)

\[ \sum_{q=1}^{3} \sum_{j=1}^{L} \langle \delta_p(x_i,u) \delta_q(x_j,u) \rangle \varphi_q(x_j) \Delta G_j = \lambda \varphi_p(x_i) \]
This form can be discretized as

\[
\sum_{q=1}^{3} \sum_{j=1}^{L} (\delta_p(x_i, u) \delta_q(x_j, u)) \varphi_q(x_j) \Delta G_j = \lambda \varphi_p(x_i)
\]

\[
d_p(u) = \left\{ \begin{array}{c}
\gamma_p(x_1, u_k) \\
\vdots \\
\gamma_p(x_L, u_k)
\end{array} \right\} - \frac{1}{S} \sum_{k=1}^{S} \left\{ \begin{array}{c}
\gamma_p(x_1, u_k) \\
\vdots \\
\gamma_p(x_L, u_k)
\end{array} \right\}
\]

\[
\gamma_p = \gamma \cdot e_p
\]

\[
D_p = [d_p(u_1) \ldots d_p(u_S)]
\]

\[
R_{pq} = \frac{1}{S} D_p D_q^T
\]

\[
W = [\Delta G_i \delta_{ij}]
\]
Design-space dimensionality reduction – Implementation

- This form can be discretized as

\[
\sum_{q=1}^{3} \sum_{j=1}^{L} \langle \delta_p(x_i, u) \delta_q(x_j, u) \rangle \varphi_q(x_j) \Delta G_j = \lambda \varphi_p(x_i)
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d_p(u) = \begin{bmatrix}
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\vdots \\
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\end{bmatrix} - \frac{1}{S} \sum_{k=1}^{S} \begin{bmatrix}
\gamma_p(x_1, u_k) \\
\vdots \\
\gamma_p(x_L, u_k)
\end{bmatrix}
\]

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\gamma_p = \gamma \cdot e_p
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\]

\[
R_{pq} = \frac{1}{S} D_p D_q^T
\]

\[
W = [\Delta G_i \delta_{ij}]
\]

\[
\sum_{q=1}^{3} \sum_{j=1}^{L} [R_{pq} W]_{ij} \{z_q\}_j = \lambda \{z_p\}_i
\]

\[
A_{ij}
\]
Design-space dimensionality reduction – Implementation

- This form can be discretized as

\[ \sum_{q=1}^{3} \sum_{j=1}^{L} \langle \delta_p(x_i, u) \delta_q(x_j, u) \rangle \varphi_q(x_j) \Delta G_j = \lambda \varphi_p(x_i) \]

\[ d_p(u) = \begin{bmatrix} \gamma_p(x_1, u_k) \\ \vdots \\ \gamma_p(x_L, u_k) \end{bmatrix} - \frac{1}{S} \sum_{k=1}^{S} \begin{bmatrix} \gamma_p(x_1, u_k) \\ \vdots \\ \gamma_p(x_L, u_k) \end{bmatrix} \]

\[ \gamma_p = \mathbf{y} \cdot e_p \]

\[ D_p = [d_p(u_1) \, \ldots \, d_p(u_S)] \]

\[ R_{pq} = \frac{1}{S} D_p D_q^T \text{ Covariance matrix} \]

\[ W = [\Delta G_i \delta_{ij}] \]

\[ Az = \lambda z \]
Design-space dimensionality reduction – “How to use”

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

\[ \lambda_k = \langle \alpha_k^2 \rangle \]

\[ \sigma^2 = \sum_{k=1}^{\infty} \lambda_k \]

- Dimensionality reduction with confidence level \( l \)

\[ \hat{\delta}(x, \nu) = \sum_{k=1}^{N} \alpha_k(\nu) \varphi_k(x) \]

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

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

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

New design variables

Variance retained by each KLE eigenfunction

Total variance
Design-space dimensionality reduction – “How to use”

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

\[ \lambda_k = \langle \alpha_k^2 \rangle \]

\[ \sigma^2 = \sum_{k=1}^{\infty} \lambda_k \]

- Dimensionality reduction with confidence level \( l \)

\[ \hat{\delta}(x, \nu) = \sum_{k=1}^{N} \alpha_k(\nu) \varphi_k(x) \]

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

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

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

New representation of the shape modification (new design space, ROM)
Design-space dimensionality reduction – “How to use”

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

\[ \lambda_k = \langle \alpha_k^2 \rangle \]

- Dimensionality reduction with confidence level \( l \)

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

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

\[ \delta(x, u) = \sum_{k=1}^{N} \alpha_k(u) \varphi_k(x) \]

All the geometric constraints are respected

\[ \sum_{k=1}^{N} \lambda_k = \sigma^2 \]

\( \lambda_k \) variance retained by each KLE eigenfunction

\( \sigma^2 \) total variance

\( N \) 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 (to avoid infeasible geometries!)

CAESES© Sobol engine
  - 12000 geometry variations
## 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.
Design-space dimensionality reduction by KLE - modes

- First four KL modes $\varphi$

![Images of KL modes for X, Y, and Z axes]
Design-space dimensionality reduction by KLE - modes

- First four KL modes $\varphi$

![Diagram of KL modes](image)
Design-space dimensionality reduction by KLE - modes

- First four KL modes $\varphi$

\[ \begin{align*}
\varphi_1 & \quad \varphi_2 & \quad \varphi_3 & \quad \varphi_4 \\
X & \quad Z & \quad Z & \quad Z \\
Y & \quad Y & \quad Y & \quad Y \\
Z & \quad Z & \quad Z & \quad Z \\
\end{align*} \]
Design-space dimensionality reduction by KLE - modes

- First four KL modes $\varphi$

![Graphs of KL modes $\varphi_1$ to $\varphi_4$ in the $X$, $Y$, and $Z$ dimensions.](image)
Design-space dimensionality reduction by KLE - modes

- First four KL modes $\varphi$

$\varphi_1$

$\varphi_2$

$\varphi_3$

$\varphi_4$
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

<table>
<thead>
<tr>
<th>Grid</th>
<th>G1</th>
<th>G2</th>
</tr>
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<tbody>
<tr>
<td>Upstream extension</td>
<td>1.5 L_{OA}</td>
<td></td>
</tr>
<tr>
<td>Downstream extension</td>
<td>3.5 L_{OA}</td>
<td></td>
</tr>
<tr>
<td>Sideways extension</td>
<td>1.5 L_{OA}</td>
<td></td>
</tr>
<tr>
<td>Body panels</td>
<td>5.2 k</td>
<td>2.6 k</td>
</tr>
<tr>
<td>Surface panels</td>
<td>6.0 k</td>
<td>3.0 k</td>
</tr>
</tbody>
</table>

Potential flow solver

- Sensitivity analysis

\[
\begin{align*}
\alpha_1 &= \{-1, 1\} \\
\alpha_2 &= 0 \\
\alpha_3 &= 0 \\
\alpha_4 &= 0 \\
\alpha_1 &= 0 \\
\alpha_2 &= \{-1, 1\} \\
\alpha_3 &= 0 \\
\alpha_4 &= 0 \\
\alpha_1 &= 0 \\
\alpha_2 &= 0 \\
\alpha_3 &= \{-1, 1\} \\
\alpha_4 &= 0 \\
\alpha_1 &= 0 \\
\alpha_2 &= 0 \\
\alpha_3 &= 0 \\
\alpha_4 &= \{-1, 1\}
\end{align*}
\]
Adaptive multi-fidelity metamodel (AMFM)

- AMFM

The adaptive sampling procedure is based on metamodel uncertainty minimization.

---

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

\[
\begin{array}{|c|c|}
\hline
\text{Fidelity} & \text{Number of simulations} \\
\hline
H & 17+10 \\
L & 17+100 \\
\hline
\end{array}
\]

Table of Fidelities and Number of Simulations
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
  - $8N_{dv}N_{of}$ particles
  - $\chi=0.721$
  - $c_1 = c_2 = 1.655$

\[
\begin{align*}
    v_{i}^{k+1} &= \chi[v_{i}^{k} + c_1(x_{i,pb} - x_{i}^{k}) + c_2(x_{i,gb} - x_{i}^{k})] \\
    x_{i}^{k+1} &= x_{i}^{k} + v_{i}^{k+1}
\end{align*}
\]

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

Simulation-based hull-form optimization

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

<table>
<thead>
<tr>
<th>Design</th>
<th>ΔL₀A %</th>
<th>ΔSₘ %</th>
<th>ΔAₜw %</th>
<th>AMFM</th>
<th>WARP</th>
<th>AMFM</th>
<th>WARP</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>20.55</td>
<td>19.60</td>
<td>-5.65</td>
<td>-28.30</td>
<td>-24.30</td>
<td>22.70</td>
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<td>C</td>
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<td>20.10</td>
<td>-11.42</td>
<td>-26.70</td>
<td>-25.70</td>
<td>25.20</td>
<td>25.10</td>
</tr>
</tbody>
</table>
Optimized hull-form
Optimized hull-form

Lower pressure gradients on hull
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


Thank you!

Questions ??
Suggestions ?!?!?!