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Innovative Ship Design Lab

Hydrodynamic Optimization of Surface Combatant using Multi-Fidelity Co-Kriging algorithm

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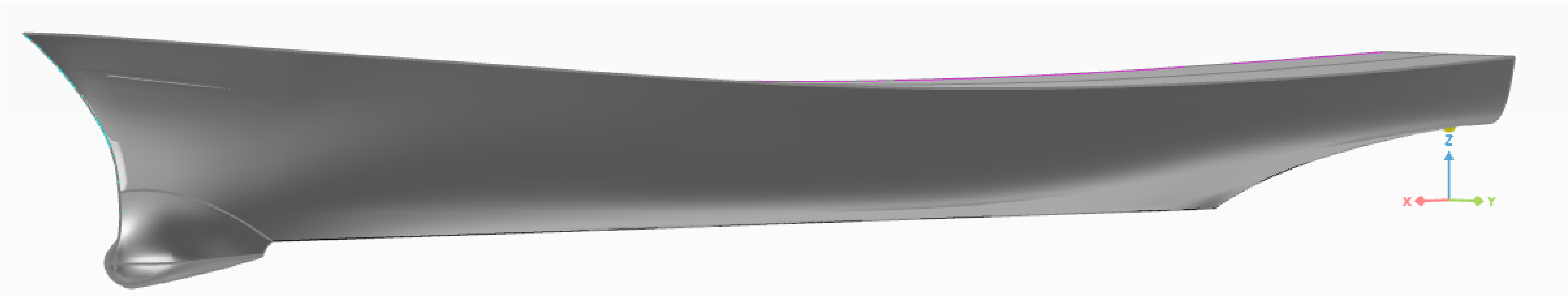
VT - iShip laboratory
Kevin T. Crofton Dept. of Aerospace & Ocean Eng.

Presentation for CAESES User Conference 04/01/2026



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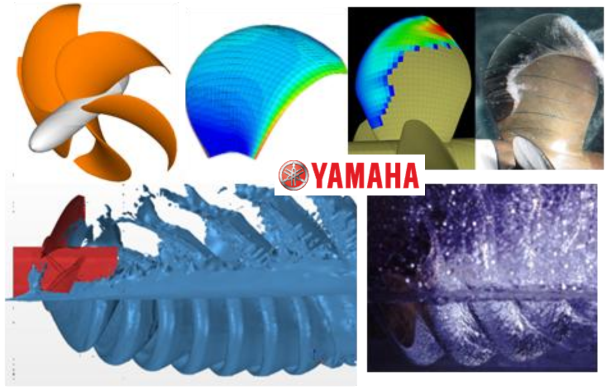
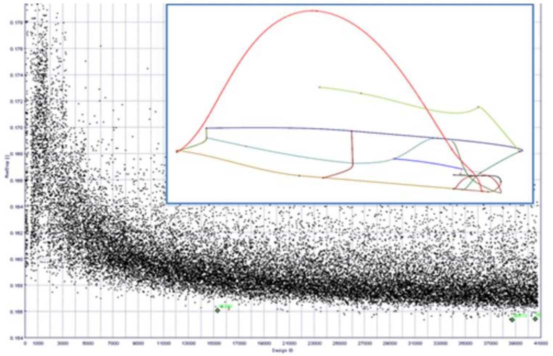
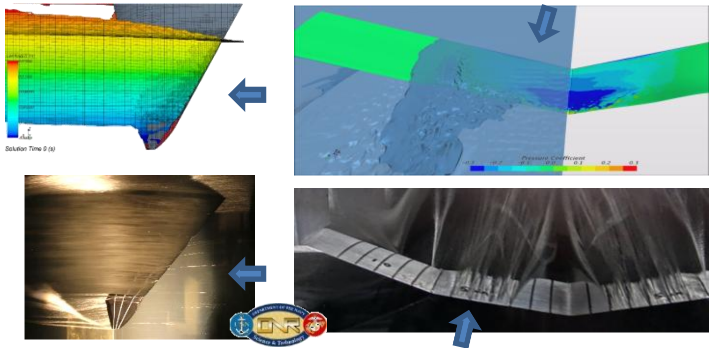
High Speed high Efficiency Propeller Design & Analysis



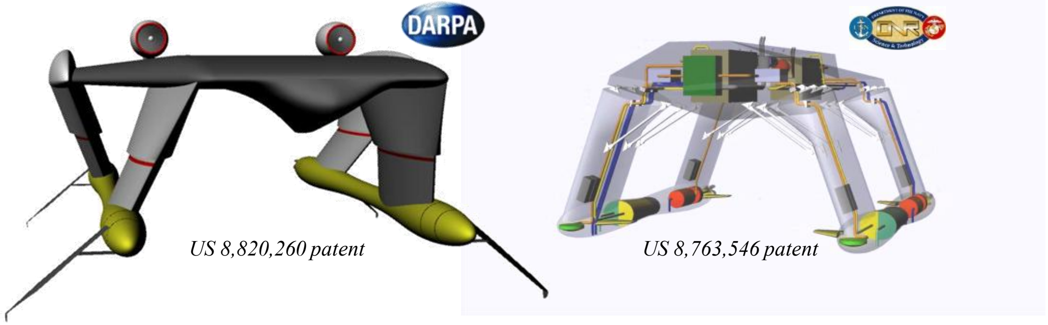
Multi-Fidelity CFD Full Parametric Hull form Optim.



Super-Cavitating Surface-Piercing Hydrofoils



2nd Generation Autonomous Surface Vessels



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VIRGINIA TECH

10 PhD students
3 MS student
11 patents (2 pending)
>5M$ res. portfolio

Dr. Stefano Brizzolara
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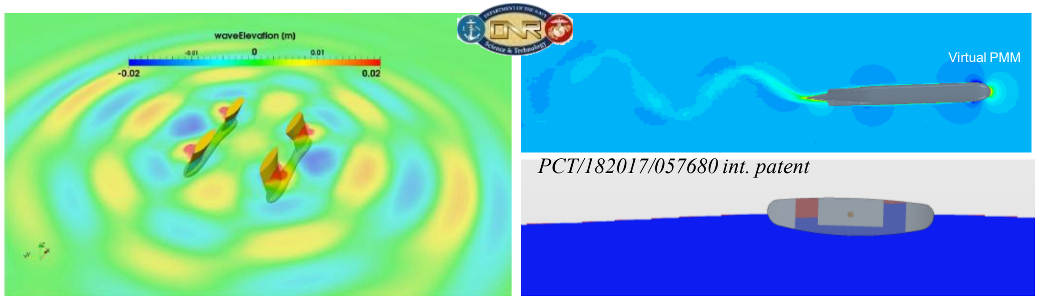
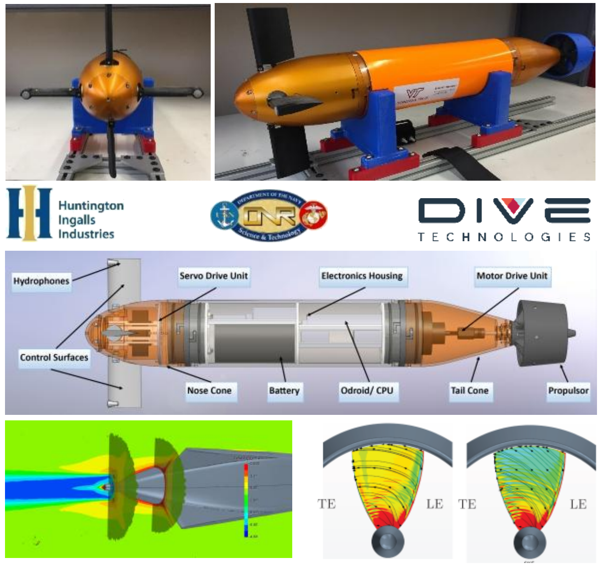
Viscous Non-linear Seakeeping & Maneuvering



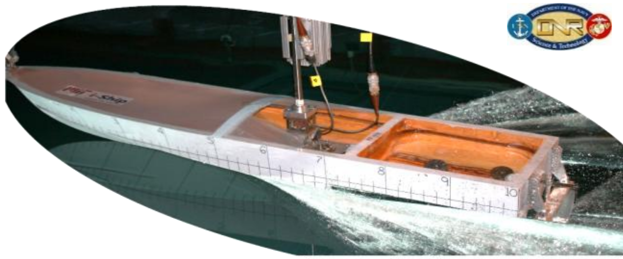
Underwater Autonomous Vehicles Hydrodynamics

Huntington Ingalls Industries

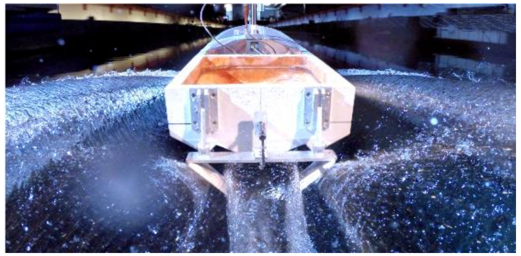
DIVE TECHNOLOGIES



High Performance High Speed (Planing) Crafts



US 10,189,544 patent



Goals

- Develop a user friendly tool to generate and hydrodynamically asses hull variations
- Exploration of Friendship/CAESES Frameworks
- Apply optimization algorithms to find ideal hull shape

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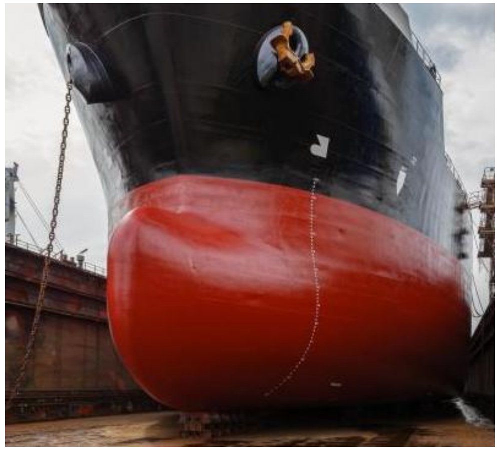
How to Design a High Performance Ship Hull



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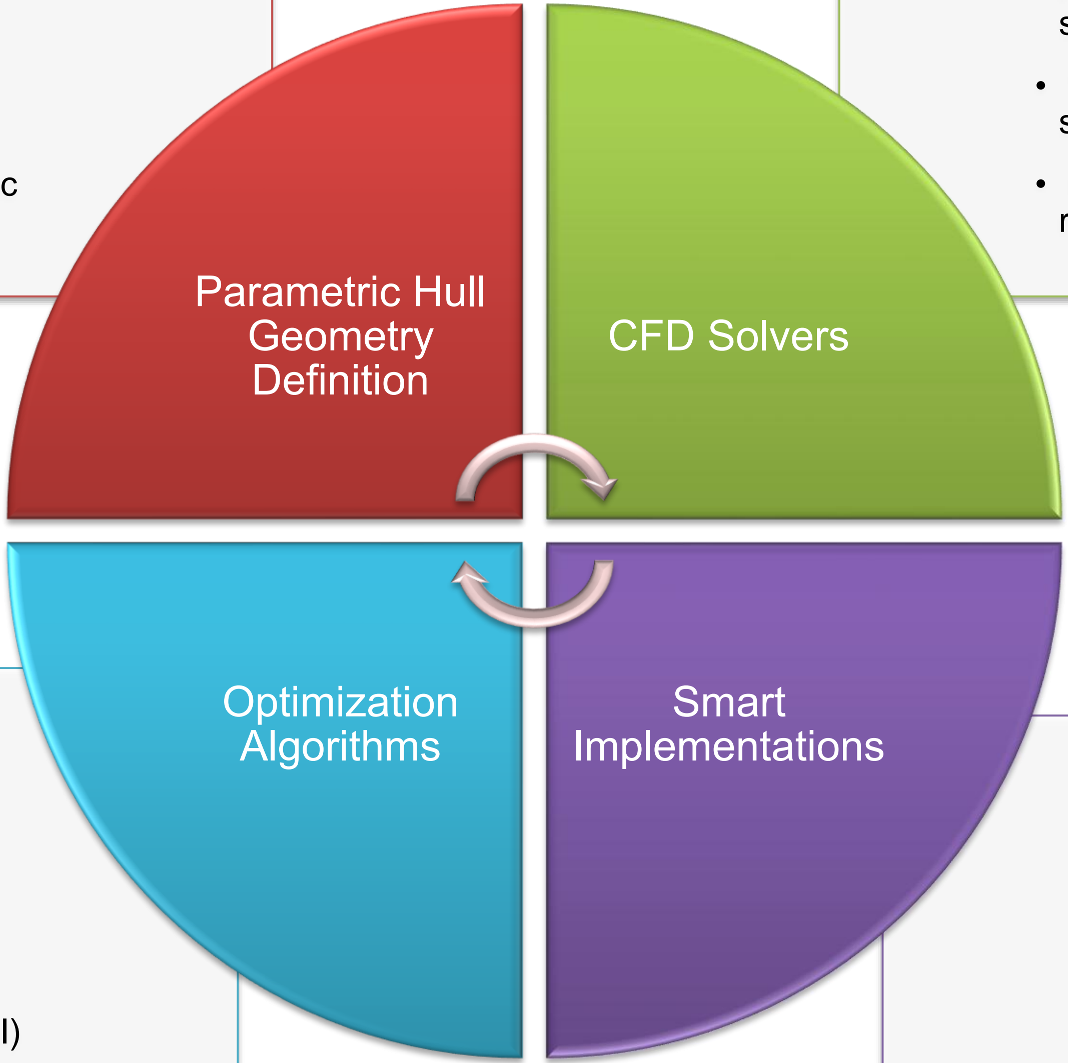
Design-by-Optimization Framework

- Partial Param. Modelling
- Full Parametric Modeling
- Full 3D based on primitive geometric parameters

- BEM for wave resistance and seakeeping
- VII (coupled thin B.L. solvers) for form drag
- RANSE for total resistance



- Deterministic (gradient based)
- Stochastic (evolutionary)
- Hybrid (local+global)
- Hybrid (multi-fidelity)

- Response Functions
- Adjoint Methods
- POD
- ROM

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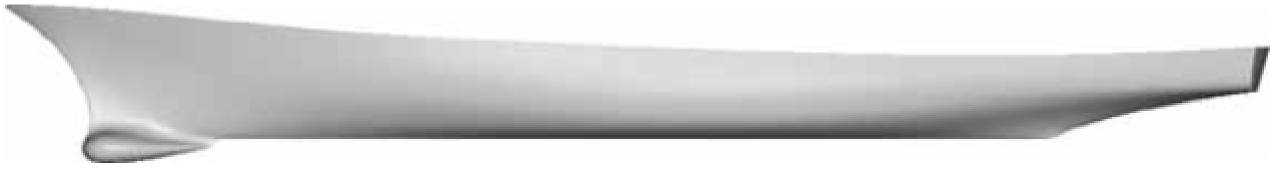
Hull Considered –DTMB 5415

Main particulars	
Lpp (m)	142.00
Lwl (m)	142.18
Bwl (m)	19.06
T (m)	6.15
Displacement (m^3)	8424.4
S w/o rudder (m^2)	2972.6
CB	0.507
CM	0.821
LCB (%Lpp), fwd+	-0.683

- Conceived in early ’80s as a preliminary design for a navy surface combatant
- Geometry includes a sonar dome but no appendages
- Wide variety of model test results and optimization strategies



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Previous Hullform Parametrizations

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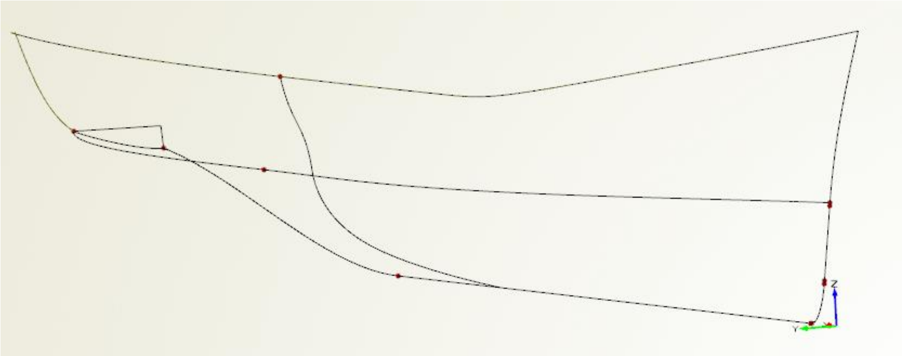
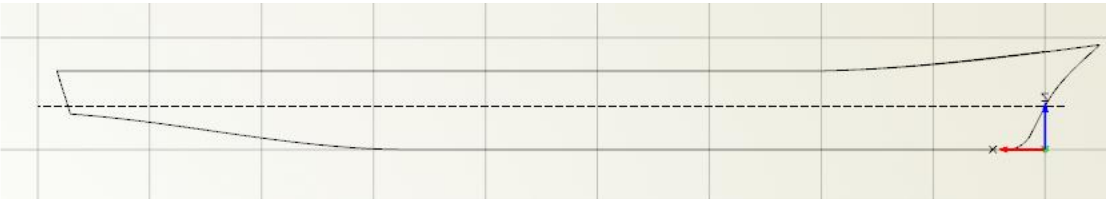
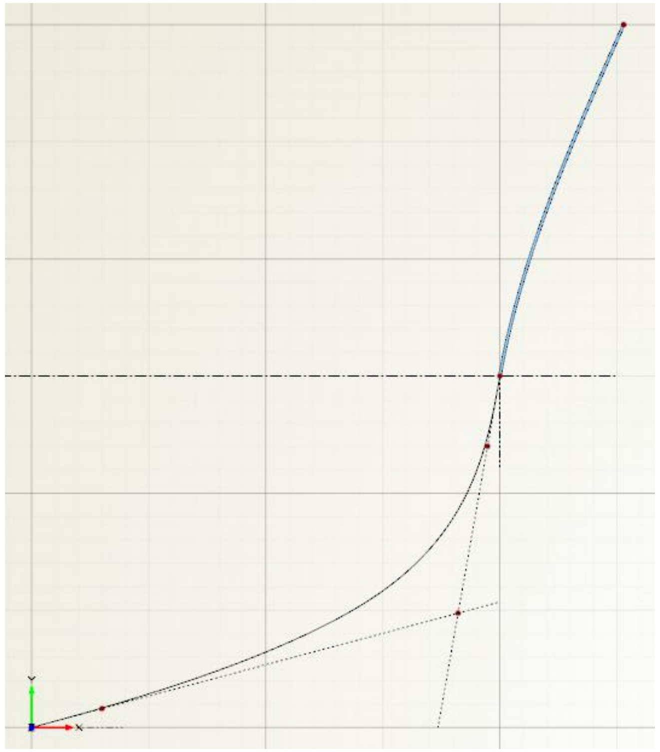
Basic Curves and Parametric Definition

- Full parametric model: the hull shape can be controlled over in its entire extension (as opposed to partial);
- Meaningful geometric parameters
- Definition that can ensure a good surface fairing (longitudinal basic curves)
- As few curves as possible
- General definition which can be easily re-created using standard 3D-CAD libraries (NURBS and c-splines) this especially holds for the transv. section







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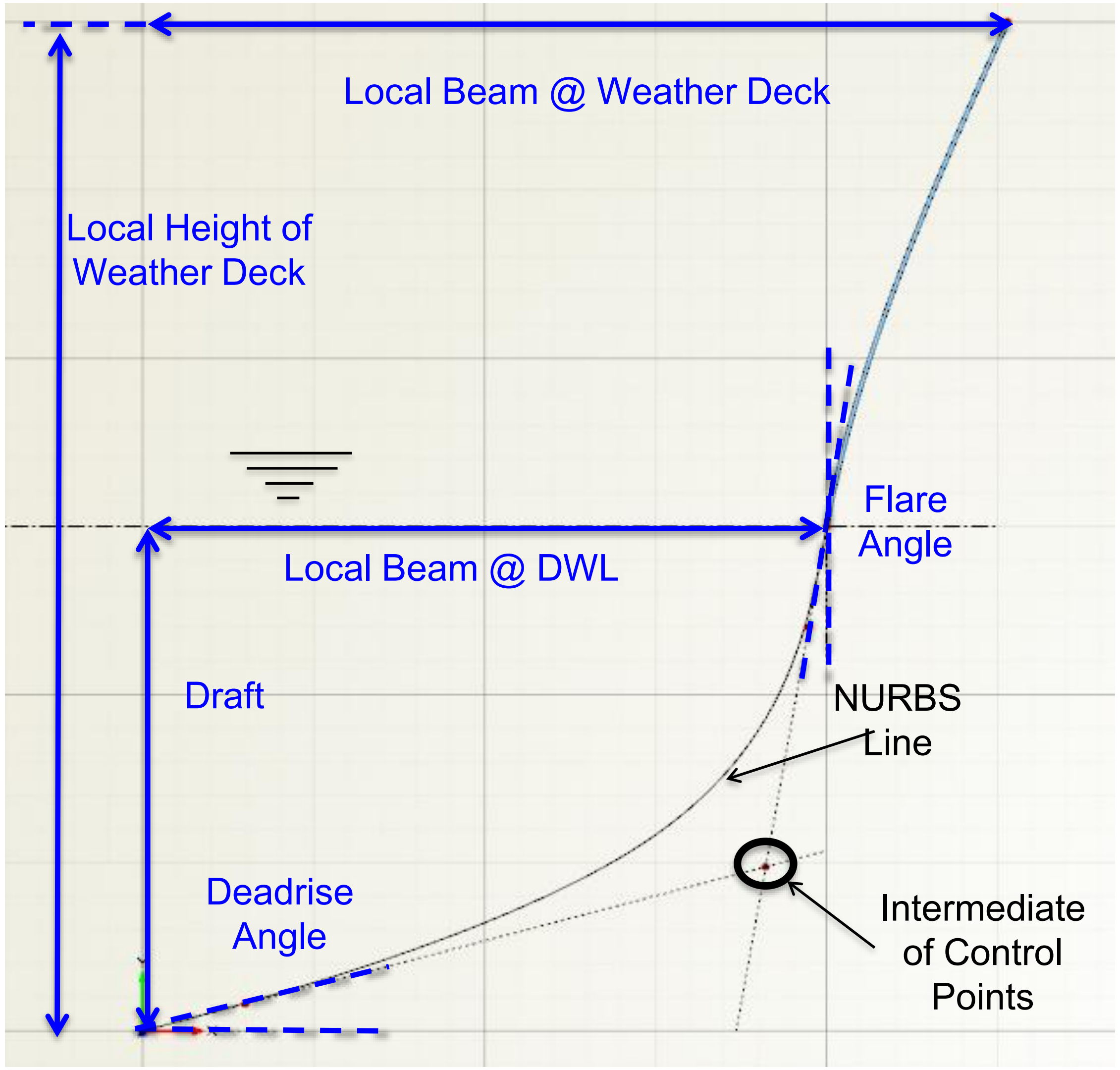
Sections Definition

- Cross Section Parameters
  - Underwater
    - Deadrise Angle
    - Flare Angle
    - Local Beam
    - Draft
    - Local Height of Keel
  - Above Water
    - Flare Angle
    - Local Beam @ Weather Deck
    - Local Height of Weather Deck

- Geometric Modelling
  - Underwater
    - NURBS curve
    - 5 points control polygon
    - Weight of intermediate point controls the fullness
  - Above Water
    - Fspline
    - Respect tangent at DWL
    - Extent till meet with the edge of the weather deck



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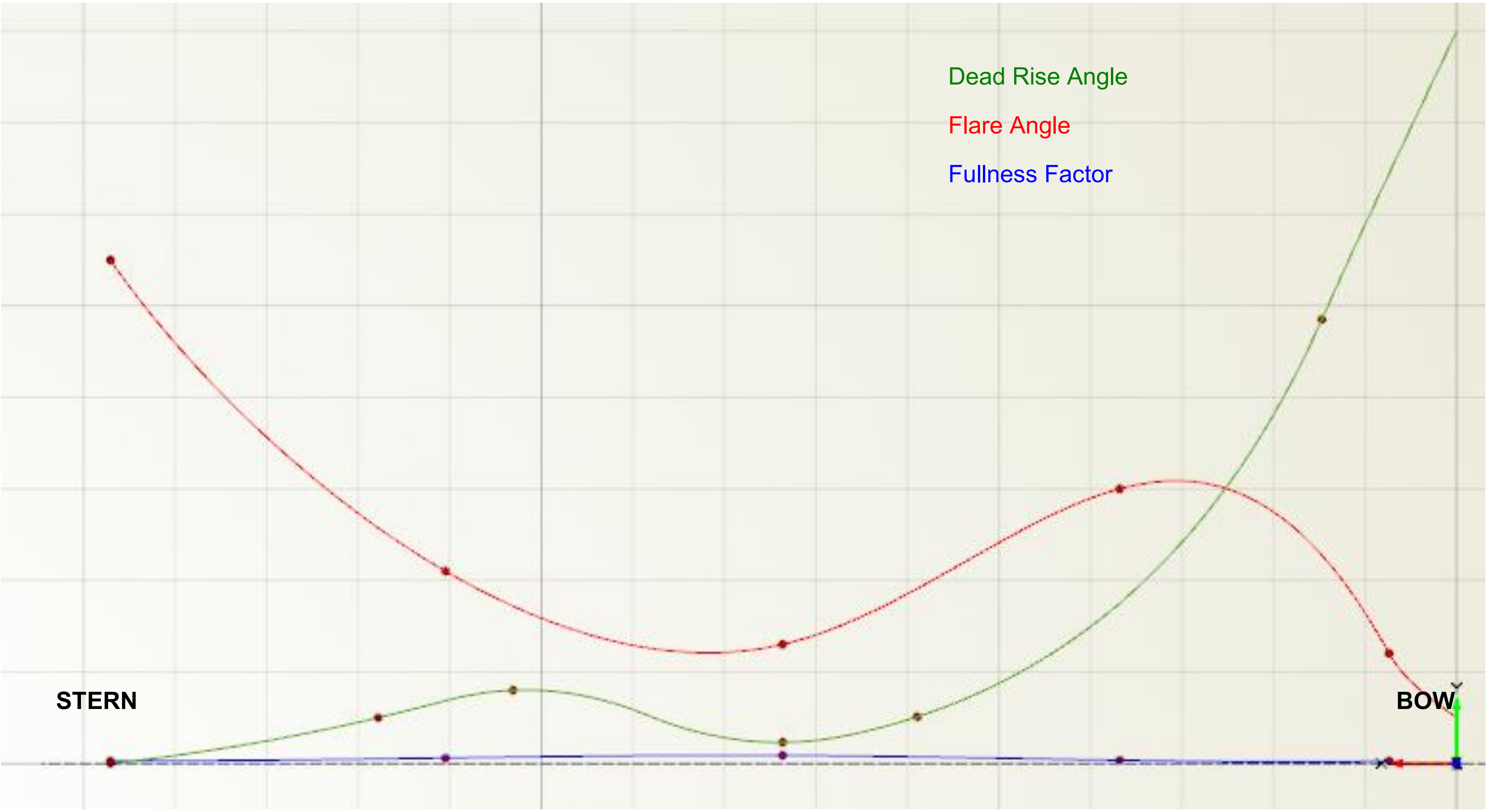
Basic Curves: Station Flare, Deadrise and Fullness

- Longitudinal Distribution of Parameters:
  - Flare Angle
  - Deadrise Angle
  - Fullness Factor
- *Purpose:*
  - *Feed information needed to the cross section at every longitudinal location*



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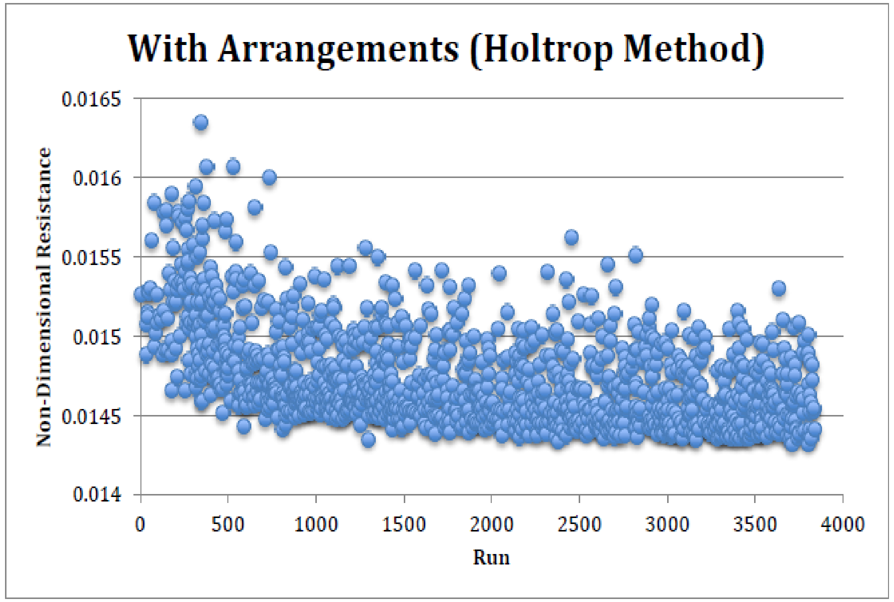
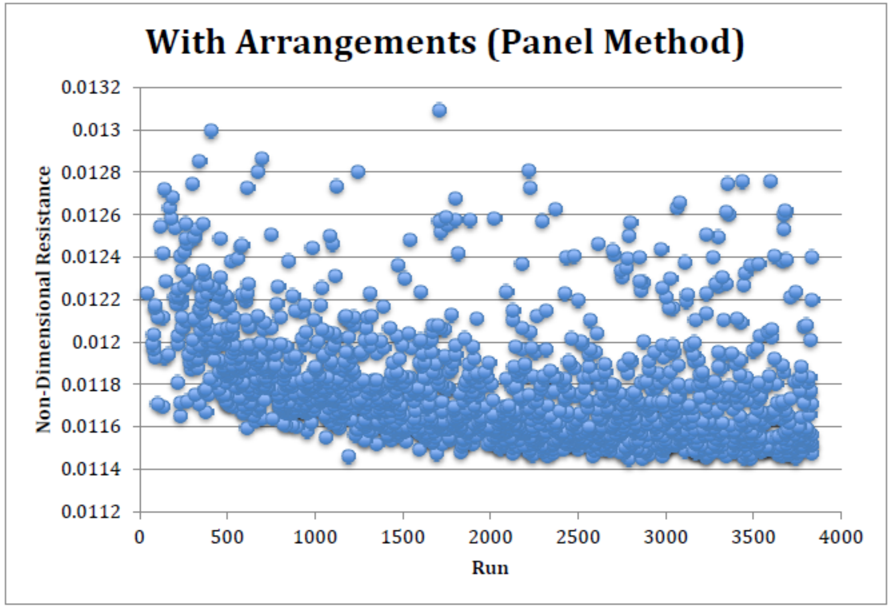
Convergence





Algorithm Settings	
Generations	60
Population per Generation	64
Total number of individuals	3,840
Crossover Probability	0.75
Mutation Probability	0.10

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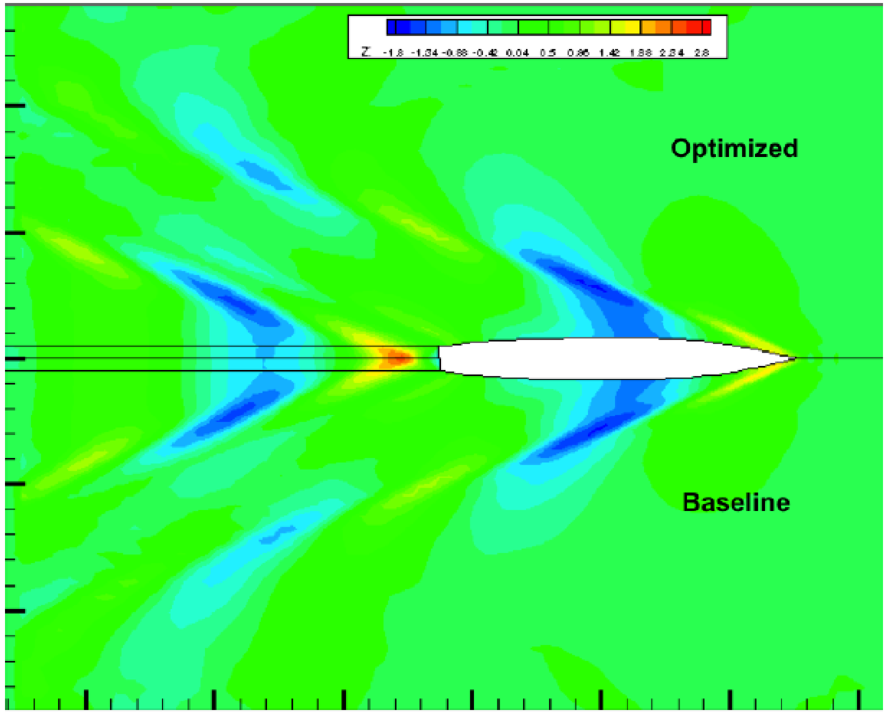
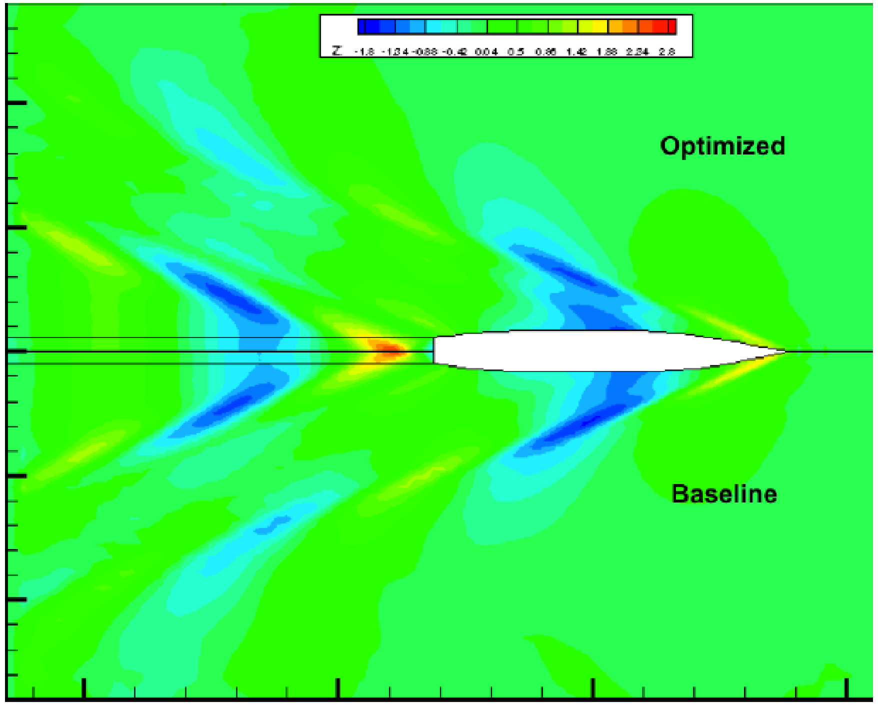
Free Wave Patterns

- Holtrop



$\delta(R_T/\Delta)$ = +1.16%

- Panel Method



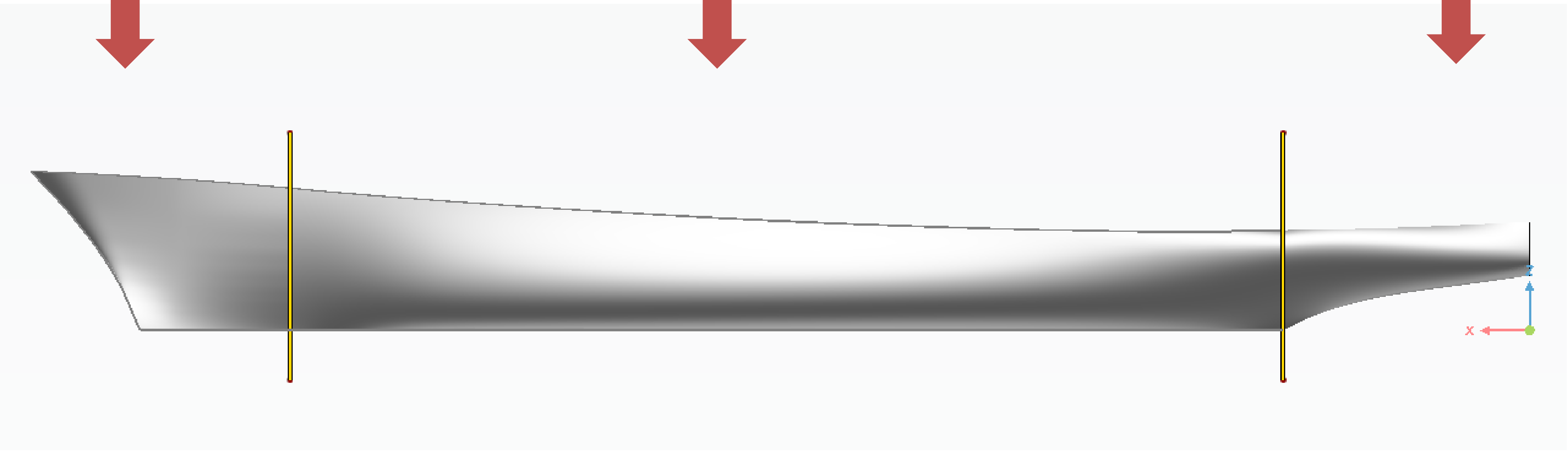
$\delta(R_T/\Delta)$ = - 5.98%

5415 Hull – Meta Surface Subdivision

FWD Section

MID Section

AFT Section



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5415 – Curve Selection

Keel

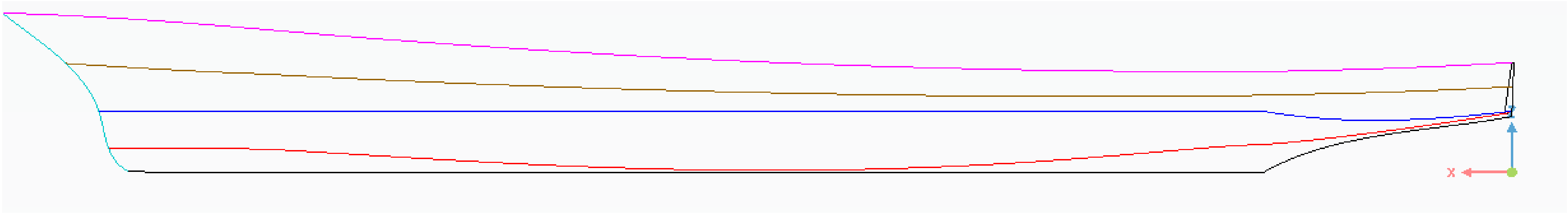
Waterline

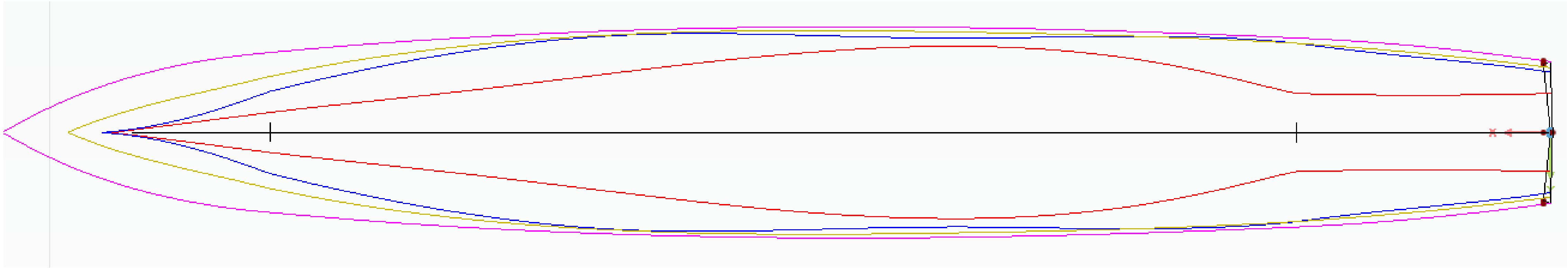
Stem

Bilge

Lower Deck

Deck





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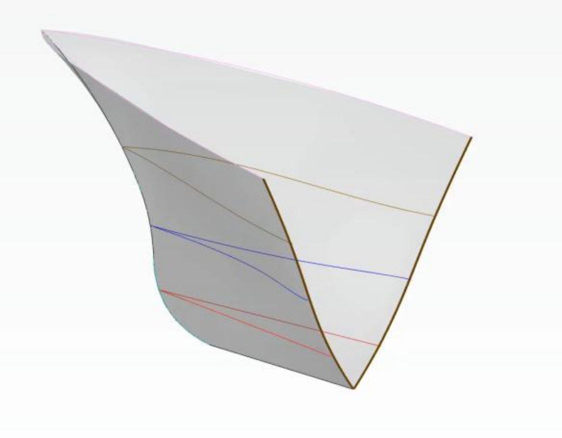
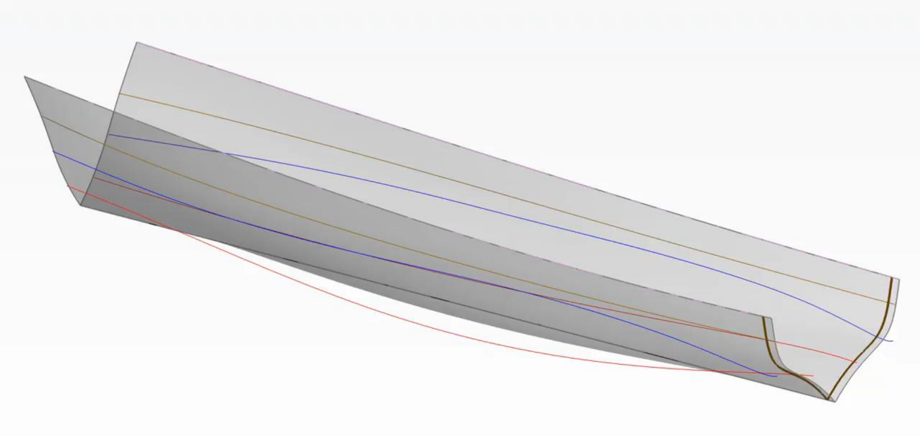
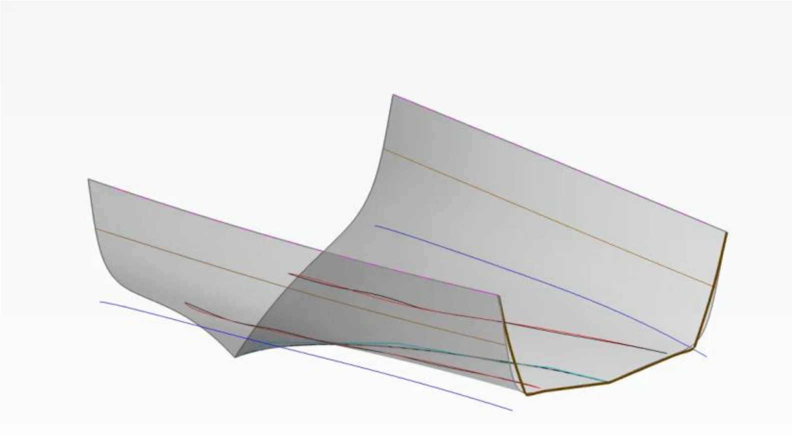
5415 – Profile parametrization







- The Profile, or transverse section, is defined as a B-spline, where the fullness is controlled by the 3 middle control curves: Bilge, Waterline and Lower Deck
- By moving the control polygon of each curve we can vary the shape of the hull
- The Keel and the Deck curves serve as rails

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Issues with current parametrization

- Discontinuity in between each section of control curves
  - Expecially in the transition from Aft to Mid sections
- Previous documentations show poor results [1]
  - Sampling led to unrealistic shapes or deformations shaped 'bubbles' or bulges
- Articles with identical approach have already been published [2]
  - Main difference being in the optimization startegy

[1] S. Brizzolara, G. Vernengo, C.A. Pasquinucci, and S. Harries, "Significance of parametric hull form definition on hydrodynamic performance optimization," in *Proc. VI International Conference on Computational Methods in Marine Engineering (MARINE 2015)*, Rome, Italy, 15–17 Jun. 2015, pp. 254–265
[2] E. F. Campana, D. Peri, Y. Tahara, and F. Stern, "Shape optimization in ship hydrodynamics using computational fluid dynamics," *Computer Methods in Applied Mechanics and Engineering*, vol. 196, no. 1–3, pp. 634–651, 2006, doi:10.1016/j.cma.2006.06.003

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New Hullform Parametrization

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5415 – Curve Selection

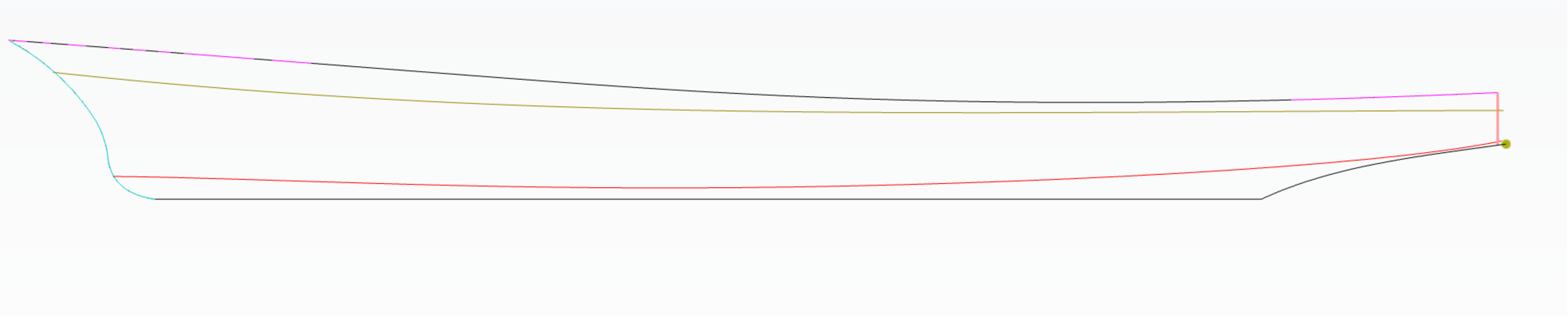
Keel

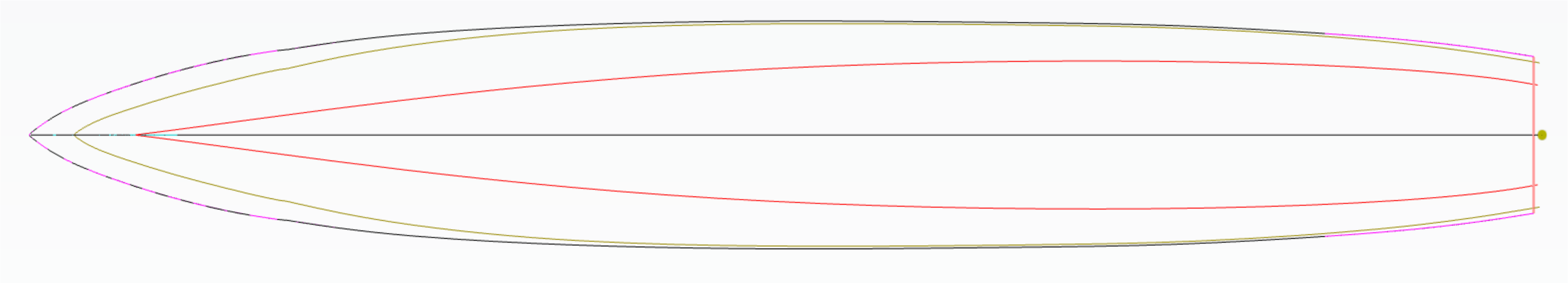
Stem

Deck

Bilge

Lower Deck





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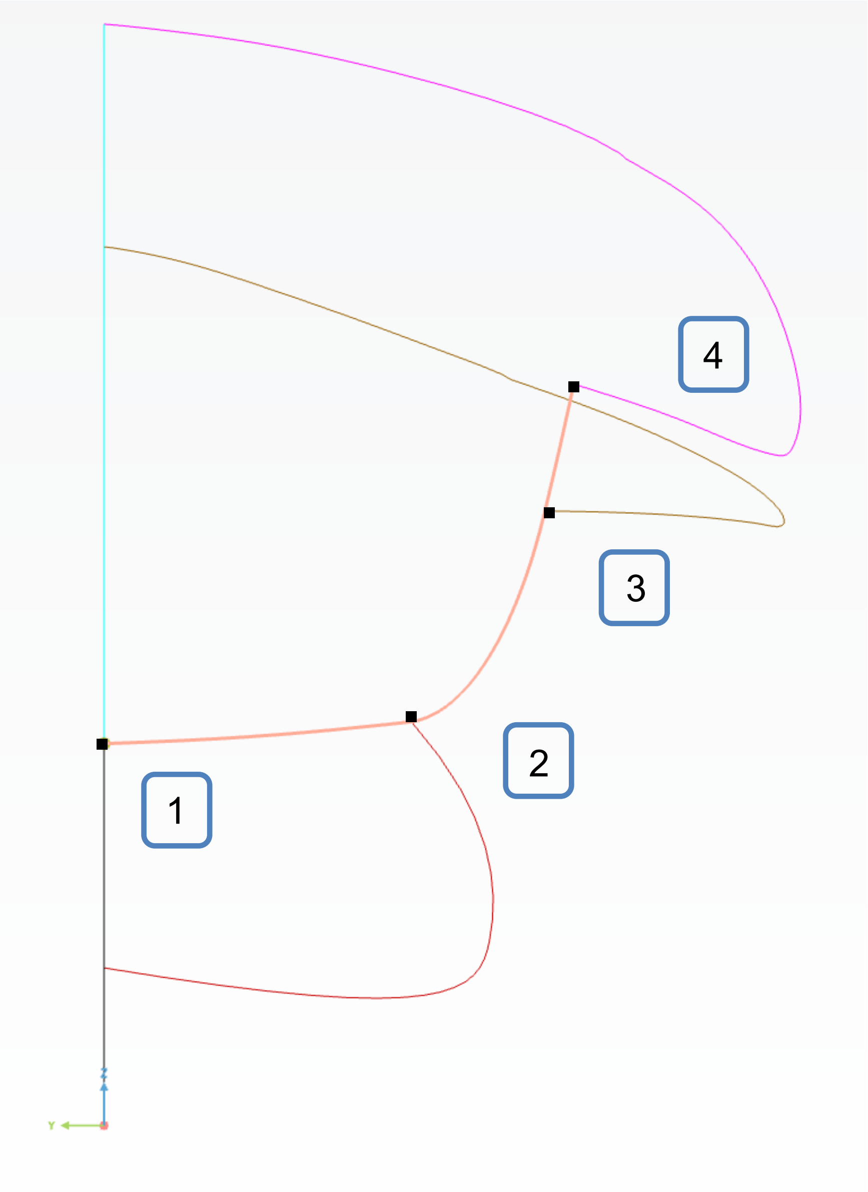
5415 – Profile Overview



- The profile has been swapped with a Multi-segmented F-spline, where each connection between the control curves is treated as an F-spline
- The Profile can now vary by changing the fullness between 3 sections: K-to-B, B-to-LD and LD-to-D
- The fullness is derived by taking the area of the curve projected on the x-y plane

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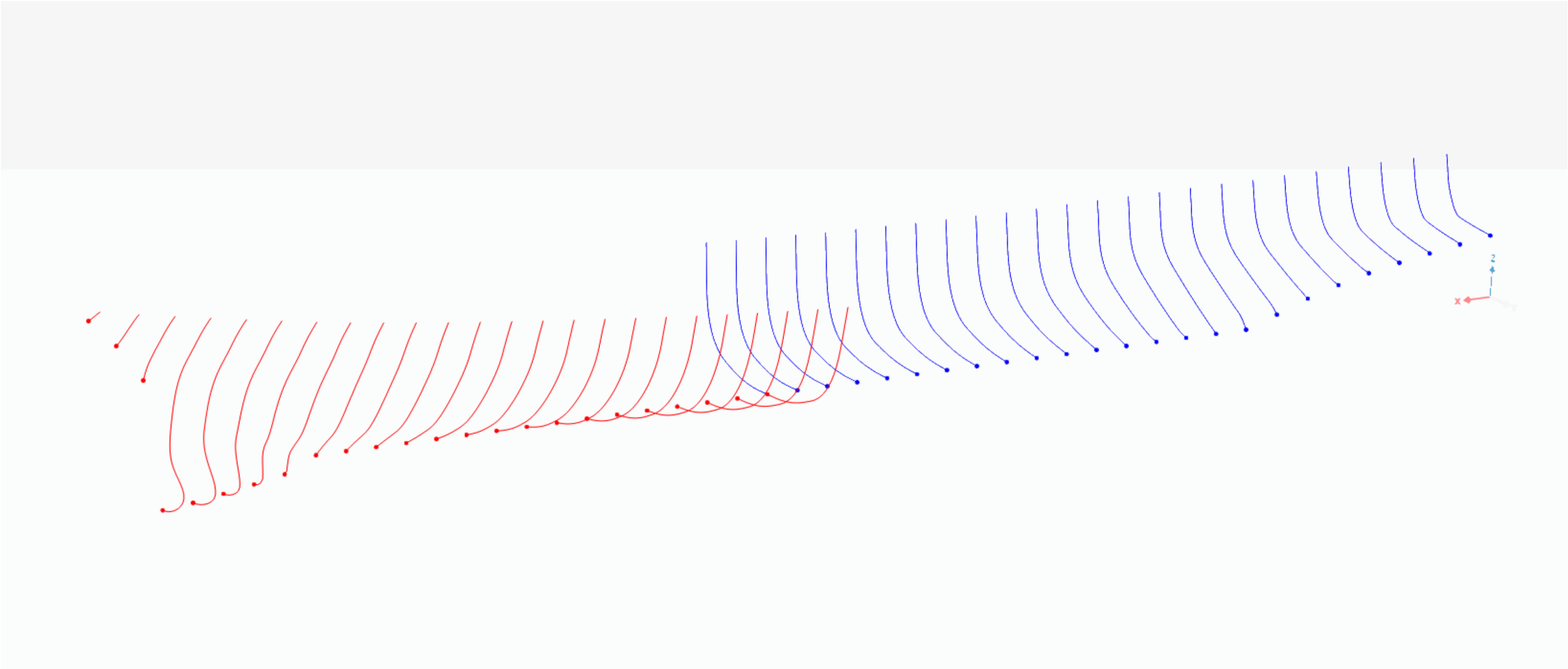
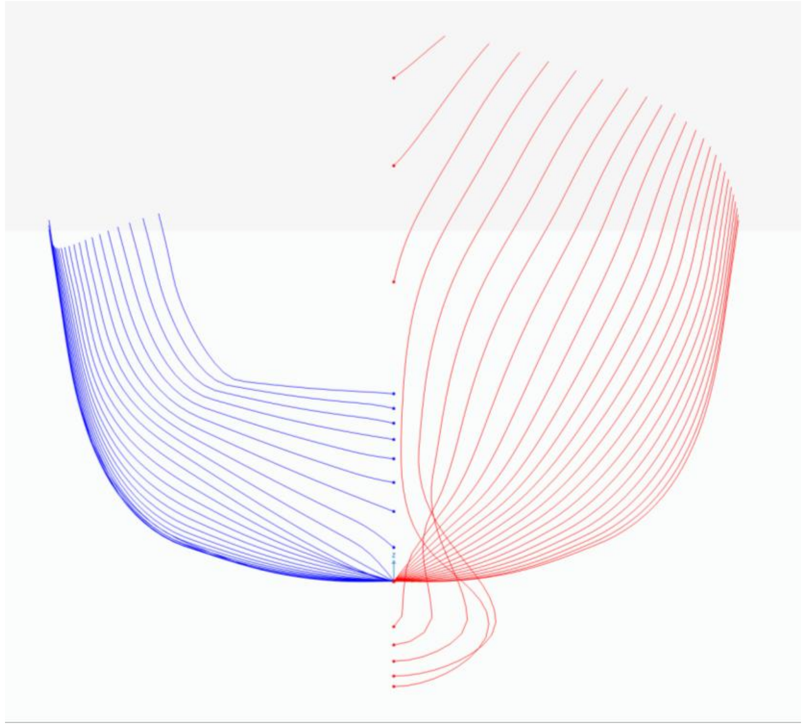
Example Hullforms





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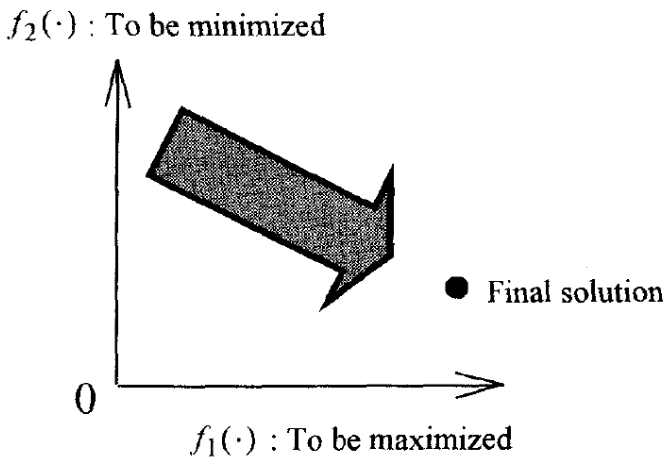
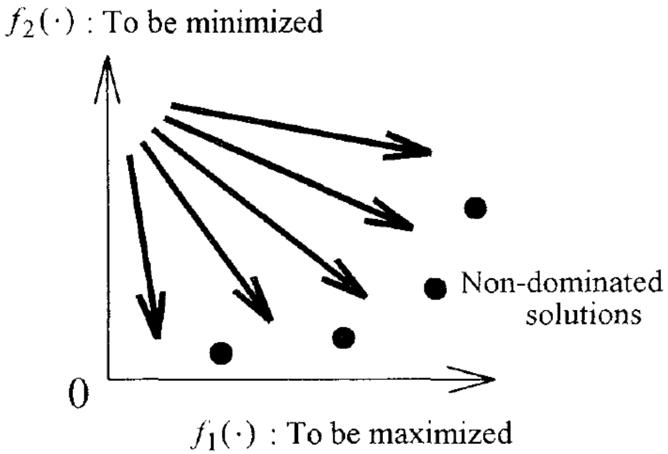
Optimization Algorithm: MFBO

- CAESES provides frequently used optimization strategies, mainly Evolutionary Algorithms (EA), such as MOGA or NSGA II
  - Require precise data to be reliable
  - High-order randomness during search process
- Multi-Fidelity Bayesian Optimization: intersection of a Multi-Fidelity surrogate and a Bayesian Optimization





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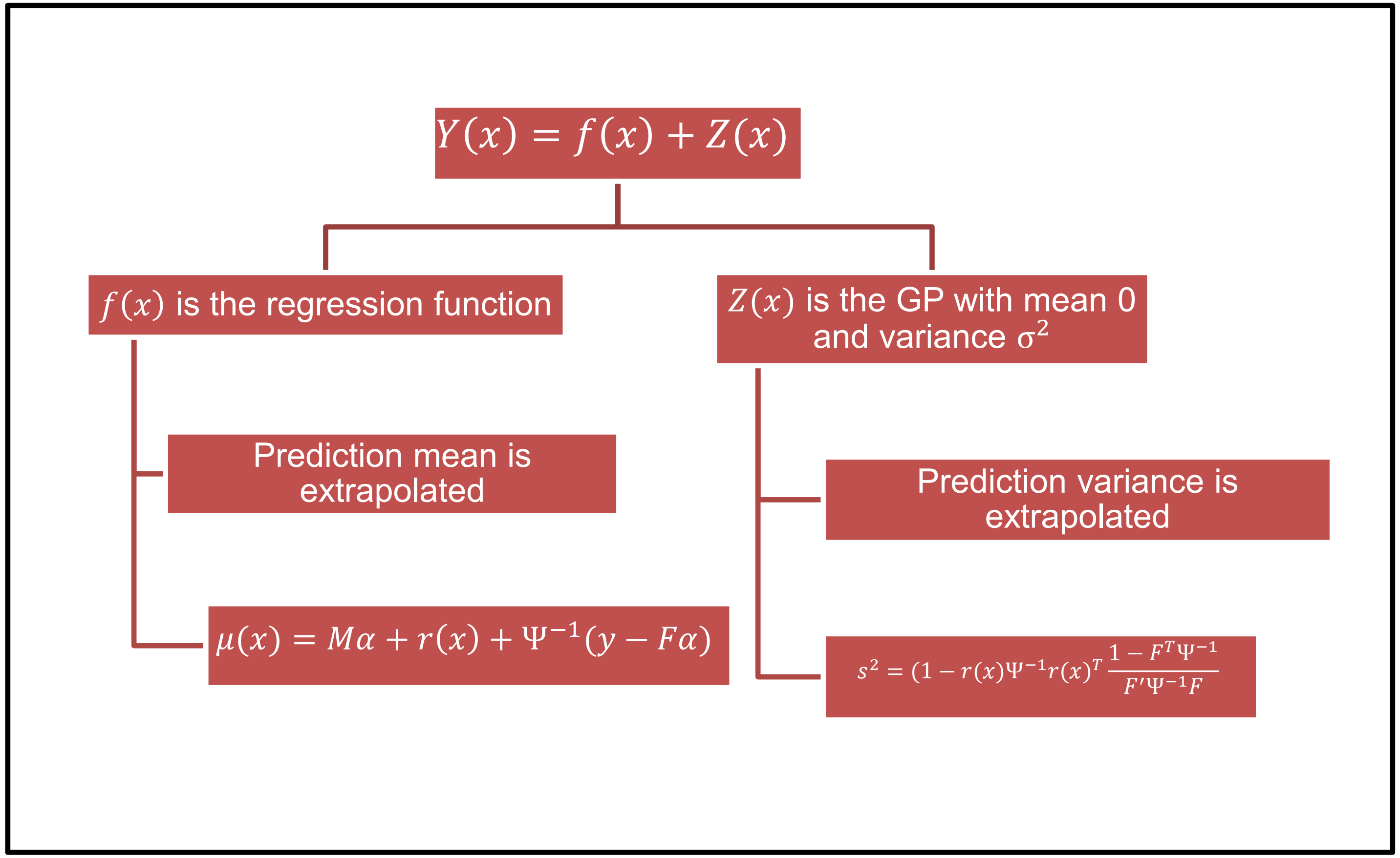
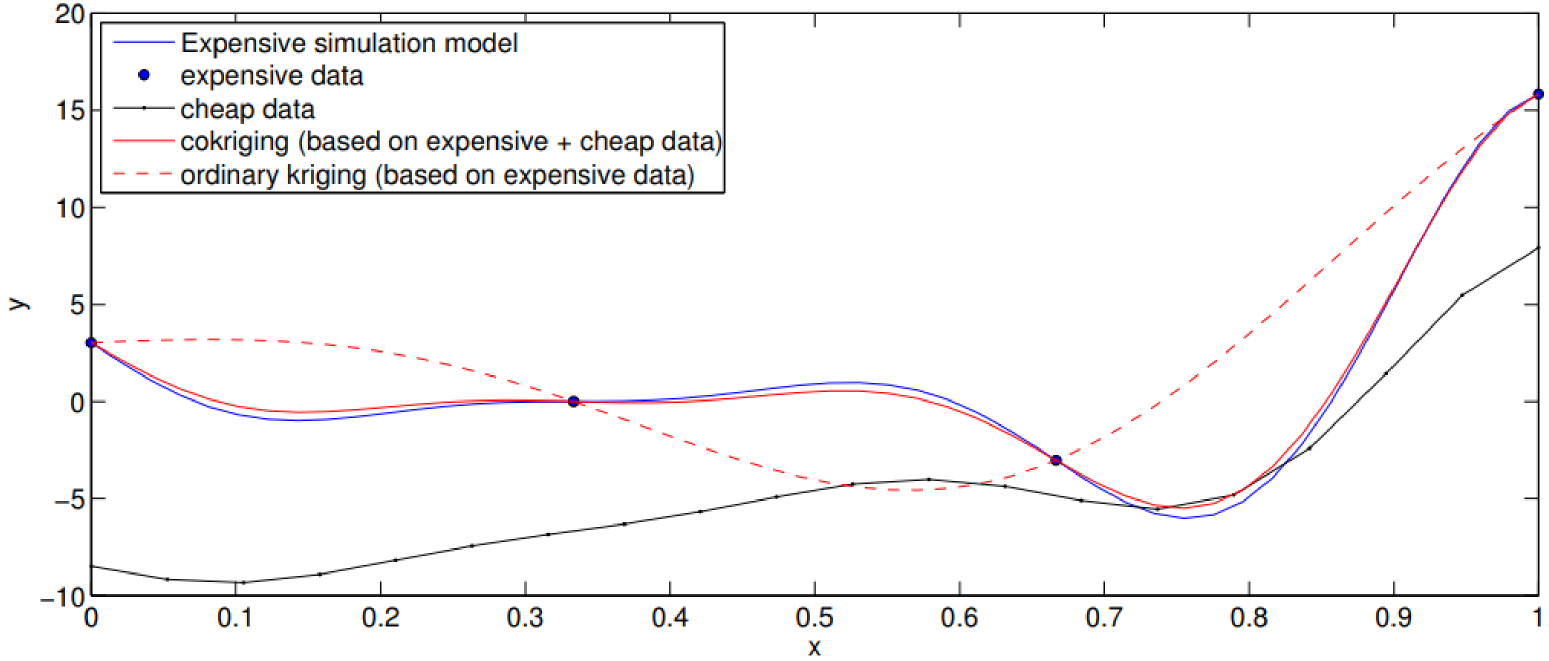
Optimization Algorithm: MFBO

- Multi Fidelity surrogate constructed using a modified Kriging approach
- Idea behind kriging is to build a regression model and the GP interpolates the residuals
  - Correlation function Ψ determines the hyperparameters necessary to build the objective function



Optimization Algorithm: MFBO

- Co-Kriging considers a two-level fidelity approach
  - Incorporates Low-Fidelity (LF) and High Fidelity (HF) data to reduce noise.
  - Decreases convergence time by a fraction
  - Proven to have same or better results than EA



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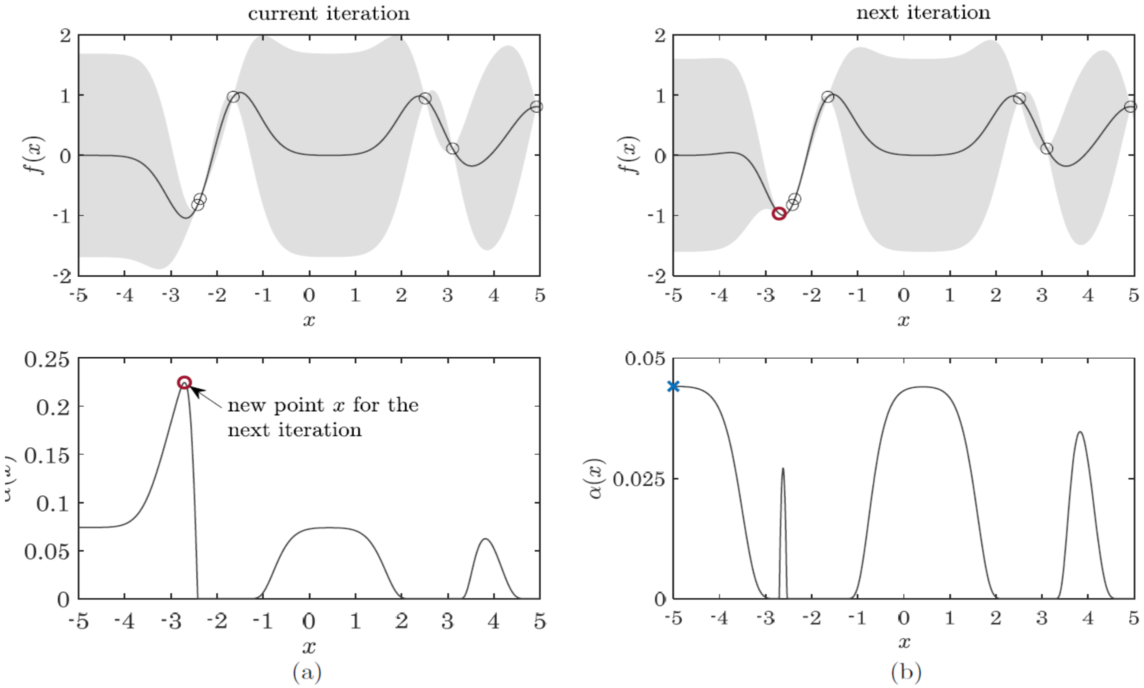
Optimization Algorithm: MFBO

- BO uses the cokriging to approximate the expensive objective function
  - Traditionally you minimize the MSE to find the ideal value
- Main Component of BO is the augmentation function
  - Determines where additional points need to be calculated to decrease error
  - Dictates weather you prioritize searching or a direct minimization



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Optimization Algorithm: MFBO

- Improvement-based
  - PI : equivalent to the chance of having a solution improvement.
  - EI: provides a balance between exploitation and exploration in optimization in the face of uncertainty
- Optimistic Acquisition
  - GP-LCB: chooses the arm that currently seems to offer the highest reward, while exploration focuses on selecting different arms to gather information about the reward distribution.

Augmentation Functions

$$\alpha(x) = \Phi(\frac{f_{min} - \mu_f^k(x) - \tau}{\sigma_f^k(x)})$$

$$\alpha(x) = w\left(f_{min} - \mu_f^k(x)\right) * \Phi\left(\frac{f_{min} - \mu_f^k(x)}{\sigma_f^k(x)}\right) + (1-w)\sigma_f^k(x)\Phi(\frac{f_{min} - \mu_f^k(x)}{\sigma_f^k(x)})$$

$$\alpha(x) = -[\mu_f^k(x) - \sqrt{\beta^k}\,\sigma_f^k(x)]$$

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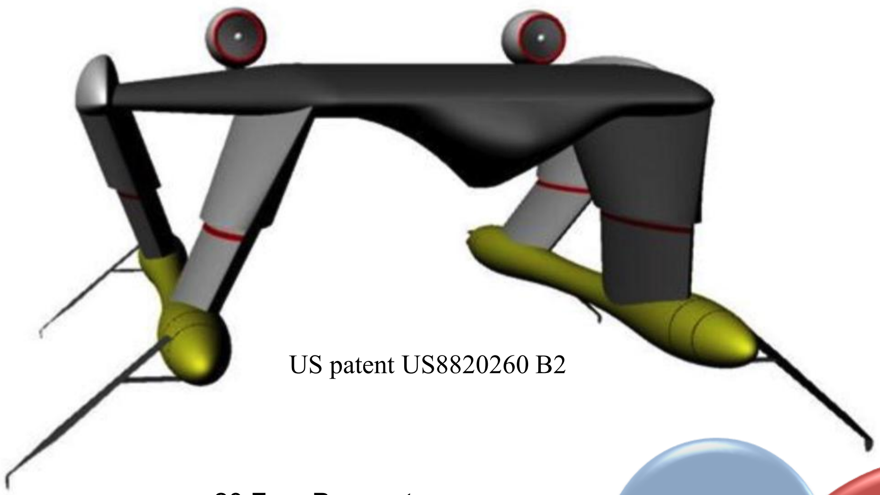
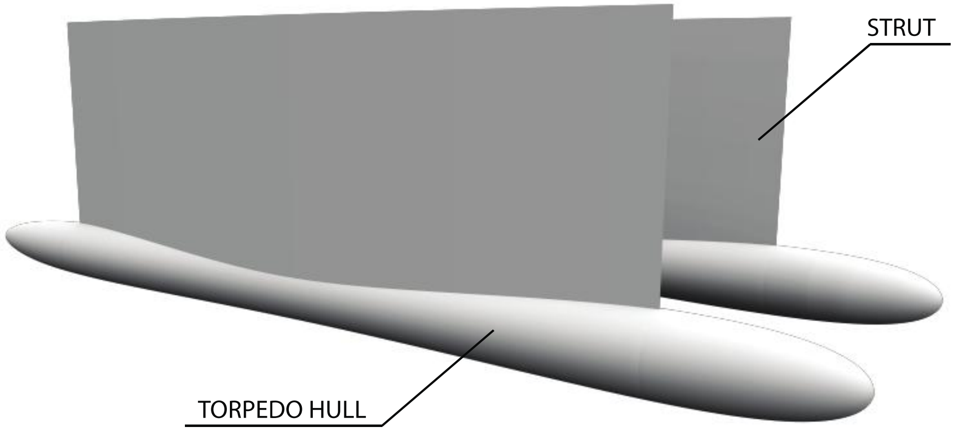
MF Bayesian Optimization of SWATH vessels

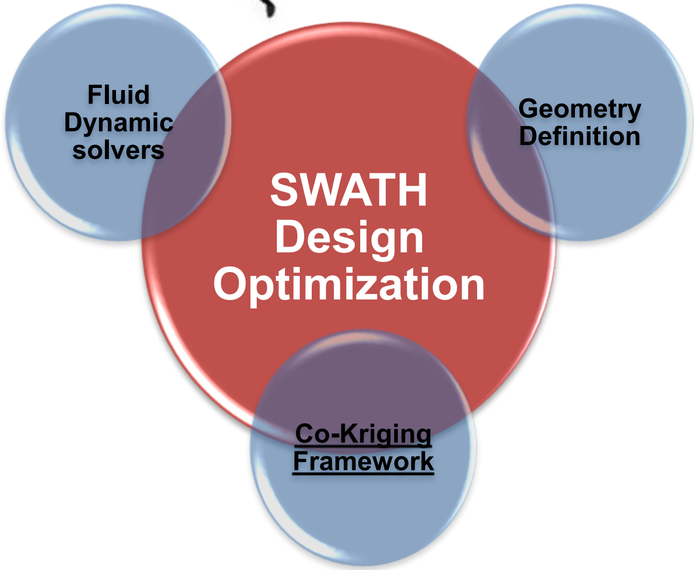
Bonfiglio L., Perdikaris P., Brizzolara S. (2019) Multi-Fidelity Bayesian Optimization of SWATH Hull Forms. *Journal of Ship Research*, 63(3):1-17. https://doi.org/10.5957/JOSR.11180102



20 Free Parameters



8 Free Parameters



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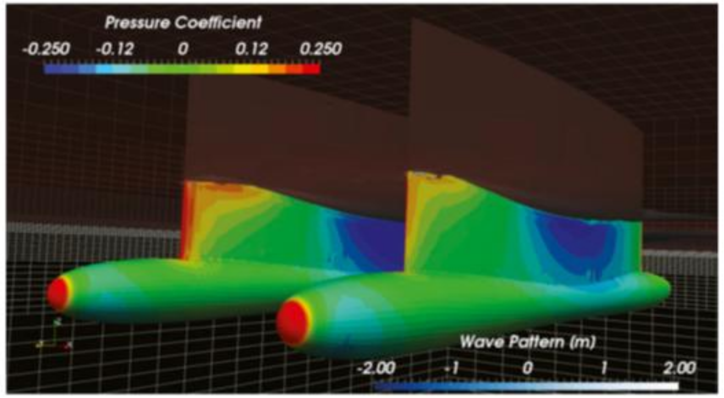
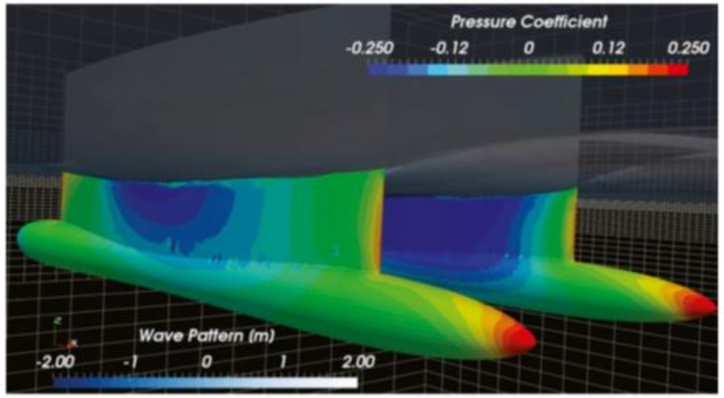
Comparison Optimized BMF Design vs. GA-LF Design

GA-LF Opt. Design

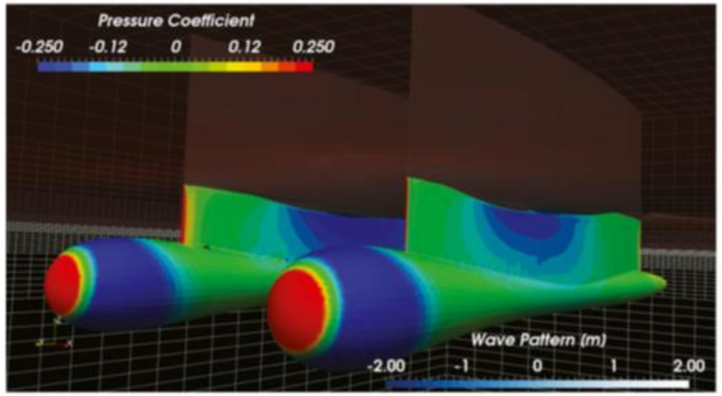


(A) Bow view

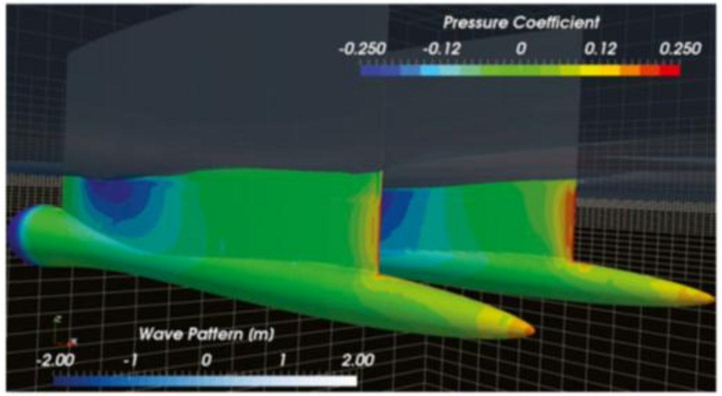


(B) Stern view

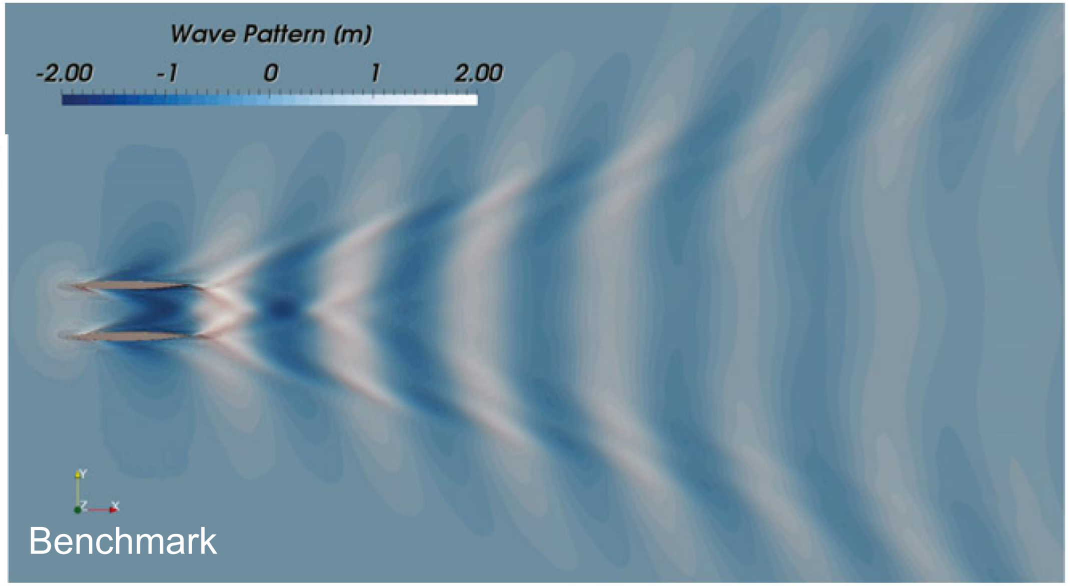
B-MF Opt. Design

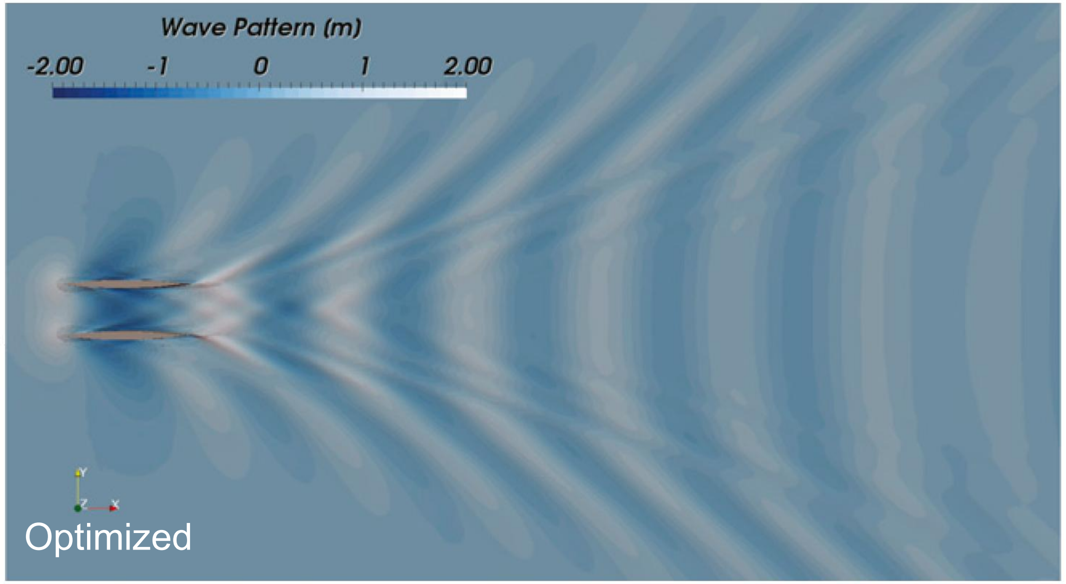


(A) Bow view



(B) Stern view





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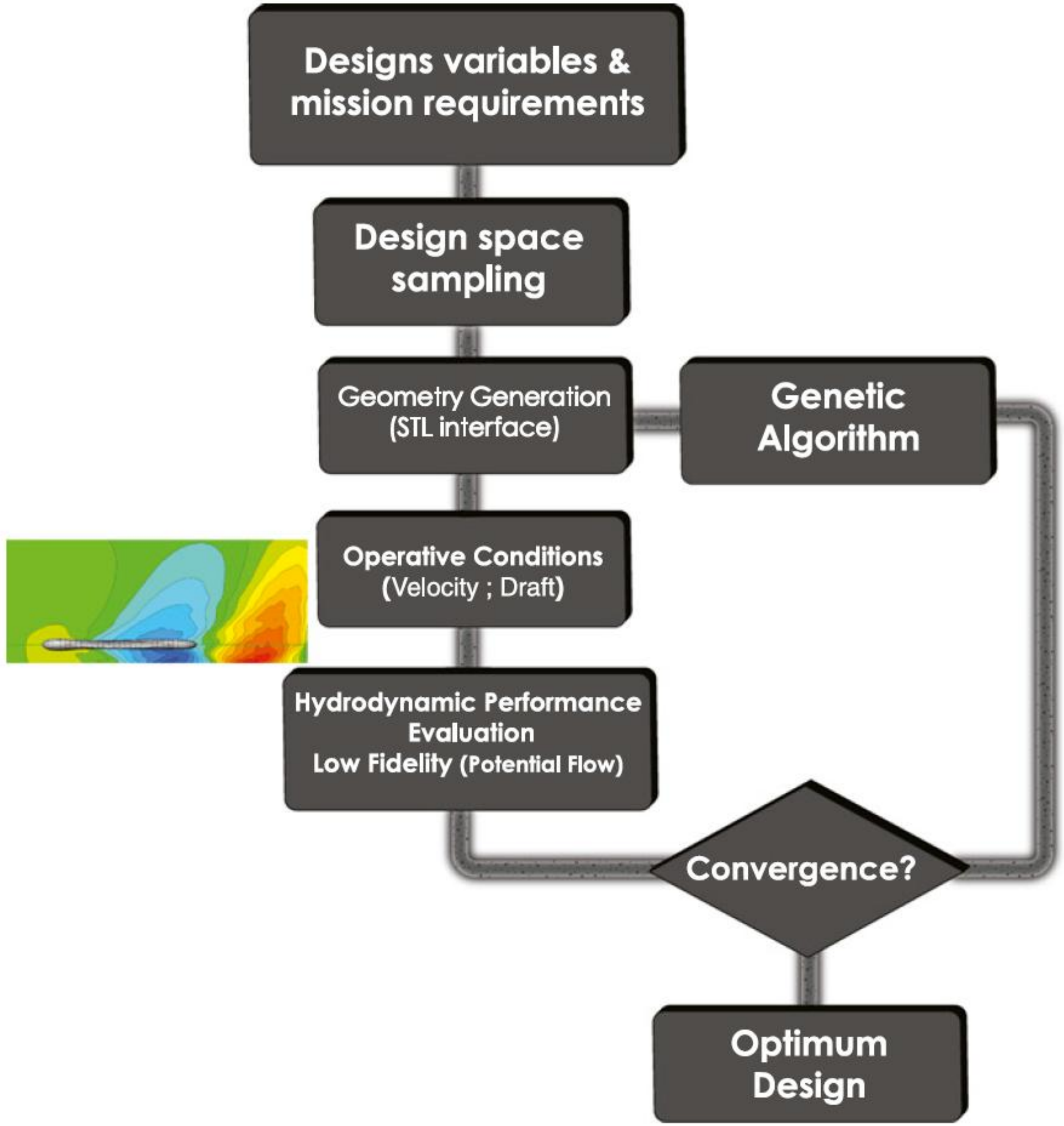
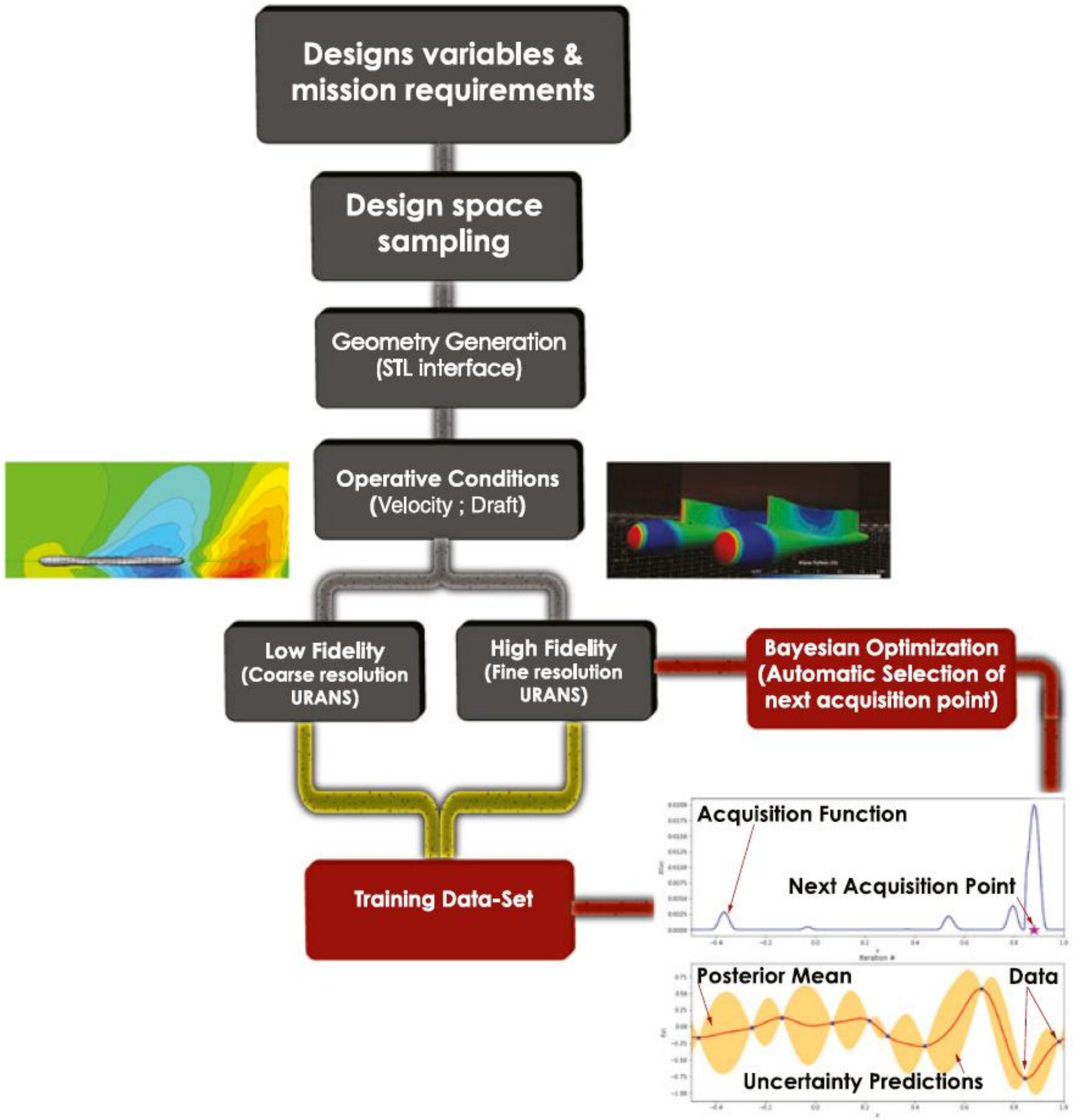
Multi-Fidelity GP Bayesian Optimization



(A) Conventional Genetic Algorithm



(B) Bayesian Multi-fidelity Optimization

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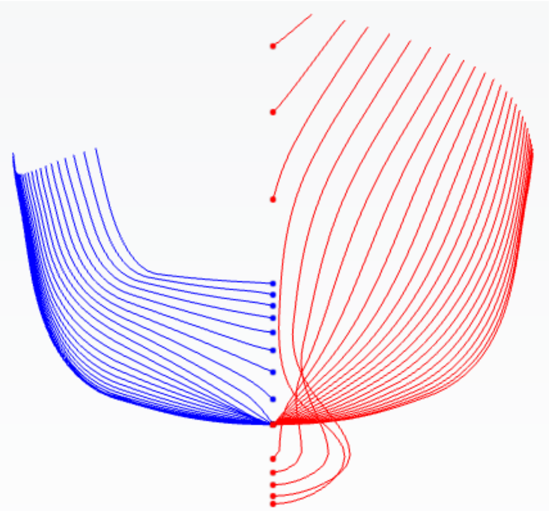
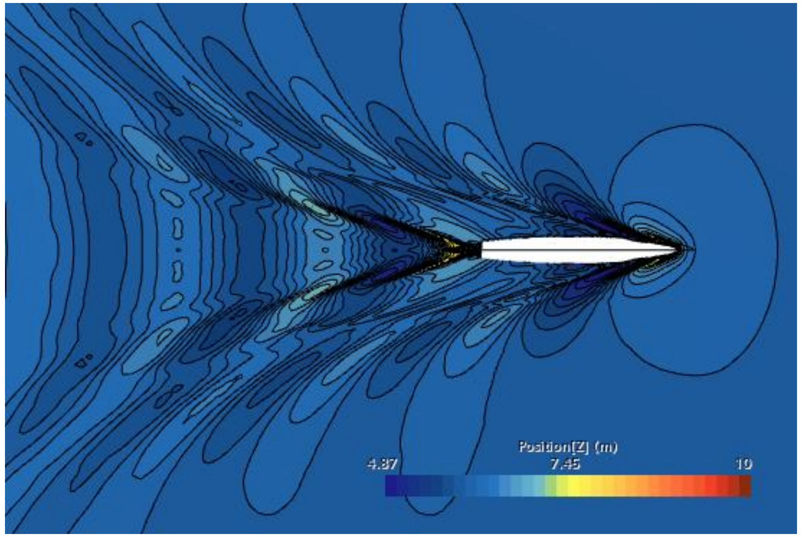
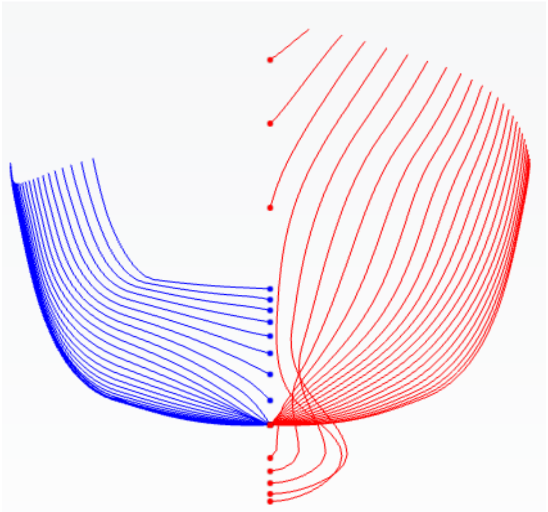
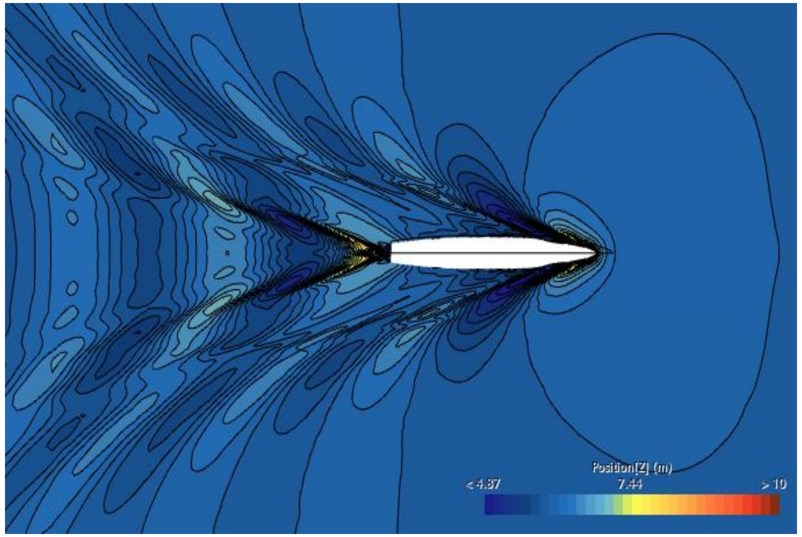
Present results – High-Fidelity





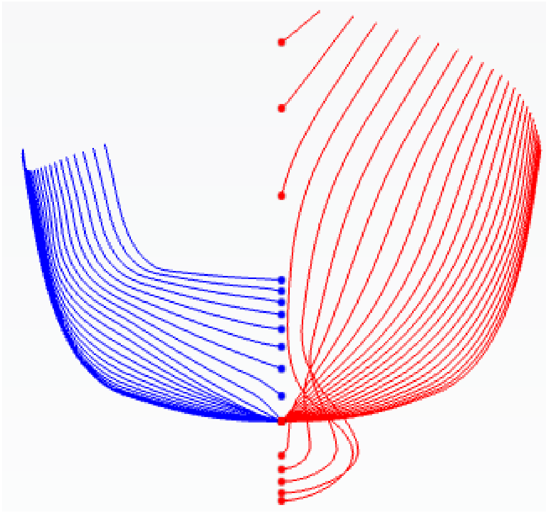
Dimension	Values	Order of Magnitude
Volume (m3)	8426.5	1
Surf. Area (m2)	2981.6	1
Press. Drag (N)	1.763	10^5
Shear Drag (N)	1.873	10^5

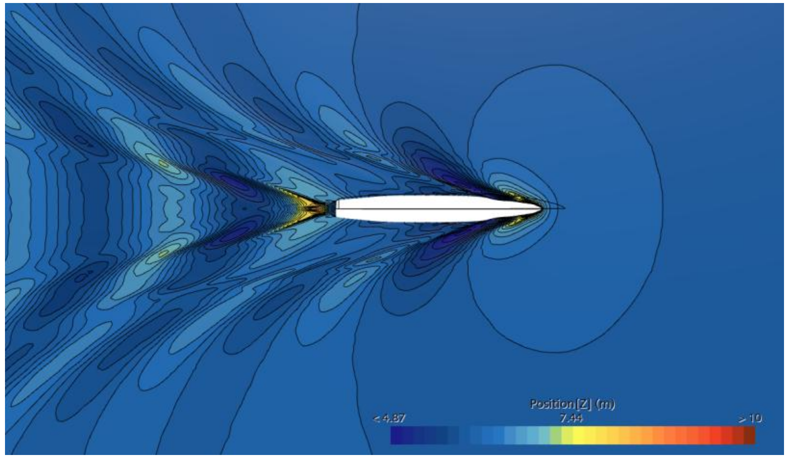




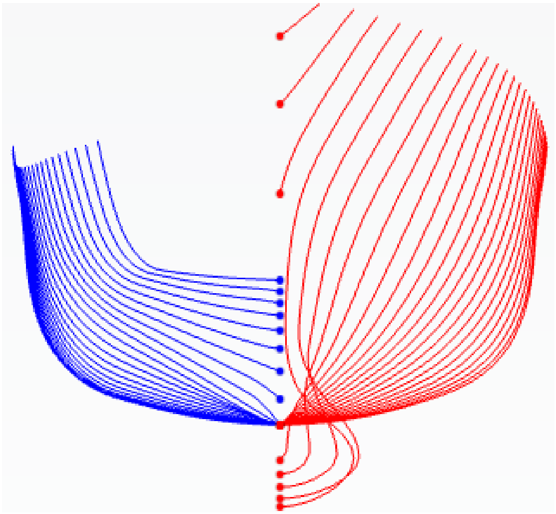
Dimension	Values	Order of Magnitude
Volume (m3)	8408.5	1
Surf. Area (m2)	2976.8	1
Press. Drag (N)	1.938	10^5
Shear Drag (N)	1.868	10^5

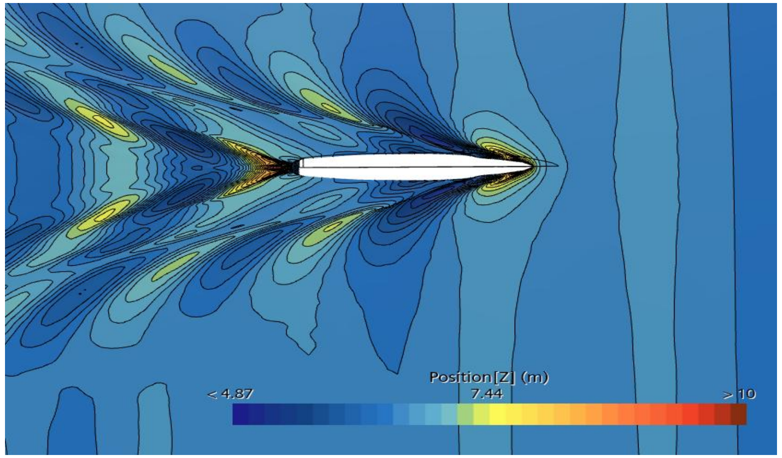
Present results – High-Fidelity





Dimension	Values	Order of Magnitude
Volume (m3)	8507.6	1
Surf. Area (m2)	2989.7	1
Press. Drag (N)	1.932	10^5
Shear Drag (N)	1.881	10^5





Dimension	Values	Order of Magnitude
Volume (m3)	8522.1	1
Surf. Area (m2)	2989.6	1
Press. Drag (N)	2.008	10^5
Shear Drag (N)	1.893	10^5

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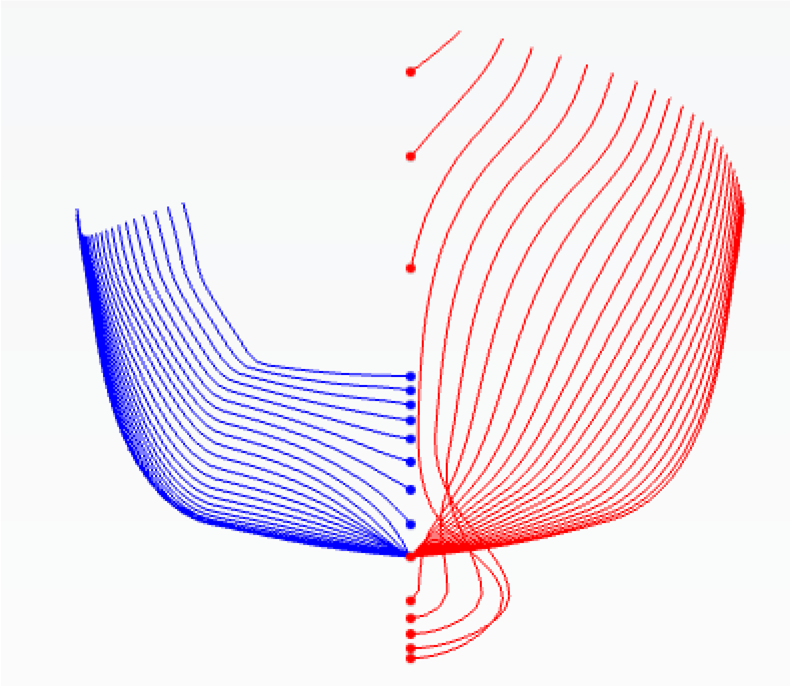
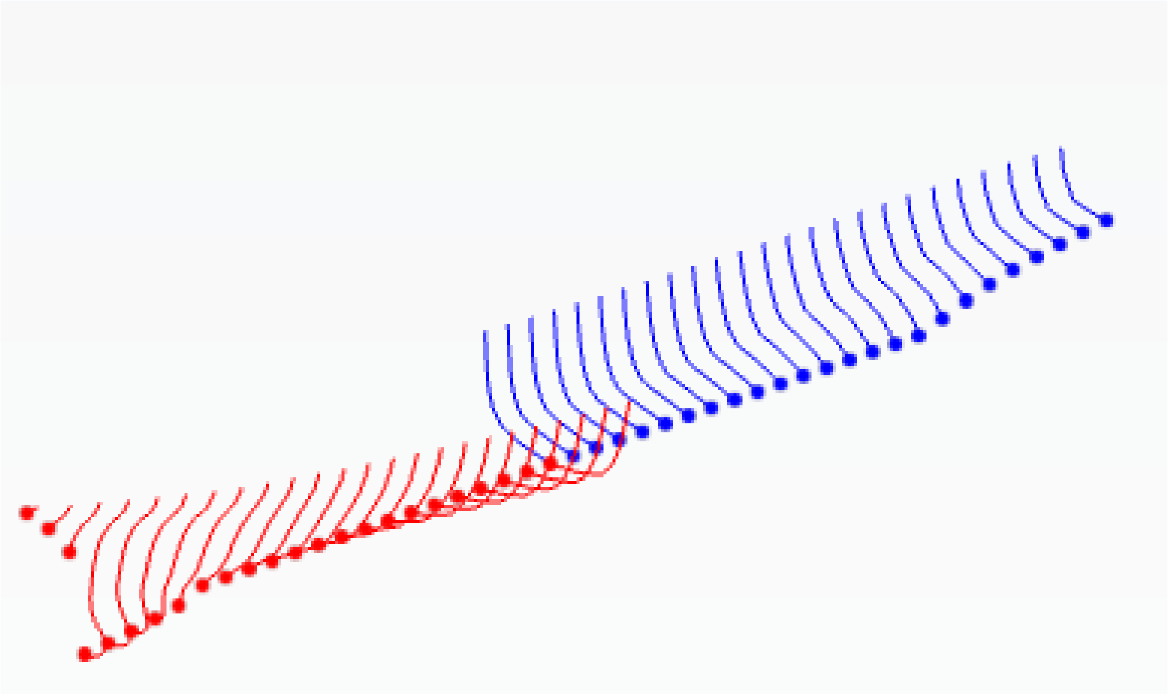
Present Results – 1st Optimization Iteration





Dimension	Values	Order of Magnitude
Volume (m3)	8152.6	1
Surf. Area (m2)	2930.7	1

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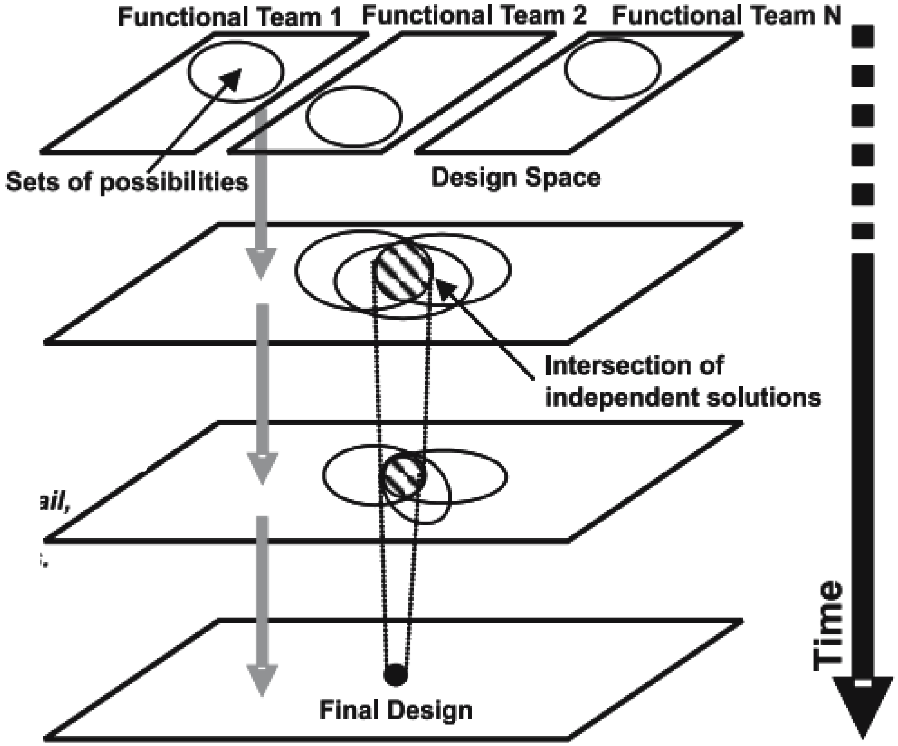
Next Steps and Conclusion

- Continue Optimization iteration until convergence is reached
  - Depends on value of prediction variance and MLE
- Add procedure into Set Based Design approach to have improved design process
  - Current methods use a linear multi-objective approach which hoes not fully incorporate user preference and



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