Hull Design Method Combining an Innovative Flow Solver Coupled with Efficient Multivariate Analysis and Optimization Strategies

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Abstract

An important application of optimization of a ship is the minimization of calm-water resistance for a given displacement. In this work, an innovative flow solver that combines free-surface effects with a viscous solution allows for an accurate drag prediction with fast turnaround times ideally suited for an optimization study. A large number of geometrical-design variables are considered in early-stage design; thus in this paper different techniques are examined to reduce the curse of dimensionality. Different methods such as multivariate analysis are used to optimize the hull with respect to resistance over a range of different speeds for a given displacement.

1. Introduction

Optimization methods applied to ship hydrodynamics usually involve large scale Computational Fluid Dynamics (CFD) models coupled with state-of-the art optimization algorithms for minimization of calm-water resistance of the hull for a given displacement assigned by the designer. Optimization methods are typically employed in the early-stage design process when different hull geometrical shapes are analyzed to assess related performance in order to meet the desired requirements. In this scenario, the tendency to reduce the time required for the pre-design optimization process while evaluating as many configuration alternatives as possible makes efficiency of optimization methods more and more challenging.

Traditional optimization methods applied to early-stage design process usually deal with a parametric geometrical model linked to an inviscid flow solver to predict flow resistance, as computational expenses required by more accurate RANSE solvers are prohibitive for a full optimization study. The drawback of using a low-fidelity model to predict merit is that a lack of accuracy may lead to the selection of an un-optimal design. In addition, the large number of design variables required to define the geometrical variation of the shape of the hull is taken into account in ship early stage design process which make the optimization problem very complex for the designer and not always feasible. The addition of design constraints imposed to characterize the design exploration phase as well as multiple objectives makes the optimization process even more challenging. Consequently, in such a scenario it may occur that the optimization process does not find the optimal solution.

In this work, an innovative flow solver that combines free-surface effects with a viscous solution is employed for accurate drag prediction with fast turnaround times ideally suited for an optimization study. The innovative CFD solver is coupled to an efficient optimization method based on an efficient Multi-Variate Analysis (MVA) approach which allows the designer to perform a fast and broad search on the global design space by identifying the set of the optimal designs using a clustering method in order to find out the optimal layout of the design solution for the given operating conditions applied.

2. Background

The need for a highly performing design solution makes the optimization process a challenging task in the context of ship hull hydrodynamics. For this purpose, there are two main critical factors for success, namely accuracy of the solution and time required for the total run. Nevertheless, the choice

of a robust and flexible parameterization method of the hull geometry is key, when the designer needs to evaluate as many design alternatives as possible while reducing the redundancy of the design parameters required defining the optimization problem properly. A detailed description of the methods applied for the ship hull optimization is provided in the following sections.

2.1. Innovative flow solver

The accuracy and the speed of CFD methods play an important role in ship hull hydrodynamic assessment. Traditional RANSE methods most accurately model the physics and can provide precise resistance prediction by including non-linear wave-breaking effects. The drawback is high computational cost in terms of grid requirements and most importantly simulation time which becomes prohibitive when it comes to optimize the hull geometrical shape. Also, it is still difficult to control and quantify numerical error.

In the approach used here, an innovative flow solver that combines RANSE methods with free-surface effects is employed for accurate drag prediction with fast turnaround times ideally suited for an optimization study. The key elements of the solver include a polyhedral finite-volume discretization of the water domain. The steady formulation of the governing equations and boundary conditions are used to pose a problem that is efficiently solved with conventional CFD techniques. A consistent linearized free-surface boundary condition for a viscous flow is applied to the approximate free surface. This novel approach is shown to retain accuracy while reducing the computational expense that is introduced when solving for arguably-negligible nonlinear features of the flow.

An example of the capability of the new method is shown in the following figures where the performance of the solver is compared to a standard interface-capturing method based on the Volume-of-Fluid technique (VOF). The geometry is a cruise ship, and the simulation is conducted at a speed near the cruise speed of a Froude number of 0.22. The fluid discretization is done with an automatic mesh generation tool that is described in more detail in Section 3.2. For the new method, the flow domain is discretized with about 415,800 cells. The VOF simulations are done on two discretizations; a coarse grid with 171,187 cells, and a close-to-systematically-refined grid with 1,185,150 cells.

Fig.1 shows the pressure and viscous forces on the hull as a function of time (for the VOF simulations) or iteration (for the steady solver used in the new method). It is seen that the pressure force shows a distinct oscillation in the time series from the VOF simulations. This is due to a long-wavelength-sloshing mode in the numerical domain that is resolved with the time-domain simulation. Also, the difference between the coarse and fine simulations renders a sense of the numerical error when solving for the fully nonlinear free surface with this type of method. The new method, which is more approximate in formulation, shows a pressure force prediction that is within the error bound of the VOF method. Also, the viscous force is shown to be predicted with very high accuracy with the new method when compared to the fine-grid VOF results (and more accurate than the coarse VOF).

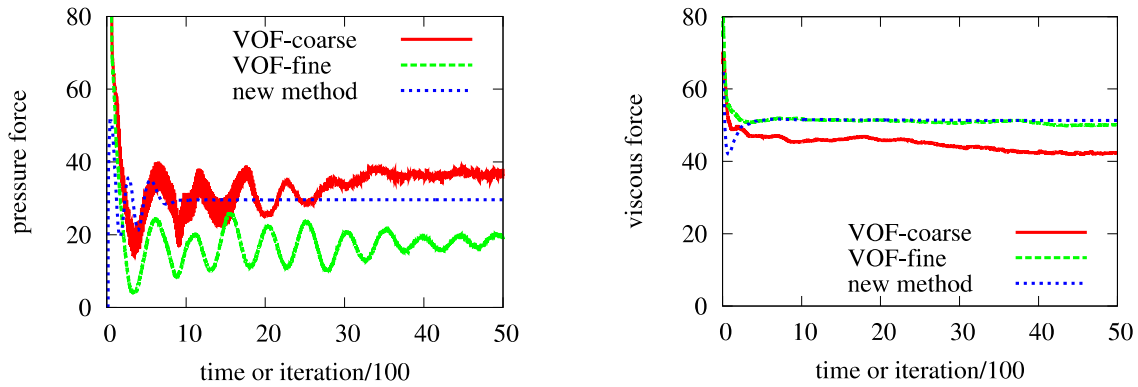

Fig. 1: Force prediction comparison for hydrodynamic solver

Next, the time required to compute the solution is assessed, because this is a paramount quantity with considering optimization. We remark that these results are done on a workstation while other work tasks are being conducted (a quite realistic scenario if the tool is to be used by designers). In Fig.2, a bar chart with the time to compute the converged solution is shown. The VOF solver on a fine grid requires about 400 cpu hours, whereas the new method converged to a solution in about 3 cpu hours.

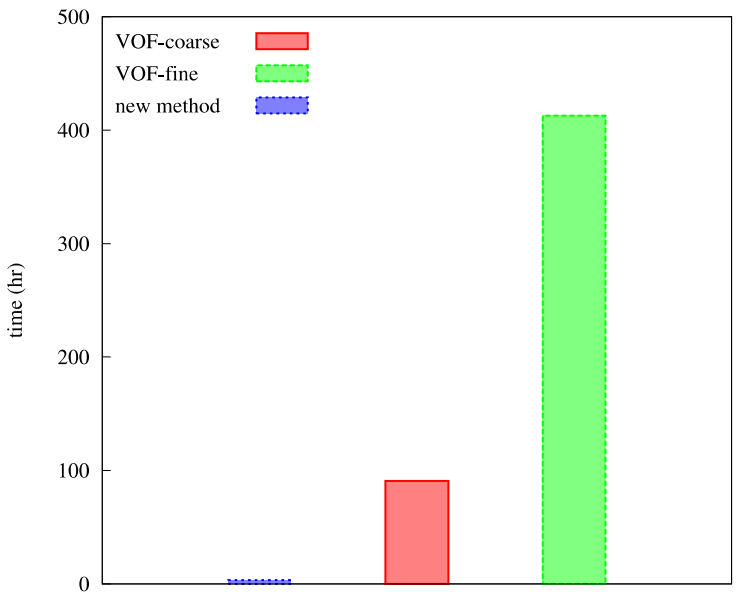

Fig. 2: Timing comparison for hydrodynamic solver

2.2. Multivariate Analysis

Traditional optimization methods applied to engineering problems usually employ algorithms designed for global search like derivative-free evolutionary algorithms. In this scenario, genetic algorithms have been successfully employed for decades as standard method for multi-objective non-linear constrained optimization problems. Robustness and capability to find the global optimal solutions are typical characteristics of genetic algorithms, but when the number of design parameters and objectives grows, the number of design evaluations can becomes relatively high. For this purpose, several approaches to speed-up the evaluations count have been proposed, ranging from Response Surface Method (RSM), Design Of Experiments to hybrid methods. In this work, a combination of DOE and MVA is applied.

In this work, a well-known space filling method like the Latin-Hypercube Sampling (LHS) is used to create a uniform sampling of the design space with respect to the range of the input variables considered. LHS is a stratified sampling method which for a given number of points M subdivides the range of the *i-th* input variable in M intervals of equal probability and adds a sample point for every interval. The combination of all the variables partition generates a multi-dimensional hypercube in such a way that every row and column has exactly one sample point. Consequently, a set of M points uniformly distributed across the range of each of the N input variables is generated. The result is an efficient tool which allows the user to have a better understanding on the design space complexity with a limited number of samples.

Inherently coupled to LHS sampling, MVA is a collection of techniques which can be employed to analyze a dataset and find out mutual relationships between variables and designs when dealing with complex multi-dimensional spaces. From among the methods available in MVA, clustering methods are techniques which are designed to group samples with similar characteristics in terms of either input variables or output responses or a combination between the two. K-Means is one of the simplest clustering algorithms to classify a set of sample points through a given K number of clusters specified.

The algorithm is designed in such a way that an iterative process calculates the centers of each cluster by minimizing an objective function defined as follows:

$$\sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_{i,j}-x_{C,j}\right\|^2$$

where $\left\|x_{i,j}-x_{C,j}\right\|^2$ is a chosen distance measure between a data point $x_{i,j}$ and the cluster centre $x_{C,j}$ and is an indicator of the distance of the n data points from their respective k cluster centers.

The approach proposed in this work consists of an initial LHS run to create a dataset having uniform probability distribution for each variable considered as well as a good coverage of the design space. Subsequently, a clustering analysis is performed, and the most favorable cluster in the design space is identified and characterized in terms of design variables values. Next, a second LHS run is carried out by restricting the search area to the actual limits of the range of the design variables for the cluster selected. Finally, a K-Means clustering is applied to the optimal group of designs in order to perform a local sensitivity analysis to quantify the effect of each input variable on the variation of the output responses. The main advantage of the method presented in this paper with respect to other traditional methods is the reduction of the number of design evaluations required, as the optimization search focuses on the area of the design space where the probability to find an optimal solution is higher.

3. Application case: ship hull hydrodynamics

The application case presented in this work consists of the shape optimization of the geometry of the bare-hull of a passenger vessel, Fig.3, provided by the FINCANTIERI Italian shipyards.

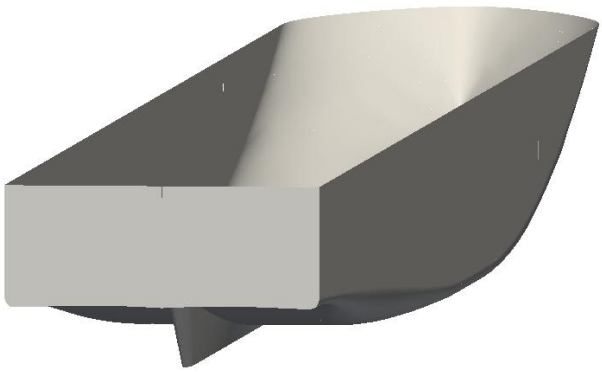

Fig. 3: FINCANTIERI bare-hull geometrical model

3.1. Parametric geometrical model

A parametric geometrical model based on morphing surfaces applied to the baseline geometry is built and a total of 21 design parameters driving the shape of the bulbous bow are identified. An automated process required by the optimization loop is setup to create different geometrical shapes based on the values of the design parameters defining the shape of the original model. A couple of different sample geometries automatically generated during the optimization run are shown in Fig.4, in which the baseline geometry is highlighted in red color.

Geometrical constraints are imposed to the minimum vertical coordinate allowed for the hull geometry, as well as to the total length of the ship. For this purpose, a preliminary study is carried out to set up a robust and efficient parameterization approach by carefully evaluating which geometrical parameters to vary and which to keep fixed to avoid unfeasible solutions in terms of geometrical requirements.

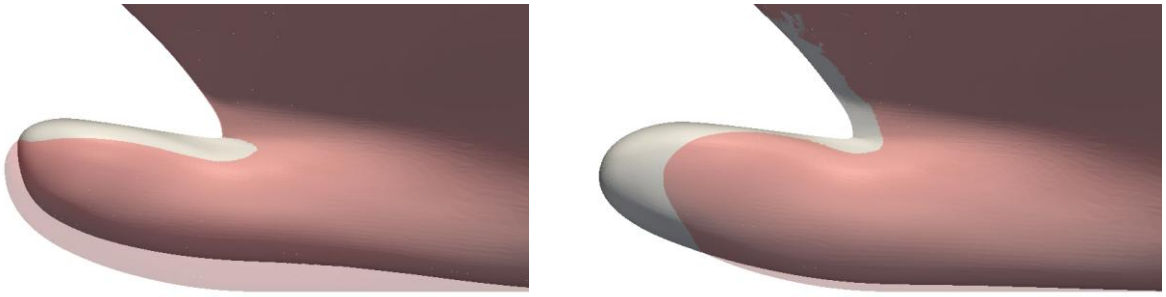

Fig. 4: Different geometrical shapes automatically created

3.2. CFD model setup

A hex-dominant mesh of 500,000 cells with five near-wall extrusion layers is created using an enhanced version of the snappyHexMesh grid generator available in OPENFOAM®. In addition to the coverage of the boundary layer with extrusion layers, the grid generator employed accurately resolves all the feature edges created by the intersection between the water free-surface and the ship hull. The mesh features are shown in Fig.5.

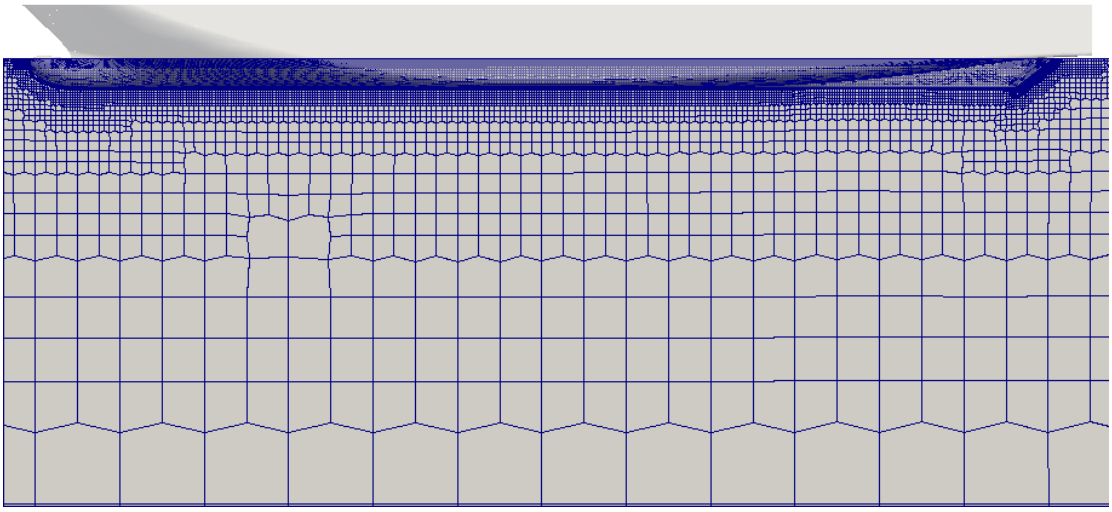

Fig. 5: Overview of the mesh for the CFD simulation

Different speeds are considered to evaluate the performance of the hull measured in terms of total resistance coefficient, ranging from a Froude number of 0.15 to 0.40. In this work, Froude numbers 0.15, 0.25 and 0.30 are selected as characteristic speeds to define the total resistance coefficient. Fig. 6 shows the computed free-surface wave pattern and the streamwise velocity contour plot for a cross-section near the stern.

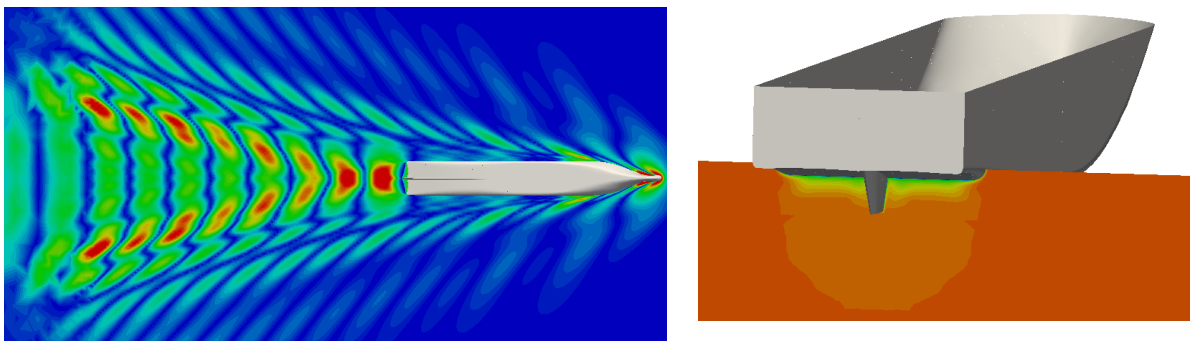

Fig. 6: Free-surface elevation (left) and streamwise velocity (right)

3.3. Initial exploration of the design space

The design objectives of the optimization study described in this paper are the minimization of the total resistance coefficient (defined in terms of viscous and pressure including wave-making components) while maintaining a fixed displacement of the ship. For this purpose, three design goals are defined to minimize the flow resistance at three different speeds. In addition, since the parameterization approach used for the hull geometry cannot handle automatic definition of geometrical parameters to keep the hull displacement always fixed regardless of the different shapes generated, a design constraint is added to the optimization problem. Such a constraint simply applies a penalization to the design objectives proportional to the difference between the actual and target displacement values.

A dataset with one hundred samples is created using a LHS technique available from the Open Source software DAKOTA. Linear correlation among the input variables is deemed sufficiently low and acceptable in terms of quality of sampling. Furthermore, it is also possible to perform a sensitivity analysis and detect global correlations between input and output variables regardless of the high number of design parameters considered. The correlation matrix calculated for the dataset is shown in Fig.7.

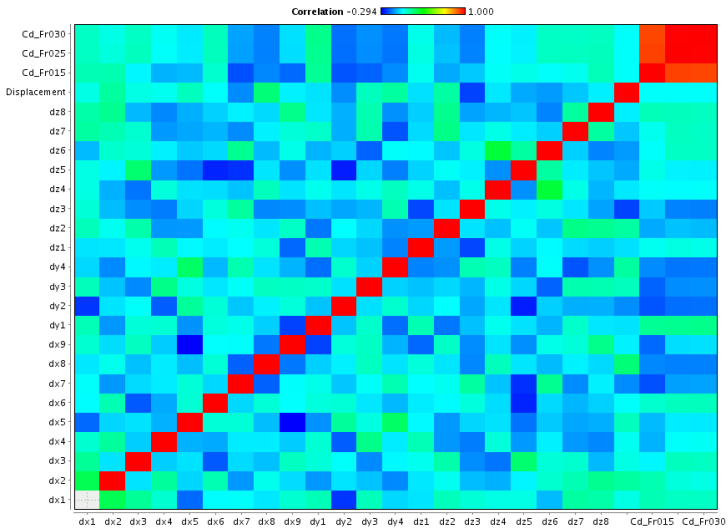

Fig. 7: Correlation matrix of the input variables and outputs on the initial dataset

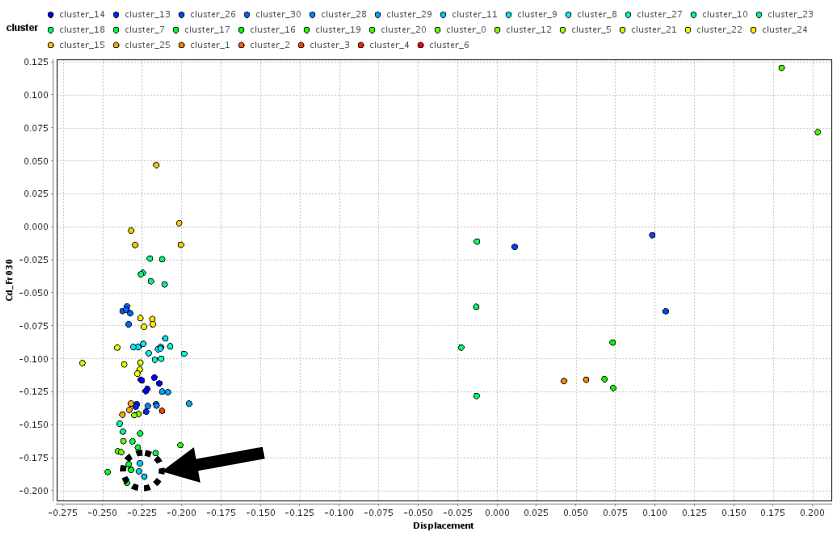

Fig. 8: Flow resistance at Fr=0.30 vs. displacement (normalized values) with clustering applied

The most important achievement of the LHS uniform sampling is a complete characterization of the design space with the smallest number of points, as required when creating an efficient partition of the designs in different clusters. Thus, a subdivision of the space using the K-Means method is applied by specifying ship displacement and total resistance coefficients for the three speeds considered as attributes for the clustering tool. Consequently, 32 clusters are identified and an optimal cluster of solutions having a displacement value close to the baseline model but with improved performance in terms of total resistance is selected. Fig.8 shows the designs belonging to the optimal cluster labeled "cluster_11" and highlighted by a dashed line.

3.4. Final run

The range of the design variables is restricted according to the actual bounds of the optimal cluster selected and a subsequent LHS run is carried out resulting in the calculation of 50 additional design solutions. Fig.9 shows the results displayed in terms of ship displacement and total resistance coefficient at Fr=0.30. The solution obtained in the second LHS sampling considerably improves the existing baseline solution.

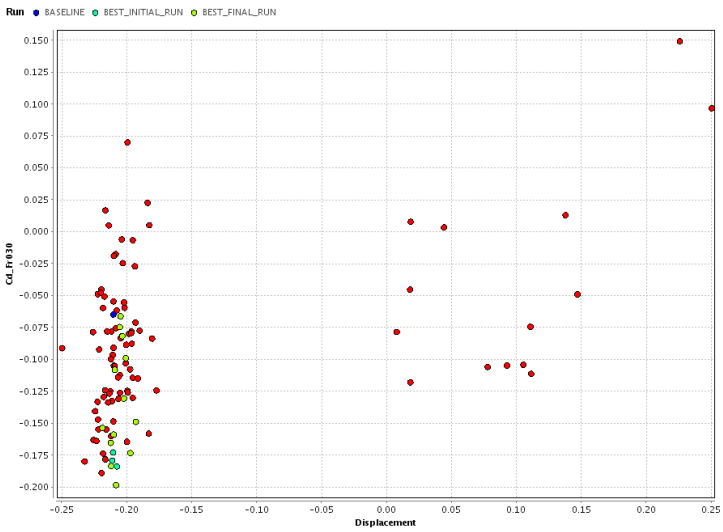

Fig. 9: Final results: flow resistance at Fr=0.30 vs. displacement (normalized values)

3.5. Selection of the optimal solution

The final step of the methodology described in this paper consists of the selection of the optimal solution and the analysis of the design space response. For this purpose, a subsequent clustering using the K-Means method is applied to the set of the optimal solutions composed of the optimal cluster identified in the first run assembled with the optimal solutions obtained in the second run. Therefore it is possible to group the solutions obtained in different clusters and detect the local correlations existing between design variables and design objectives. Each cluster represents a candidate solution for the optimization problem and two clusters are identified from the dataset as shown in the parallel coordinates chart of Fig.10 where solely the most influential input variables for the design objectives are displayed in the vertical axes. For each of the two clusters considered, the thick line represents the mean value for each variable, whereas the bandwidth is proportional to the standard deviation of the variable itself. Each arrow represents the way the solution changes when moving from one cluster to another. In this particular case, if the user wants to select a solution having low total resistance coefficients, a low displacement value is expected as well. Vice versa, if the designer wants to increase displacement, total resistance coefficient must be increased. Most importantly, when moving from the cluster with highest displacement to the cluster with lowest total resistance, the user understands that dx8, dy1 and dy2 are to be increased, whereas dy4 and dz8 are to be decreased.

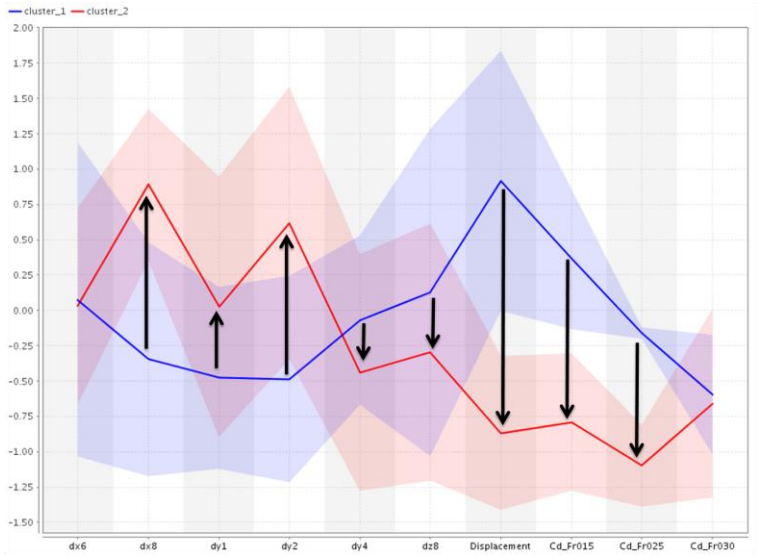

Fig. 10: Parallel coordinates chart for the optimal solutions with clustering applied

Consequently, the designer can quantify local correlations existing within the set of the optimal solutions and thus is able to understand the main reasons why one solution has a different behavior with respect to another one by simply looking at the parallel coordinates chart of Fig.10. The indications about local correlation given by the parallel coordinates chart are in line with the correlation matrix calculated for the set of the optimal solutions displayed in Fig.11.

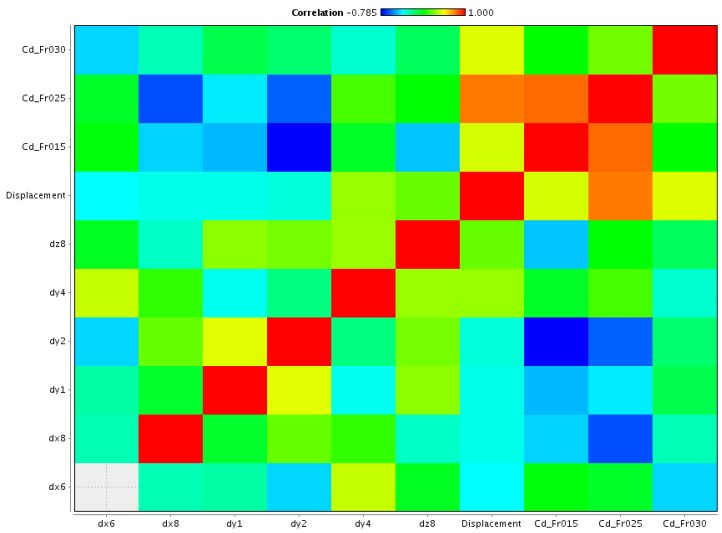

Fig. 11: Local correlation in the optimal solutions dataset

The results of a candidate optimal solution selected from the final dataset are compared to the baseline shape. Table I highlights the improvements obtained in terms of flow resistance at high speeds at an expense of a small increase of resistance for low Froude numbers while keeping almost constant the displacement value.

Table I: Results of the optimization study (normalized values)

	Displacement	Total Resistance Coefficients [delta %]		
		Froude number 0.15	Froude number 0.25	Froude number 0.30
Baseline	-	-	-	-
Optimal Solution	-0.001%	+2%	-3%	-6%

4. Conclusions

The proposed RANSE solver with free-surface effect to predict flow resistance coupled to MVA methods allowed a fast optimization run compatible with the more and demanding timings required by the initial phase of ship hull design process. Using the proposed approach, the optimal solution can be retrieved with far fewer evaluations with respect to the traditional methods, thus saving considerable amount of computational time such that it is possible to use high-fidelity CFD simulations. Finally, the application of MVA methods allows the designer to have a better insight into the design space, which becomes crucial in the decision-making phase of the design process.

References

ADAMS, B.M.; BOHNHOFF, W.J.; DALBEY, K.R.; EDDY, J.P.; ELDRED, M.S.; GAY, D.M.; HASKELL, K.; HOUGH, P.D.; SWILER, L.P. (2010), *DAKOTA, A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 5.0 User's Manual*, Sandia Technical Report SAND2010-2183, December 2009. Updated December 2010 - Version 5.1

EDWARDS, A.L. (1976), *The correlation coefficient*, in An Introduction to Linear Regression and Correlation, W. H. Freeman, pp.33-46

GIUNTA, A.A. (2002), *Use of data sampling, surrogate models, and numerical optimization in engineering design*, 40th AIAA Aerospace Sciences Meeting and Exhibit, Reno

KAUFMAN, L.; ROUSSEEUW, P.J. (1990), *Finding Groups in Data: An Introduction to Cluster Analysis*, Wiley

MARCO, N.; LANTERI, S.; DESIDERI, J.A.; PÉRIAUX, J. (1999), *Evolutionary Algorithms in Engineering and Computer Science*, Wiley, Chapter 22, pp.445-456

McKAY, M.D.; CONOVER, W.J.; BECKMAN, R.J. (1979), *A comparison of three methods for selecting values of input variables in the analysis of output from a computer code*, from Latin Hypercube Sampling, Technometrics 21(2), pp. 239-245